Investigating Group Threat's Role in the Relationship Between Attitudes Towards Black People and State-Level Punitiveness

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Chapter 1: Introduction to Punitiveness and Group Threat Theory

This thesis is about understanding the relationship between group threat and punitiveness at the state level. In Chapter 1, I begin by giving an account of the history of racialized mass incarceration and how it's been especially harmful for the Black community. Then, I discuss group threat theory and how it relates to White people's attitudes concerning Black people and states' levels of punitiveness. In Chapter 2, I attempt to understand the motivation for White voters who support punitive policies by looking at how group threat impacts White voters' attitudes towards Black people as well as their attitudes towards police at the individual-level. In Chapter 3, I replicate and extend a paper that provides a way of measuring punitiveness across different dimensions, and then I look at how ethno-racial demography and White people's attitudes concerning Black people may work together to predict state-level punitiveness.

The Costs of Racialized Mass Incarceration

As readers may know, mass incarceration grew dramatically in the later part of the twentieth century. From 1980 to 2000, "the number of people incarcerated in our nation's prisons and jails soared from roughly 300,000 to more than 2 million" (Alexander, 2020, p. 60). The Black community bears the brunt of the consequences of mass incarceration because they are disproportionately targeted by the criminal justice system's policies and practices. According to Western, "Drug arrests rates escalated in the 1980s…much faster for blacks than whites," and, further highlighting just how disparate criminal justice outcomes were, "At the peak of racial disparity, African Americans were eight times more likely to be incarcerated than whites" (2018, pp. 157-158).

The consequences of mass incarceration are far-reaching and insidious. Bruce Western has found that consequences of the racial oppression have become so pronounced that an entire "generation of black men carry the stigma of a prison record that limits their social and economic opportunities," and keeps these Black men working "minimum-wage jobs" while also being overwhelmed by "economic security" (2018, p. 158).

Western emphasizes that, at the most basic level, mass incarceration impacts individuals in that "multiple disadvantages—untreated mental illness, addiction, poor physical health, housing insecurity—accumulate among people involved in the criminal justice system" (2018, p. 176). People with conditions and experiences that made them vulnerable prior to entering prison end up leaving prison with their preexisting conditions exacerbated—as well as with the possible addition of new vulnerabilities.

Due to the highly regimented nature of prison life, leaving prison can also be overwhelming for people because they have to go back to living a life that is full of people, noises, and choices (Western, 2018). Prison life itself is stressful due to the violence and constant "possibility of beatings, stabbings, and retaliation;" however, leaving prison wasn't enough to escape the consequences of incarceration because people still find themselves overwhelmed with "panic, depression, loneliness, and the unfamiliarity of free society" (Western, 2018, pp. 28 & 177).

Moreover, beyond the individuals most directly impacted, mass incarceration harms the families those individuals come from because it introduces separation, instability, and a number of legal and financial obligations that pose considerable burdens for those already living in poverty. Studies show that children tend to have worse school grades, mental health, and economic outcomes when one or both parents are incarcerated (Morsy & Rothstein, 2016). A parent spending extended periods of time in prison introduces instability and stress into the children's lives because suddenly there is only one parent providing financial support for the household.

And finally, beyond both the individuals and their families, mass incarceration has huge implications for the communities that people are disproportionately taken from. One of the consequences that mass incarceration can have on the community is worse labor market outcomes. On the one hand, a large number of men being removed from low-income Black communities results in the families within those communities struggling and "Roberts (2004, p. 1294) points out that "the spatial concentration of incarceration . . . impedes access to jobs for youth in those communities because it decreases the pool of men who can serve as their mentors and their links to the working world . . . generating employment discrimination against entire neighborhoods." (Roberts, 2004, p. 1294 as cited in Clear, 2008, p. 115).

When considering the full context of mass incarceration—the most accurate estimate of the number of people that have been harmed by the criminal justice system—it's crucial to take into account the people who have been incarcerated at some point in their lives and the people who are adjacent to the criminal justice system. While there are about 1.9 million people currently incarcerated, "there are another 822,000 people on parole and…2.9 million people on probation" (Sawyer & Wagner, 2022). Overall, at least 79 million people in the United States have a criminal record and 113 million adults are related to someone that has been incarcerated (Sawyer & Wagner, 2022). Plus, about 34% of people in state prison have spent time in juvenile detention centers, with 76% of Black people in state prison having previously served time as juveniles (Wang et al., 2022).

Scholars have found that mass incarceration disproportionately thrusts people from low-income marginalized communities into "cycles of arrest, incarceration, and supervision," which results in a system that effectively exacerbates the disadvantage that people from these communities already faced—particularly those from Black communities (Wang et al., 2022).

Ultimately, the criminal justice system has devastating effects on everyone that gets ensnared—on the people directly tied to the criminal justice system and everyone that those people are socially tied to; therefore, it's essential that we try to better understand the factors that contributed to the expansion of the carceral state.

A Sociological Sketch of the History of Racialized Mass Incarceration

Since the beginning of American colonization, there have been considerable efforts made to enforce racial hierarchies and exert social control, and these efforts have included slavery, genocide, and indentured servitude among others. As Michelle Alexander puts it, since the very beginning of the United States, "African Americans repeatedly have been controlled through institutions such as slavery and Jim Crow, which appear to die but then are reborn…tailored to the needs and constraints of the time" (2020, p. 27).

It is commonly thought that mass incarceration started in the 1970s, likely as a response to the Civil Rights Movement—during the period of early 1950s to late 1960s—when it became apparent that "the old caste system was crumbling" as Black people mobilized alongside White people to protest the segregation, discrimination, and disenfranchisement they faced (Alexander, 2020, pp. 27-28). With "the emergence of each new system of control," there are seeds that "are planted long before each new institution begins to grow," and, in the case of mass incarceration, it was a matter of public attention gradually transitioning from focusing on civil rights to the criminal justice system because there was an increase in the "national crime rate" and "civil rights were being identified as a threat to law and order" (Alexander, 2020, pp. 27 & 51). In the thesis below, I will try to add to this by using and testing theories of group threat to deal with some might consider the implicit functionalism in this account.

Michelle Alexander goes on to theorize that, when Dr. Martin Luther King, Jr. was assassinated, riots followed, which only made things worse as "the racial imagery associated with the riots gave fuel to the argument that civil rights for blacks led to rampant crime," and politicians immediately leapt at the opportunity to "[exploit] the riots and fear of Black crime" in their presidential campaigns (2020, p. 52). Katherine Beckett adds that, in order to criminalize the act of protesting, "southern officials called for a crackdown on the 'hoodlums,' 'agitators,' 'street mobs,' and 'lawbreakers' who challenged segregation and black disenfranchisement," which effectively characterized Black communities as being inherently criminal (1997, p. 30).

Patrick Sharkey enters the discussion here, as he says that, a little later on, "young Black men" became "most closely linked with" the increase in "lethal violent crime" in the minds of popular commentators in the media and in the minds of the voting public (2018, p. 3). Sharkey goes on to add that many people started to spread the idea that the young teenagers were to blame. One of the most influential and persistent voices was political scientist John DiIulio had a lot to do with the changing perceptions on who commits crime—and the increase in threatening racial imagery overall—as he "diagnosed problem of violence as a moral crisis and pointed to a new form of impulsive, remorseless youth criminal," and these youth were "impulsive, brutally remorseless youngsters…who murder, assault, rape, rob, burglarize, deal deadly drugs, join gun-toting gangs and create serious communal disorders" (DiIulio as cited in Sharkey, 2018, p. 3).

Michelle Alexander, Katherine Beckett, and Patrick Sharkey are just a few of the researchers who argue that imagery proved to be especially significant to the beginning of mass incarceration and its continuance today—the narratives that were told about the Black community stoked the public's fear and gave voters reason to support the politicians who advocated for punitive policies.

Patrick Sharkey helps us to see that narratives continued to play a critical role in how mass incarceration evolved, especially where the War on Poverty and the War on Drugs were concerned. The War on Poverty began with President Lyndon B. Johnson's administration in the 1960s. Moreover, beginning with President Johnson, there were a series of various legislation passed that increased the presence of police on the streets within predominantly poor Black communities and increased the penalties for different types of crime—especially the crimes associated with Black people, like in the crack-cocaine sentencing disparities (2020). These federal changes resulted in a wave of legislation being passed by the states to increase the punitiveness of their own criminal justice systems.

At first, Sharkey says, there was interest in understanding how the causes of the rampant poverty within urban settings might be associated with "inequality and injustice" (2018, p. 127). This interest was, in part, caused by the "Kerner Commission report," which was "an unflinching acknowledgment of racism in America" that "blamed white Americans for urban unrest and implicitly suggested that the president's major legislative achievements, the programs that composed the War on Poverty, had failed to address the crisis in the nation's cities" (Sharkey, 2018, pp. 122-125).

However, Sharkey discusses how another narrative began to take over gradually, and the urban crisis ended up being attributed to "growing lawlessness and disorder" (Sharkey, 2018, pp. 128). Suddenly, the "solution to the problem did not involve uncovering the root causes of poverty, expanding civil rights, or fighting injustices," rather it "was to support the police, both with expanded resources and with a call for deference and respect" (Sharkey, 2018, p. 123). This shift in narrative led to a decrease in the "federal resources for urban neighborhoods," and there was a “forceful takeover of the ghetto by the police” as well as the development of “an increasingly punitive criminal justice system” (Sharkey, 2018, p. 129).

Additionally, according to scholars, throughout all of this, politicians became more concerned with differentiating between the worthy and the unworthy poor, and people started to “[attribute] poverty at least in part to the characteristics and lifestyle choices of the poor” (Beckett, 1997, p. 33). Beckett emphasizes that, while criticizing crime, politicians declared that the expansion of the welfare state was behind the increase in crime, thereby making “images of (nonwhite) ‘welfare cheats’ and their dangerous offspring…staples of American political discourse” (Beckett, 1997, p. 36). Scholars like Michelle Alexander highlight how conflating moral characteristics, Black people, and poverty proved to be an effective way of decreasing public support for welfare in different states, and conservative politicians made sure to characterize the issue of welfare as being “a contest between hardworking, blue-collar whites and poor blacks who refused to work” (Alexander, 2020, p. 60).

Later, the War on Drugs began with Reagan’s Administration in the 1980s. When the war was declared, “fewer than 2% of those polled identified drugs as the nation’s most important problem,” indicating that the War on Drugs wasn’t started because there was any public concern about drug usage (Beckett, 1997, p. 25). However, once politicians had already sown the seed and the matter became more publicized, people became more invested. This, of course, does not justify the country’s response to these issues, which were clearly influenced by racial prejudice and discriminatory beliefs in general.

Michelle Alexander emphasizes that racializing drug users and drug dealers helped garner support for increasingly punitive drug legislation and this eventually led to policies passing that formally introduced sentencing disparities in crack and cocaine sentencing and required harsh penalties for crimes involving marijuana (2020).

While there was certainly violent crime happening during this time that was associated with drugs, Sharkey, in describing what the US needs to address urban inequality and violent crime, says the US does not need "a war on crime that is waged through the police and the prison," nor "a war on drugs that is waged through feel-good public service announcements and brutal enforcement on the streets," because the fear-mongering and racialization of crime have ultimately caused more harm than good—and scholars like Monica Bell (2017) would certainly concur (Sharkey, 2018, p. 184).

The Role of Punitiveness in Mass Incarceration

To begin with, research suggests that two of the most important factors leading to mass incarceration are the War on Drugs and people being sent to prison for longer amounts of time. According to Alexander, "Convictions for drug offenses are the single most important cause of the explosion in incarceration rates…Drug offenses alone account for…more than half of the rise in state prisoners between 1985 and 2000" (2020, p. 60). During the War on Drugs, the criminal justice system focused on pursuing drug arrests and establishing harsh legal penalties for drug offenses, which ended up causing a lot of people to be sent to prison for low-level drug offenses.

In addition to the War on Drugs, another factor that played a huge role in bringing about the era of mass incarceration is "the adoption of punitive sentencing laws," which meant that "more people who are arrested are ending up in prison or jail, and the people who are sent to prison have been staying there for longer periods of time" (Beckett, 2018, pp. 249 & 253). The increase in the amount of time that people were spending in prison can be attributed to "the exercise of prosecutorial discretion and changes to sentencing policy" (Beckett, 2018, p. 249). Examples of the punitive policies that were passed include mandatory minimum sentences, three strikes sentencing laws, and truth-in-sentencing laws—all of these sentencing policies increased the amount of time that people had to spend in prison.

Mandatory minimum sentences forced "judges to impose a sentence of a term of imprisonment of at least the time specified in a statute," and they were typically "triggered by the offense of conviction and/or the defendant's recidivism" (Lidhu, 2023, p. 1). Three strikes laws "ratcheted up penalties for subsequent convictions," which meant that people were being automatically sentenced to longer periods of time in prison if they'd been previously convicted of certain offenses (Urban Institute, para. 19). Truth-in-sentencing laws were a part of the "wave of legislation in the 1980s and '90s…[that] limited or eliminated…'good time' or 'earned time' credits" (Urban Institute, para. 26). In addition to these policies, people were also kept in prison for longer periods of time due to the "popularity of life without parole sentences [exploding] as states sought alternatives to capital punishment," which had been "temporarily banned" by the Supreme Court "in 1972" (Urban Institute, para. 45).

In this thesis, I attempt to understand why voters support punitive policies and practices—especially when the harm they've caused has been well-documented. One theory that appears to be very plausible is group threat. Group threat says that dominant groups, when they feel threatened, will use discriminatory policies and practices to assert and enforce power over minority groups. In the empirical chapters of this thesis, I explore several implications of this theory as I try to better understand the motivations of voters who supported racialized mass incarceration. In the next section, I will explain the basics of theories of group threat.

Group Threat Theory

When attempting to determine what makes certain states more punitive than others, it is helpful to focus on theories that explain why members of certain groups push for policies and practices that are blatantly discriminatory and oppressive against members of other groups. The focus of this thesis, ultimately, will be how group threat theory, specifically in the form of racial threat theory, fits into the story of increased punitiveness at the state level.

The foundations of group threat theory are founded in the work of classical sociologists Herbert Blumer (1958) and W.E.B. Dubois (2007[1935]). Blalock developed these ideas and helps us to better understand the dynamics coloring the interactions between the Black and White communities—he, specifically, theorizes possible causes for discriminatory behavior against Black people (1967). With the racial threat hypothesis, the idea is that the size of the Black community and movement of Black people into communities dominated by White people results in White people feeling threatened, which leads to purposeful actions being taken to exert social control over Black people (Blalock, 1967). Then, racial disparities and inequalities arise due to the discriminatory practices and policies that were implemented as a form of social control.

There are three forms of racial threat: economic, political, and symbolic. The two most applicable to this paper are economic racial threat and political racial threat. With economic racial threat, "we would expect to find increasing discriminatory behavior" when the "minority percentage increases" because of insecurity about the availability of different economic resources, especially jobs (Blalock, 1967, pp. 148). Historically speaking, economic racial threat can be seen in how "poor Whites in the South" went on to "regulate Negro competition…by…political action and intimidation" when more Black people entered the labor market and began to compete for the low-wage jobs because of the fear of economic competition (Blalock, 1967, p. 150).

On the other hand, political racial threat is more concerned with “limiting minority mobilization,” through attempts “to restrict Negro registration” because, otherwise, Black people would have a sizable amount of political influence, which would be a threat to the maintenance of the status quo (Blalock, 1967, p. 162). There is the fear that “the minority might gain political dominance” (Blalock, 1967, p. 29). Many states impose voting restrictions on those who have felony convictions, and, “Among the adult African American population, 5.3 percent is disenfranchised compared to 1.5 percent of the adult non-African American population” (Uggen et al., 2022, p. 2). Furthermore, “the sharp increase in African-American imprisonment goes hand-in-hand with changes in voting laws” (Behrens et al., 2003, p. 598).

Following Blalock, other researchers have helped flesh out the racial threat theory in a variety of ways. Researchers looking at criminal sentencing disparities between Black, White, and Latino populations in Florida discovered that there is an especially prominent racial disparity in prison sentencing “in places that experienced greater Black population growth” (Feldmeyer et al., 2015, p. 81). Black defendants are likelier to “receive longer sentences in places with growing Black populations,” and this poses an issue in the context of mass incarceration because one of the main reasons for the prison boom is the increased amount of time that people are spending in prison (Feldmeyer et al., 2015, p. 83; King & Wheelock, 2007).

Putting the Pieces Together

According to this thesis, group threat is essential to the story of increased punitiveness. Group threat theory overall suggests that dominant groups push for discriminatory policies in order to address their own feelings of being threatened. Per this theory, both the minority group size and changes in the minority group size can trigger the dominant group to feel threatened—in my empirical chapters, I will focus on the overall minority group size.

As we have seen, Michelle Alexander, Patrick Sharkey, Bruce Western, and others have developed historical and sociological accounts of mass incarceration that emphasize the role of longer sentences, over-policing, and punitive policies during the age when politicians advocated for the War on Drugs and criminal justice policies and practices that were seen as “tough on crime”. These authors not only illustrated the criminal justice system’s role in mass incarceration, but they also discussed the role of the White voters that supported the increased punitiveness of the criminal justice system.

White people, knowingly or unknowingly, vote for punitive criminal justice policies and practices that disproportionately harm Black people. According to this narrative, they continue to support these policies, even though everyone ultimately suffers from mass incarceration, because of the irrational fear that the Black community needs to be controlled.

According to my theory, shifting ethnoracial demographics change the preferences of voters. I presume that white voters feel threatened because they fear the loss of power. In response to the shifting ethnoracial demographics, it is not that they just become more "prejudiced" but that they might (a) feel less warmth towards Black neighbors/society members and/or (b) feel "racial resentment," which involves thinking that Black people are getting better treatment than they deserve. Then, there might be an increase in the support for the policies and receptiveness to racist politicians overall, which then results in more legislation being passed that reflects the attitudes of White people towards Black people. White individuals in states with more Black people are likelier to feel less warmth towards Black people and potentially more racial resentment than White individuals in states with less Black people—this is reflected in the legislation because the majority of White voters in these states either push for more stringent legislation or they simply decide to remain indifferent to the harm being done to Black people through the criminal justice system.

These attitudes, aggregated, would likely correlate with varying punitiveness at the state-level—states with more Black people are more punitive than states with less Black people because the carceral system is being used as a means of control.

In recent years, several scholars have made similar arguments. Punitiveness has been increasing over time through White people's irrational perceptions regarding the threat that Black people pose economically and politically. A desire for harsher and more punitive policies is stoked by the desire to exert social control over Black people, when Black people are believed to be a threat in some way, even if that isn't actually the case—in the labor market, politics, etc. (Bobo & Hutchings, 1996). In fact, according to some researchers, "the perception that African Americans are a strain on material resources, more so than perceptions of African Americans as threats to public safety, is a particularly salient predictor of punitiveness," and White people are predominantly concerned with "managing those perceived as menacing material resources" in the form of jobs and welfare. (King & Wheelock, 2007, p. 1272).

Looking Ahead to the Empirical Chapters Below

In the second chapter of this thesis, I work with American National Election Study data, across multiple years, and joined with American Community Survey and Decennial Census data about state and congressional-district-level demographics, to answer the following question: What are the motivations for voters who support punitive policies? As discussed in the previous section, sociological scholars have proposed group threat as a possible answer to this question. I consider the possibilities that group threat's impact on punitiveness works through impacts on white voters warmth towards Black neighbors as well as through racial resentment.

I include the variable *feeling thermometer for policemen* as a proxy for measuring attitudes concerning police, which might give us some idea of their feelings regarding the criminal justice system.

At the end of Chapter 3, I build on the results of Chapter 2 by aggregating White people's feelings regarding Black people to see how that predicts different dimensions of punitiveness at the state-level. In order to create the measure for punitiveness, I combined data from many different sources. Afterwards, I run a series of regressions to see whether percent Black residents predicts higher punitiveness, as my theory would suggest.

I examined how warmth toward the Black population and racial resentment are impacted by proportion of Black residents. I tested these hypotheses at the individual-level and included demographic data for the state-level and district-level.

Breakdown of Hypotheses:

H1 – Net of appropriate controls, White individuals in places with larger black populations will feel less warmth towards Black people than those places states with smaller Black populations. In order for feelings of group threat to activate, there has to be the belief that the minority group is likely to topple the superiority of the dominant group. It's logical to assume then that places with higher proportions of Black residents would also have higher levels of group threat because White people are seeing more Black people in the spaces that they occupy, which might result in White people feeling less warmth towards Black.

H2 – Net of appropriate controls, White individuals in places with larger Black populations will have higher racial resentment levels than those in places with smaller Black populations. Group threat theory indicates that group threat varies with the size, or visibility, of the minority population, so it would then follow that White individuals would feel more racial resentment in places with larger Black populations because they feel a greater sense of group threat than White individuals in states with fewer Black people.

H3 - Net of appropriate controls, White individuals in places with larger Black populations will feel more warmth for police officers than those in places with smaller Black populations. If, in accordance with group threat theory, punitive policies and practices are understood to primarily target Black populations, then it would make sense that White respondents would feel more warmth towards the police when they are in places with larger Black populations.

After exploring how group threat might explain what causes White voters to become more hostile and resentful concerning the Black population at the local level, I move onto looking at how group threat might explain punitiveness at the state-level in Chapter 3.

Measuring Punitiveness Through Replicating and Extending a Study

Background of the Measure of Punitiveness Used

In the third chapter of this paper, I build on a replication (described in Appendix B) of the study "Explaining dimensions of state-level punitiveness in the United States: The roles of social, economic, and cultural factors," by Katharine A. Neill, Juita-Elena (Wie) Yusuf, and John C. Morris, where they examine social, economic, and cultural factors to determine why there has been an increase in state punitiveness over time and understand the differences in the types of punitiveness of different states over time. In the 2015 study by Neill et al., the researchers use the measure for punitiveness that was first developed by Kutateladze in 2008. This thesis actually combines elements of both studies due to the abundance of information as to the specifics of the measure for punitiveness developed by Kutateladze in 2008 and the inclusion of various social, economic, and cultural factors as ways of understanding trends in state punitiveness by Neill et al., in 2015.

In Chapter 3, I focus on describing how I extended the study by expanding the range of years included within it. I discuss those results before then aggregating individual-level ANES attitude variables to understand the impact of White voters' attitudes towards Black people on punitiveness—and to connect Chapters 2 and 3. However, in Appendixes A and B, I go into more detail about the whole process of the replication—what Kutateladze and Neill et al. got for their results and what results I got once I'd replicated the study (2008 & 2015).

Breakdown of Hypotheses:

H4 — Net of appropriate controls, states with larger Black populations are likelier to be more punitive across all of the dimensions. Understanding increased punitiveness as correlating with higher levels of group threat leads me to think that states with larger Black populations would be more punitive than states with smaller Black populations because White people are seeing more Black people in the spaces that they occupy—resulting in more of a sense of the need for some way of controlling the Black population.

H5a – Net of appropriate controls, White voters' racial resentment towards Black people mediates the relationship between percent Black and punitiveness. It is logical to assume that Percent Black is important to the story of increased punitiveness in certain states through the racial resentment felt by voters.

H5b – Net of appropriate controls, White voters' warmth towards Black people mediates the relationship between percent Black and punitiveness. Similarly to the previous hypothesis, I think Percent Black influences state-level punitiveness through the warmth (or lack thereof) felt towards Black people. Feeling less warmth would make one likelier to sit aside while injustices are being committed against Black people through criminal justice policies and practices—and one would be less likely to feel warmth towards Black people in states where there are a larger amount of Black residents.

I proceed with these plans in the next two chapters of the thesis beginning with fuller discussion of my methods and working through results as well as parsing out the implications of those results.

Chapter 2: Group Threat in the Context of White Voters' Attitudes

In the previous chapter, I discussed group threat theory and how I believe it fits into the story of the increased punitiveness at the state-level that has fueled mass incarceration. In this chapter, I will work with ANES data to investigate how the proportion of Black residents at the state-level predicts individual-level attitudes towards Black people generally. Then, I look at how the proportion of Black residents at the congressional district-level impacts individual-level attitudes. Afterwards, in the next chapter, I connect this to state-level policies and differences in their levels of punitiveness.

Methods

To begin with, I'm interested in understanding what individual- and state-level characteristics influence people's level of racial resentment and overall feelings towards Black people. Specifically, I am looking at how changing racial demographics at the state level impact voters' (particularly White voters) attitudes towards Black people at the individual level—while also controlling for individual level characteristics that would likely exert an impact on respondents' answers.

I worked with the American National Election Studies (ANES) survey data, which "is the oldest continuous series of survey data investigating electoral behavior and attitudes in the United States" (https://www.icpsr.umich.edu/web/ICPSR/series/3). I specifically gathered data from the following years: 1990, 2000, 2008, and 2016.

I believe that at the individual level, group threat should work through a decrease or absence in warmth or sympathy in White people towards Black people or through an increase in racial resentment as the proportion of Black residents increases.

Additionally, I use a variable measuring warmth towards police as a loose proxy for views about criminal justice policy more generally. Below, I go into more depth about my focal

Y variables, focal X variables, and the variables I used as controls. In addition to carrying out my analyses with state-level demographic variables, I also run the same regressions but with district-level demographic variables to get more of a sense of how using more local data would impact our findings regarding the impact of Percent Black and other variables on White voters' attitudes towards Black people.

Focal Y Variables

To begin with, there are three focal Y variables: Thermometer —Blacks, Racial Resentment, and Thermometer — Police.

Thermometer – Blacks

I use the Thermometer – Blacks ANES item to measure respondents' warmth or indifference to Black people. On ANES, the question was a part of a series of feeling thermometer questions where the interviewers asked respondents to rate how "favorably and warm" they feel towards certain groups (American National Election Studies, 2021, p. 91). This thermometer helps me to determine the level of warmth that White respondents normally have towards Black people versus non-White respondents and observe whether the size of the Black population impacts the amount of warmth that White individuals feel towards Black people.

Racial Resentment Scale

Following in the footsteps of earlier studies (Kinder & Sanders, 1996; Carmines et al., 2011), I developed a racial resentment scale through consolidating the scores for four separate items from the ANES survey data:

1. "Over the past few years, blacks have gotten less than they deserve."
2. "Irish, Italian, Jews, and many other minorities overcame prejudice and worked their way up. Blacks should do the same without any special favors."

3. "It's really a matter of some people not trying hard enough: if blacks would only try harder they could be just as well off as whites."
4. "Generations of slavery and discrimination have created conditions that make it difficult for blacks to work their way out of the lower class." (Carmines et al., 2011, p. 113; American National Election Studies).

I was able to create the racial resentment index due to all four of these items having the same basic makeup—a scale from 1 to 5 with the addition of 8 and 9, where 1 represented strongly agree, 5 represented strongly disagree, and 8 and 9 represented missing values.[1] I had to change the values for two of the racial policy variables (Blacks could overcome prejudice without any special favors and Blacks must try harder) to ensure that the data all pointed in the same direction, where, as the values increased, racial resentment increased. Originally, for the racial policy variables that I just mentioned, the values indicating the most racial resentment were 1 and 2, while the other two variables (Conditions make it harder for Blacks and Blacks have

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[1] One of the most important ways that ANES data has been used to measure racism is through the racial resentment scale developed by Kinder & Sanders in 1996. Kinder & Sanders used the racial resentment index to measure racial prejudice. However, Carmines et al., later found that "racial resentment does not reflect primarily racial prejudice," and instead, "racial resentment measures primarily racial policy attitudes" (2011, p. 112).

In 2019, Roos et al. had findings that disagreed with the notion that racial resentment and racial policy attitudes are interchangeable; however, Roos et al. had "findings that were consistent with arguments that racial resentment is a primary determinant of white opposition to policies that would attempt to ameliorate racial inequality" (p. 13).

gotten less than deserved) were 4 and 5. I reversed the order of the values for the two with the most racial resentment being represented by 1 and 2 to 4 and 5.

In this thesis, I use the focal Y variable racial resentment to determine the level of racial resentment that White respondents normally have towards Black people versus non-White respondents and to observe whether the size of the Black population impacts the racial resentment that White individuals have towards Black people. In Table 2.1, I present the reliability of the racial resentment index as far as internal consistency.

Table 2.1 Cronbach's Alpha Score for Racial Resentment Index

Level	Cronbach's Alpha	Internal Consistency Rating
Individual	0.9359379	Excellent

Thermometer – Police

And finally, in addition to thermometer and racial resentment, another variable that I analyze as a focal y is Thermometer – Police. As mentioned previously, ANES doesn't really include variables pertaining to voters' perspective on punitiveness. I'm using Thermometer – Police as a sort of loose proxy for punitive preferences. Like with the two other outcomes, I'm interested in determining how much warmth White respondents have towards the police relative to non-White respondents and observing whether that warmth changes with the size of the Black population.

Focal X variables

The focal X variables of this section are White and the interaction term Percent Black * White. White is a dummy variable created from the categorical variable racial-ethnic group summary. 1 represents respondents who identify as being "White" and 0 represents non-White respondents—including "Black," "Hispanic," "Other," and "multiple races." I created the variable White so that I could easily understand how the average White respondent feels about

Black people compared to a respondent who isn't White. I'm specifically interested in group threat as it impacts White voters' behavior and reactions.

The interaction term Percent Black * White can also be considered a focal X variable because it gives us valuable information as to how the effect of identifying as White on attitudes towards Black people and police changes as the Black population size at the state-level increases.

Control variables

In the following regressions, I mainly controlled for variables like employment, gender, party, family income group, education, region, age, percent that graduated high school at the state level, and percent poverty at the state level. For the regressions on Thermometer – Police, I also include violent crime rate and property crime rate measured at the state level.

Employment, gender, party, family income group, education, better off/worse off, and region were all categorical variables; all of the levels except one for each of these variables were coded as dummy variables and the one value not coded as a dummy variable was used as the reference group.

I created the employment variable using the work status variable from ANES. I imputed 1 if "Employed" and a 0 if the respondent was "Not employed," "Retired," a "Homemaker," or a "Student." I included this variable out of the belief that respondents being employed or not employed would definitely have at least some bearing on how threatened they feel by Black residents—as we've heard in political discourse time and time again, especially through the Trump era, there is a constant fear in White voters that "others" will steal their jobs.

Gender is a categorical variable that I've controlled for in case it turns out that attitudes towards Black people are gendered on average. Plus, I wanted to try to account for the possibility that group threat is felt differently by the different genders based on the differing experiences/privileges people have due to their gender. The only categories that ANES had for this variable were Female, Male, and Other, and Female is the reference group.

Party simply represented a respondent's political affiliation, and it was made up of three levels, two of which were automatically encoded as individual dummy variables in the regression model: Democrats (the reference group), independents, and Republicans. A respondent's party is important to control for because their political affiliation would likely correlate with their attitudes towards Black people overall, the amount of racial resentment they have, and their attitudes towards the police. Party is especially crucial in the sense that I believe racial resentment truly does measure White voters' attitudes towards racial policies, and these policies don't always appeal to every party—sometimes they appeal to one more than the others, and that often appears to be the case with Democrats.

Family income group represents the income percentile that a respondent's family is in. This is another categorical variable, and, again, the levels of this variable became dummy variables in the regression: 0 to 16 percentile (the reference category), 17 to 33 percentile, 34 to 67 percentile, 68 to 95 percentile, and 96 to 100 percentile. Income is important to control for because it likely has an impact on how threatened a person might feel—essentially the same reasons I mentioned above in the discussion on the employed variable.

I added education as a covariate, and the levels were grade school, high school, some college, and college. All of these levels but college, which serves as the reference, were turned into separate dummy variables. Education was important to control for as a person's level of education can sometimes influence their attitudes towards people of other races, especially if they go to schools that are majority-White for a good portion of their academic journey.

Better or Worse Off was included because I felt it made sense that individuals' reactions towards Black people would vary based on what they predicted their financial situation would look like the next year. If one is a part of the majority group and feels threatened by Black people to some extent already, which is often the case anyways, then the thought that they might be in a financially insecure position in the next year might heighten those feelings of hostility. The levels for this were "Worse" (the reference), "Same", or "Better.," "Worse," or "Off."

The last categorical variable I'll focus on is region. Region has Northeast, North Central (reference group), South, and West. Including region as a covariate made sense because it allowed me to get more of a spatial understanding of the impact of racial-ethnic composition on different dimensions of punitiveness.

Some of the variables that were measured numerically were age, percent that graduated high school at the state level, percent poverty at the state level, and, in some cases, violent crime rate and property crime rate. I created the percent that graduated high school variable by using Social Explorer's Decennial Census survey variable Educational Attainment for Population 25 Years and Over for years 1990 and 2000. I created the variable again for 2008 and 2016, but this time using Social Explorer's American Community Survey 1-year estimates. Percent poverty at the state level measures the number of families that were living beneath the poverty line, and this was also obtained from the Decennial Census Survey and American Community Survey. Violent crime rate and property crime rate—data I got from the Federal Bureau of Investigation's Uniform Crime Reporting program— were included to account for trends in crime being committed.

Table 2.2 Descriptive Statistics for Categorical Variables (Individual-Level & State-Level Data)

Variable	Description	N	%
Gender	Respondent's gender identity		
Female		5656	0.545
Male		4671	0.450
Other		11	0.001
Party of respondent	Respondent's party affiliation		
Democrats		5206	0.502
Independents		1303	0.126
Republicans		3777	0.364
Respondent family - Income group	Income percentile for respondent's family		
0 to 16 percentile		1655	0.159
17 to 33 percentile		1744	0.168
34 to 67 percentile		3072	0.296
68 to 95 percentile		2726	0.263
96 to 100 percentile		406	0.039
Respondent racial-ethnic group	Dummy variable manually created using the racial-ethnic summary group variable		
White respondent	(includes "White")	7029	0.677
Non-White respondent	(includes "Black," "Hispanic," and "Other or multiple races")	3269	0.315
Respondent - Education			
Grade school		393	0.038
High school		3669	0.354
Some college		3162	0.305
College or advanced degree		3062	0.295
Respondent - Work status	Dummy variable manually created using the work status variable		
Employed	(includes "Employed")	6418	0.618
Not employed	(includes "Not employed," "Retired," "Homemaker," and "Student")	3928	0.378
Census Region	Respondent's region		
Northeast		1657	0.160
North Central		2366	0.228
South		4078	0.393
West		2278	0.219
Better or worse off in next year	Variable capturing whether respondents believe their financial situation would be better or worse in the next year		
Better		3599	0.347
Same		5083	0.490
Worse		1321	0.127

Table 2.3 Descriptive Statistics for Numeric Variables (Individual-Level & State-Level Data)

Variable	Description	Mean	Standard Deviation	Minimum	Maximum
Respondent - Age	Respondent's age	47.019	18.517	0	97
Thermometer - Blacks	How warm or cold the respondent feels about Black people	72.874	21.866	0	99
Thermometer - Whites	How warm or cold the respondent feels about White people	76.221	19.878	0	99
Thermometer - Policemen/Police	How warm or cold the respondent feels about the police	78.467	21.892	0	99
Conditions make it difficult for Blacks to succeed	How much a respondent agrees or disagrees with the statement (1-5)	4.243	2.727	1	9
Blacks should not have special favors to succeed	How much a respondent agrees or disagrees with the statement (1-5)	3.747	2.926	1	9
Blacks must try harder to succeed	How much a respondent agrees or disagrees with the statement (1-5)	4.069	2.798	1	9
Blacks have gotten less than they deserve over the past few years	How much a respondent agrees or disagrees with the statement (1-5)	4.455	2.593	1	9
Racial Resentment	Index of 4 variables to identify attitudes concerning racial policies	3.280	1.043	1	5
% Black	Percent of the population that identifies as Black (non-Hispanic)	12.405	8.074	0.260	37.970
% Graduated High School	Educational attainment for population 25 years and over, specifically the percentage of people that identify as a high school graduate (or equivalent)	28.254	4.445	20.130	39.650
% Poverty	Families living with an income beneath the poverty level	9.852	2.390	4.020	16.990
Violent Crime Rate	Rate of violent crime arrests	0.048	0.022	0.006	0.131
Property Crime Rate	Rate of property crime arrests	0.130	0.028	0.066	0.239

I obtained Decennial Census and American Community Survey data from Social Explorer at the congressional-district-level to get more of an idea about how differing demographics affect people at a more local level rather than the state level. In attempting to gauge how group threat affect White voters' behaviors, it made sense to aggregate to get more of an idea of more localized group behaviors instead of state behaviors.

From these data, I was able to create the following variables aggregated at the congressional district-level: percent Black, percent graduated high school, percent poverty, and rate of employment. Social Explorer used the 110th congressional district map for the 2000 variables and the 115th congressional district map for the 2016 variables. I gathered the demographics data from Social Explorer at the congressional district level for the years 2000 and 2016 (I couldn't get 1990 and 2008, unfortunately).

Table 2.4 Descriptive Statistics for Numeric Variables (Individual-Level & District-Level Data)

Variable	Description	Mean	Standard Deviation	Minimum	Maximum
Respondent - Age	Respondent's age	73.172	22.070	0	97
Thermometer - Blacks	How warm or cold the respondent feels about Black people	73.172	22.070	0	99
Thermometer - Whites	How warm or cold the respondent feels about White people	76.400	20.036	0	99
Thermometer - Policemen/Police	How warm or cold the respondent feels about the police	78.467	21.892	0	99
Racial Resentment	Index of 4 variables to identify attitudes concerning racial policies	3.257	1.094	1	5
% Black	Percent of the population that identifies as Black (non-Hispanic)	11.964	13.453	0.260	66.600
% Graduated High School	Educational attainment for population 25 years and over, specifically the percentage of people that identify as a high school graduate (or equivalent)	27.526	6.265	9.040	48.260
% Poverty	Families living with an income beneath the poverty level	9.737	4.680	1.880	39.860
% Employed	Employment rate for the civilian population in the labor force (16 years and over)	94.311	1.796	79.690	97.790
Violent Crime Rate	Rate of violent crime arrests	0.048	0.021	0.006	0.110
Property Crime Rate	Rate of property crime arrests	0.128	0.028	0.066	0.214

Table 2.5 Descriptive Statistics for Categorical Variables (Individual-Level & District-Level Data)

Variable	Description	N	%
Gender	Respondent's gender identity		
Female		3248	0.534
Male		2777	0.457
Other		11	0.001
Party of respondent	Respondent's party affiliation		
Democrats		2827	0.465
Independents		803	0.132
Republicans		2409	0.396
Respondent family - Income group	Income percentile for respondent's family		
0 to 16 percentile		912	0.150
17 to 33 percentile		1038	0.171
34 to 67 percentile		1699	0.280
68 to 95 percentile		1792	0.295
96 to 100 percentile		231	0.038
Respondent racial-ethnic group	Dummy variable manually created using the racial-ethnic summary group variable		
White respondent	(includes "White")	4388	0.722
Non-White respondent	(includes "Black," "Hispanic," and "Other or multiple races")	1638	0.270
Respondent - Education			
Grade school		105	0.017
High school		1691	0.278
Some college		2044	0.336
College or advanced degree		2191	0.361
Census Region	Respondent's region		
Northeast		1015	0.167
North Central		1451	0.239
South		2287	0.376
West		1324	0.218
Better or worse off in next year	Variable capturing whether respondents believe their financial situation would be better or worse in the next year		
Better		2150	0.354
Same		3001	0.494
Worse		717	0.118

I use mostly the same variables that I discussed for the state-level demographic variables and individual-level ANES data, except I've controlled for the employment rate at the congressional district-level instead of adding a categorical employment variable.

Ultimately, I tested three hypotheses, and created models that, at first, paired individual ANES data with state-level ACS data from Social Explorer and then I paired together individual-level ANES data with district-level ACS data from Social Explorer. They are listed below in the Hypotheses section. In running these regressions, I included data for the years 1990, 2000, 2008, and 2016 where they were available (and controlled for years); however, not all variables were available for all of the years, as indicated in the below table. This means that, while all of the years were included in the regressions with Thermometer – Blacks, Thermometer – Whites and Thermometer – Police have reduced samples because they only have data for 2000, 2008, and 2016 and just 2016, respectively.

Table 2.6 Availability of Data Over the Years

Variable	1990	2000	2008	2016
Gender	x	x	x	x
Party of respondent	x	x	x	
Congressional district of residence	x	x		x
Respondent family - Income group	x	x	x	x
Race-Ethnicity summary	x	x	x	x
Respondent - Education	x	x	x	x
Respondent - Age	x	x	x	x
Respondent - Work status	x	x	x	x
State Code - FIPS	x	x		x
Census Region	x	x	x	x
Thermometer - Blacks	x	x	x	x
Thermometer - Whites		x	x	x
Thermometer - Policemen/Police				x
Conditions make it difficult for Blacks to succeed	x	x		x
Blacks should not have special favors to succeed	x	x		x
Blacks must try harder to succeed	x	x		x
Blacks have gotten less than they deserve over the past few years	x	x		x
Better or worse off in next year	x	x	x	x

Results

Individual-Level ANES and State-Level Demographic Variables Regressions

Hypothesis 1

Net of appropriate controls, White individuals in places with larger black populations will feel less warmth towards Black people than those in places with smaller Black populations. In order for feelings of group threat to activate, there has to be the belief that the minority group is likely to topple the superiority of the dominant group. It's logical to assume then that places with higher proportions of Black residents would also have higher levels of group threat because White people are seeing more Black people in the spaces that they occupy, which might result in White people feeling less warmth towards Black. If this hypothesis is supported, then I would expect to see a negative coefficient on White and Percent Black * White. I am including results from the same model, but with the feeling thermometer towards whites response variable, for comparison's sake.

Table 2.7 Regressing Thermometer – Blacks on White and Percent Black * White

Thermometers (Individual-Level & State-Level)

	Thermometer Blacks			Thermometer Whites		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	73.51	68.25 – 78.77	**<0.001**	66.63	61.51 – 71.74	**<0.001**
Percent Black	0.38	0.27 – 0.48	**<0.001**	0.03	-0.08 – 0.14	0.588
White	-2.39	-4.22 – -0.55	**0.011**	1.34	-0.49 – 3.16	0.151
Employed	0.22	-0.82 – 1.25	0.679	0.35	-0.71 – 1.40	0.519
Age	0.02	-0.01 – 0.05	0.122	0.12	0.09 – 0.15	**<0.001**
Gender [Male]	-3.37	-4.26 – -2.49	**<0.001**	-2.30	-3.21 – -1.39	**<0.001**
Gender [Other]	7.97	-5.12 – 21.06	0.233	-7.02	-19.13 – 5.10	0.256
Education [Grade School or Less]	-6.85	-9.56 – -4.14	**<0.001**	2.78	-0.47 – 6.03	0.094
Education [High School]	-3.55	-4.76 – -2.35	**<0.001**	1.82	0.58 – 3.06	**0.004**
Education [Some College]	-1.41	-2.56 – -0.26	**0.016**	0.85	-0.29 – 1.99	0.144
Region [Northeast]	0.17	-1.28 – 1.62	0.820	-0.14	-1.66 – 1.38	0.855
Region [South]	0.40	-1.09 – 1.89	0.596	0.42	-1.10 – 1.94	0.587
Region [West]	2.31	0.54 – 4.08	**0.011**	-1.41	-3.22 – 0.41	0.128
Party [Independents]	-4.40	-5.80 – -3.00	**<0.001**	-1.06	-2.49 – 0.37	0.145
Party [Republicans]	-4.66	-5.65 – -3.67	**<0.001**	0.89	-0.14 – 1.92	0.092
Family Income [17 to 33 percentile]	0.40	-1.10 – 1.89	0.601	-0.65	-2.18 – 0.88	0.403
Family Income [34 to 67 percentile]	-1.11	-2.50 – 0.28	0.117	-0.95	-2.37 – 0.47	0.191
Family Income [68 to 95 percentile]	-0.80	-2.30 – 0.70	0.294	-0.46	-2.00 – 1.08	0.560
Family Income [96 to 100 percentile]	0.81	-1.69 – 3.32	0.524	2.17	-0.41 – 4.75	0.099
Better or Worse [Same]	-0.83	-1.81 – 0.15	0.096	-0.59	-1.58 – 0.40	0.244
Better or worse [Better]	-2.40	-3.84 – -0.97	**0.001**	-2.05	-3.56 – -0.55	**0.008**
Percent Graduated High School	0.09	-0.05 – 0.23	0.203	0.02	-0.12 – 0.16	0.809
Percent Poverty	0.02	-0.22 – 0.25	0.895	0.31	0.06 – 0.56	**0.015**
Year 2000	0.41	-1.15 – 1.96	0.608			
Year 2008	1.44	0.01 – 2.87	**0.049**	-0.30	-1.70 – 1.11	0.679
Year 2016	1.90	0.60 – 3.21	**0.004**	-0.37	-1.62 – 0.89	0.564
Percent Black * White	-0.39	-0.51 – -0.28	**<0.001**	-0.03	-0.14 – 0.08	0.591
Observations	9072			7356		
R^2 / R^2 adjusted	0.070 / 0.067			0.024 / 0.020		

There is significant support provided for my hypothesis within this regression model. The two focal variables White and Percent Black * White are significant at the 0.05 level.

As expected, White respondents on average tended to have lower feelings of warmth towards Black people than non-White respondents, and this negative effect increased in response to the respondent's state having a higher proportion of Black residents. Specifically, the coefficient on White is -2.39, and, this means that, in a state with 0% of Black residents, the average White respondent would feel 2.39 points less warmth towards Black neighbors than the average non-White respondent.

The interaction term Percent Black * White has a significant coefficient of -0.39, which means that as Percent Black increases by 1, the gap between White and non-White respondents' feelings of warmth towards Black people widens by 0.39. This finding supports my hypothesis and overall theory that White people in states with more Black residents feel less warmth towards Black people than states with less Black people.

A respondent having less education was associated with lower feelings of warmth towards Black people. Over the years, the feelings of warmth towards Black people appeared to increase. Interestingly enough, when a respondent felt that their financial situation would be better off in the next year, they felt even less warmth towards Black people than those that believed their situation would remain the same or turn worse.

Hypothesis 2

Net of appropriate controls, White individuals in places with larger Black populations will have higher racial resentment levels than those in places with smaller Black populations. Group threat theory indicates that group threat varies with the size, or visibility, of the minority population, so it would then follow that White individuals would feel more racial resentment in places with larger Black populations because they feel a greater sense of group threat than White individuals in places with fewer Black people. If this hypothesis is supported, then I would expect to see a positive coefficient on White and Percent Black * White.

Table 2.8 Regressing Racial Resentment on White and Percent Black * White

Racial Resentment Scale (Individual-Level & State-Level)

	Racial Resentment		
Predictors	*Estimates*	*CI*	*p*
Intercept	1.6873	1.4311 – 1.9436	**<0.001**
Percent Black	-0.0203	-0.0254 – -0.0152	**<0.001**
White	-0.0690	-0.1568 – 0.0188	0.124
Employed	0.0761	0.0265 – 0.1257	**0.003**
Age	0.0061	-0.0364 – 0.0486	0.777
Gender [Male]	-0.7180	-1.3119 – -0.1241	**0.018**
Gender [Other]	0.0044	0.0030 – 0.0057	**<0.001**
Education [Grade School or Less]	0.6777	0.5369 – 0.8184	**<0.001**
Education [High School]	0.6128	0.5553 – 0.6704	**<0.001**
Education [Some College]	0.4623	0.4083 – 0.5163	**<0.001**
Region [Northeast]	-0.0790	-0.1492 – -0.0088	**0.027**
Region [South]	0.0703	-0.0011 – 0.1418	0.054
Region [West]	-0.0911	-0.1762 – -0.0060	**0.036**
Party [Independents]	0.4446	0.3768 – 0.5124	**<0.001**
Party [Republicans]	0.7695	0.7218 – 0.8171	**<0.001**
Family Income [17 to 33 percentile]	-0.0142	-0.0868 – 0.0583	0.701
Family Income [34 to 67 percentile]	0.0859	0.0186 – 0.1532	**0.012**
Family Income [68 to 95 percentile]	0.0695	-0.0029 – 0.1420	0.060
Family Income [96 to 100 percentile]	0.0029	-0.1195 – 0.1253	0.963
Better or Worse [Same]	-0.0179	-0.0645 – 0.0287	0.451
Better or Worse [Worse off]	0.0923	0.0226 – 0.1619	**0.009**
Percent Graduated High School	0.0098	0.0032 – 0.0164	**0.004**
Percent Poverty	0.0204	0.0090 – 0.0317	**<0.001**
Year 2000	0.3091	0.2271 – 0.3911	**<0.001**
Year 2008	0.3470	0.2697 – 0.4243	**<0.001**
Year 2016	0.0950	0.0221 – 0.1680	**0.011**
Percent Black * White	0.0273	0.0219 – 0.0328	**<0.001**
Observations	7298		
R^2 / R^2 adjusted	0.254 / 0.252		

There are some interesting mixed results here. White is not significant at the 0.05 level and it has a coefficient of -0.069, which is surprising in that it seemingly would indicate that White respondents apparently have less racial resentment towards Blacks than non-White respondents when there is 0% Black residents at the state-level. Of course, there is no state with 0% Black residents so that coefficient is basically an artifact of the model. Percent Black * White is significant and positive, though, so there is support here for the idea that larger Black populations are associated with more racial resentment among white respondents (specifically 0.0273 units per each additional 1% Black population).

Some of the other variables that are significant at the 0.05 level are Employed, Gender, the different levels of Education, Family Income [34 to 67 percentile], different regions, different levels for political parties, Better or Worse Off [Worse Off], and all of the years.

Overall, a person being employed also seems to result in a slightly higher racial resentment level than a person who's unemployed. A respondent being a man resulted in a racial resentment score that's -0.718 lower than women's racial resentment score on average. More education seems to predict decreased levels of racial resentment (with college serving as the reference group). A respondent being in the Family Income [34 to 67 percentile] would have a racial resentment score that is 0.0859 higher than respondents from the 0 to 16 percentile, which has interesting implications for the relationship between poverty and racial resentment.

As expected, in this model, respondents who identified as Republican on average have a racial resentment level that is 0.7695 more than respondents that identified as Democrat. A respondent expecting that their financial situation would be worse in the next year was associated with higher in racial resentment.

Hypothesis 3

Net of appropriate controls, White individuals in places with larger Black populations will feel more warmth for police officers than those in places with smaller Black populations. If, in accordance with group threat theory, punitive policies and practices are understood to primarily target Black populations when white populations feel threatened, then it would make sense that White respondents would feel more warmth towards the police when they are in places with larger Black populations. If this hypothesis is supported, then I would expect to see a positive coefficient on White and Percent Black * White.

Table 2.9 Regressing Thermometer – Police on White and Percent Black * White

Thermometers (Individual-Level & State-Level)

	Thermometer Police		
Predictors	*Estimates*	*CI*	*p*
Intercept	62.32	54.07 – 70.58	**<0.001**
Percent Black	-0.27	-0.44 – -0.10	**0.002**
White	2.99	0.26 – 5.72	**0.032**
Employed	0.71	-0.76 – 2.19	0.342
Gender [Male]	-2.45	-3.74 – -1.16	**<0.001**
Gender [Other]	-8.50	-21.27 – 4.27	0.192
Education [Grade School or Less]	3.88	-2.78 – 10.53	0.253
Education [High School]	4.34	2.58 – 6.11	**<0.001**
Education [Some College]	2.98	1.44 – 4.52	**<0.001**
Region [Northeast]	0.57	-1.51 – 2.65	0.591
Region [South]	-0.41	-2.61 – 1.78	0.713
Region [West]	-1.96	-4.53 – 0.62	0.136
Party [Independents]	1.03	-0.96 – 3.03	0.310
Party [Republicans]	9.20	7.76 – 10.65	**<0.001**
Family Income [17 to 33 percentile]	0.07	-2.19 – 2.33	0.951
Family Income [34 to 67 percentile]	2.35	0.32 – 4.38	**0.023**
Family Income [68 to 95 percentile]	3.44	1.34 – 5.55	**0.001**
Family Income [96 to 100 percentile]	3.45	-0.50 – 7.40	0.087
Age	0.17	0.13 – 0.20	**<0.001**
Percent Graduated High School	-0.00	-0.22 – 0.22	0.992
Percent Poverty	0.48	0.11 – 0.85	**0.012**
Violent Crime Rate	-50.60	-90.09 – -11.11	**0.012**
Property Crime Rate	-15.80	-39.77 – 8.17	0.196
Percent Black * White	0.24	0.06 – 0.41	**0.007**
Observations	4037		
R^2 / R^2 adjusted	0.121 / 0.116		

Before reporting the results, I would like to note that, as reported in Table 2.6, the feeling thermometer for police was only recorded in 2016 and none of the other years that this thesis focuses on, so I do not control for year in this regression model.

The results of this regression model provide ample support for my hypothesis as well. In a hypothetical state with 0% Black residents, a respondent being White was associated with a difference of 2.99 in warmth towards police compared to a non-White respondent. As Percent Black residents increases by 1, White individuals' greater warmth of feeling towards the police increases by 0.24 on average.

The higher the income percentile a respondent came from, the higher that their warmth towards police tended to be. An increase in the level of poverty was associated with an increase of 0.48 in warmth towards police in respondents.

Some of the other variables that have significant coefficients are Gender [Male], Education [High School], Education [Some College], and Party [Republicans]. Being a male respondent was associated with a decrease in feelings of warmth towards the police compared to female respondents (by -2.45). According to this model, a respondent identifying as having had a high school education would have an increase of 4.34 in feelings of warmth compared to respondents with college or an advanced degree. Republicans on average tended to have much higher feelings of warmth towards the police than those that identified as Democrats.

Individual-Level ANES and District-Level Demographic Variables Regressions

Hypothesis 1

Now, I will re-test my same 3 hypotheses but with congressional-district-level data rather than state-level data for the contextual measures. This is useful because district-level data is much more local than state-level data, so it's likely a better way of capturing the contextual variables that are visibly relevant within respondents' lives—important especially if Black people are clustered within certain localized geographies. Like before, I am including results from the same regression model, but with the feeling thermometer towards whites response variable, for comparison's sake.

Table 2.10 Regressing Thermometer – Blacks on White and Percent Black * White with Contextual Variables Measured at the District Level

Thermometers (Individual-Level & District-Level)

	Thermometer Blacks			**Thermometer Whites**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	74.87	18.60 – 131.14	**0.009**	119.29	67.46 – 171.13	**<0.001**
Percent Black	0.15	0.07 – 0.22	**<0.001**	-0.04	-0.11 – 0.03	0.255
White	-3.56	-5.43 – -1.68	**<0.001**	2.09	0.35 – 3.82	**0.018**
Gender [Male]	-2.29	-3.46 – -1.12	**<0.001**	-2.10	-3.18 – -1.03	**<0.001**
Gender [Other]	8.94	-4.43 – 22.32	0.190	-8.36	-20.68 – 3.96	0.183
Education [Grade School or Less]	0.67	-4.10 – 5.43	0.784	7.15	2.76 – 11.54	**0.001**
Education [High School]	-2.61	-4.21 – -1.00	**0.001**	2.15	0.67 – 3.63	**0.004**
Education [Some College]	-0.61	-2.04 – 0.82	0.403	1.27	-0.05 – 2.58	0.058
Region [Northeast]	0.50	-1.41 – 2.41	0.611	0.29	-1.47 – 2.05	0.748
Region [South]	1.49	-0.13 – 3.11	0.072	1.61	0.12 – 3.11	**0.035**
Region [West]	0.60	-1.51 – 2.70	0.578	-2.92	-4.85 – -0.98	**0.003**
Party [Independents]	-4.77	-6.60 – -2.94	**<0.001**	-1.41	-3.10 – 0.28	0.102
Party [Republicans]	-5.38	-6.69 – -4.07	**<0.001**	1.52	0.31 – 2.72	**0.014**
Family Income [17 to 33 percentile]	1.08	-0.93 – 3.09	0.293	-0.95	-2.80 – 0.90	0.315
Family Income [34 to 67 percentile]	-0.44	-2.29 – 1.41	0.644	-0.76	-2.47 – 0.94	0.382
Family Income [68 to 95 percentile]	0.79	-1.13 – 2.72	0.417	0.12	-1.65 – 1.89	0.896
Family Income [96 to 100 percentile]	1.62	-1.77 – 5.01	0.348	2.28	-0.84 – 5.40	0.153
Percent Graduated High School	-0.16	-0.27 – -0.04	**0.008**	-0.15	-0.25 – -0.04	**0.007**
Percent Poverty	0.13	-0.09 – 0.34	0.261	0.00	-0.20 – 0.20	0.992
Rate of Employment	0.07	-0.50 – 0.64	0.808	-0.42	-0.94 – 0.11	0.120
Year 2016	-0.13	-1.50 – 1.25	0.857	-1.31	-2.57 – -0.04	**0.043**
Percent Black * White	-0.18	-0.27 – -0.09	**<0.001**	-0.05	-0.13 – 0.04	0.275
Observations	5355			5355		
R^2 / R^2 adjusted	0.056 / 0.053			0.016 / 0.012		

This table provides significant support for my hypothesis, qualitatively consistent with the state regressions above, because the values on White and Percent Black * White are negative and significant. These variables indicate that not only does a respondent being White already result in less warmth towards Black people than non-White respondents, but also this effect becomes more pronounced for the White respondents in congressional districts with more Black people.

In a hypothetical district with 0% Black people, it appears that White individuals have attitudes towards Black people that are less warm than non-White respondents' attitudes by 3.56. As Percent Black residents increases by 1, White individuals' warmth of feeling towards Black people decreases by 0.18 on average.

A respondent having a high school education (as opposed to college), identifying as male (as compared to female), and being in a congressional district where more people graduated high school also had negative impacts on warmth towards Black people in this model.

Hypothesis 2

At this point, I turn to look at how Percent Black impacts White respondents' feelings of racial resentment at the congressional-district-level. If my hypothesis is supported, then I would expect to see positive values for White and Percent Black * White.

Table 2.11 Regressing Racial Resentment on White and Percent Black * White with Contextual Variables Measured at the District Level

Racial Resentment Scale (Individual-Level & District-Level)

	Racial Resentment		
Predictors	*Estimates*	*CI*	*p*
Intercept	4.6790	2.0645 – 7.2935	**<0.001**
Percent Black	-0.0090	-0.0126 – -0.0055	**<0.001**
White	0.1150	0.0258 – 0.2043	**0.012**
Gender [Male]	0.0131	-0.0414 – 0.0677	0.637
Gender [Other]	-0.7550	-1.3619 – -0.1481	**0.015**
Education [Grade School or Less]	0.6543	0.4204 – 0.8882	**<0.001**
Education [High School]	0.5849	0.5103 – 0.6595	**<0.001**
Education [Some College]	0.4262	0.3601 – 0.4922	**<0.001**
Region [Northeast]	-0.0992	-0.1877 – -0.0107	**0.028**
Region [South]	0.0883	0.0126 – 0.1639	**0.022**
Region [West]	-0.1063	-0.2042 – -0.0085	**0.033**
Party [Independents]	0.5891	0.5027 – 0.6756	**<0.001**
Party [Republicans]	0.9659	0.9052 – 1.0267	**<0.001**
Family Income [17 to 33 percentile]	-0.0638	-0.1586 – 0.0310	0.187
Family Income [34 to 67 percentile]	0.0378	-0.0494 – 0.1250	0.395
Family Income [68 to 95 percentile]	0.0078	-0.0828 – 0.0984	0.865
Family Income [96 to 100 percentile]	-0.0547	-0.2125 – 0.1031	0.497
Percent Graduated High School	0.0159	0.0105 – 0.0213	**<0.001**
Percent Poverty	-0.0104	-0.0205 – -0.0003	**0.044**
Rate of Employment	-0.0262	-0.0527 – 0.0004	0.053
Year 2016	-0.1596	-0.2239 – -0.0954	**<0.001**
Percent Black * White	0.0094	0.0051 – 0.0137	**<0.001**
Observations	4577		
R^2 / R^2 adjusted	0.297 / 0.294		

This model again supports my hypothesis because both White and Percent Black * White are positive and significant at the 0.05 level. In a hypothetical congressional district with 0% Black people, White respondents, on average, feel 0.12 more racial resentment towards Black people than non-White respondents. With the addition of the interaction term, we see that at the Black population at the congressional district-level increases by 1%, the racial resentment White respondents feel also increases by 0.009. It's just as my theory states: White individuals living in districts with larger Black populations will feel more racial resentment towards Black people than White people in districts with smaller proportions of Black residents--though even at 0, there is a noticeable difference in the level of racial resentment that White people feel towards Black people versus how non-White respondents feel.

Some other variables that are significant include Percent Black, Gender [Other], the different levels of region, the different levels of party, Percent Graduated High School, Percent Poverty, and Year 2016. I'm especially interested in, but not at all surprised by, the increase higher levels of racial resentment that individuals in the South and Republican party feel (compared to the reference group of North Central and Democrats). Party [Republican], in fact, has a pretty high coefficient at 0.966.

Hypothesis 3

Now, I investigate to see how respondents' feelings of warmth towards the police correlate with congressional-district-level contextual factors.

Table 2.12 Regressing Thermometer – Police on White and Percent Black * White

Thermometers (Individual-Level & District-Level)

	Thermometer Police		
Predictors	*Estimates*	*CI*	*p*
Intercept	69.10	63.17 – 75.02	**<0.001**
Percent Black	-0.12	-0.20 – -0.03	**0.006**
White	5.69	3.55 – 7.83	**<0.001**
Gender [Male]	-2.57	-3.89 – -1.26	**<0.001**
Gender [Other]	-10.62	-23.55 – 2.31	0.107
Education [Grade School or Less]	6.47	-0.25 – 13.18	0.059
Education [High School]	4.07	2.25 – 5.88	**<0.001**
Education [Some College]	2.74	1.16 – 4.32	**0.001**
Region [Northeast]	0.70	-1.41 – 2.80	0.518
Region [South]	0.39	-1.45 – 2.24	0.675
Region [West]	-1.51	-3.85 – 0.83	0.207
Party [Independents]	0.31	-1.74 – 2.35	0.770
Party [Republicans]	9.36	7.88 – 10.83	**<0.001**
Family Income [17 to 33 percentile]	0.09	-2.21 – 2.39	0.938
Family Income [34 to 67 percentile]	2.96	0.92 – 5.00	**0.004**
Family Income [68 to 95 percentile]	3.80	1.70 – 5.90	**<0.001**
Family Income [96 to 100 percentile]	3.55	-0.48 – 7.58	0.084
Percent Graduated High School	0.07	-0.06 – 0.20	0.298
Percent Poverty	0.06	-0.14 – 0.26	0.548
Violent Crime Rate	-31.85	-69.87 – 6.18	0.101
Property Crime Rate	-14.46	-38.73 – 9.82	0.243
Percent Black * White	0.07	-0.04 – 0.18	0.199
Observations	3979		
R^2 / R^2 adjusted	0.101 / 0.097		

This table does not provide much support my hypothesis because Percent Black * White is not significant; however, the coefficient is positive (0.07), which, if significant, would indicate that there is an increase in feelings towards the police as the proportion of Black residents increases. White is significant and it shows that, even when there are 0% Black residents in a hypothetical congressional district, White respondents had a 5.69 higher warmth score than non-White respondents on average.

Other variables that are significant are Percent Black, Gender [Male], Education [Some college], Party [Republicans], and most of the levels of family income percentile group.

Discussion

There was significant support provided for most of my hypotheses when looking at the individual-level data with both the state-level and district-level demographics data. It appears that White individuals in places with larger Black populations have lower feelings of warmth towards Black people, more racial resentment, and more warmth towards police compared to the places that have less Black people. This pattern holds when contextual variables are measured at the state-level and mostly holds when they are measured at the congressional-district-level, with the exception of the police feeling thermometer variable in the latter case.

In the next chapter, I will first observe how punitiveness at the state-level changes with racial demographic trends. Then, I will take the variables Thermometer – Blacks and Racial Resentment from this chapter and aggregate them so they're at the state-level because I hope to be able to investigate my theory that White people's attitudes towards Black people moderate the relationship between Percent Black and punitiveness.

Chapter 3: Group Threat in the Context of Punitiveness

To recap, I believe that group threat, specifically racial threat, explains White voters' differing attitudes towards Black people; I believe those attitudes, aggregated at the state-level, would then mediate the relationship between Percent Black and states' punitiveness. Though the supposition of the study by Neill et al. (2015), foundational to my analysis as I discuss below, is that the mechanism for increased punitiveness involves social control and racial threat, they don't explore the mechanisms through which this might work. This chapter seeks to explore whether, implied by the theory, citizens' attitudes mediate the relationship between demographic and socioeconomic factors and criminal justice policy implementation.

In the previous chapter, I focused on understanding how differences in Black population size at the state-level can explain the variation in White people's attitudes towards Black people in terms of warmth and racial resentment at the individual-level. Now, in this chapter, I build on the foundation of Kutateladze (whose work on measuring dimensions of punitiveness I reconstruct, across a wider set of years, as discussed in Appendix A) and Neill et al. (whose important paper on predictors of state-level punitiveness I replicated, as described in Appendix B).

First, I carry out a series of analyses to see whether state-level differences in percent Black residents predict differences in the punitiveness of state policies. Then, in order to connect White voters' attitudes and state-level punitiveness, I proceed to aggregate the individual-level attitude measures from Chapter 2—racial resentment among White residents and warmth towards Black people—at the state-level. Afterwards, I regress the dimensions of punitiveness on the attitudes, exploring both whether the attitudes predict punitiveness and whether including the aggregated attitude variables causes the coefficient on my focal X variable to change.

Method

In the beginning, I focused on expanding the data set from my initial replication, again described in the appendices, so that I could look at changes in punitiveness across time. I decided that I wanted to look at the years 1990-2018, since data before 1990 would likely be hard to obtain (some of the data wouldn't even exist) and data after 2018 might be affected by the COVID-19 pandemic—in ways that I likely wouldn't anticipate. I decided to divide the time period up into three waves—1990-1999, 2000-2009, and 2010-2018—and chose years that were in the middle of those waves: 1995, 2005, and 2015. I attempted to collect the 44 variables by finding data sources that were produced either exactly in 1995, 2005, and 2015 or when those precise years weren't available, the closest year available. I go into more depth about the process of collecting data for the variables in the appendices.

I began by collecting data for the 44 variables across the years 1990 to 2018, and then I ran the same regressions from the replication. Afterwards, I took the ANES variables thermometer Black and racial resentment, aggregated the responses to get a mean measure for them at the state-level, and then I ran regressions once more to see how well White voters' attitudes predicted the different dimensions of punitiveness.

Focal Y Variables

My focal outcome variables are simply the five dimensions of punitiveness that are included in Kutateladze's dissertation, which, as described in Appendix A, I reconstructed from scratch: political and symbolic punishment, incarceration, punishing immorality, conditions of confinement, and juvenile justice (2008). The five dimensions of punitiveness were measured using 44 variables, and all of the variables that went into measuring these dimensions were numeric. For each of the variables, the states were divided up into quintiles based on their positions relative to each other and the states were then assigned a criterion punitiveness score. The scores ranged from 0 to 4, where 0 represented the least punitive states while 4 was assigned to the states that were most punitive according to a given measure. At the end, the states were given overall punitiveness scores by calculating the average criterion punitiveness score that each state had across the 44 variables. Following in the steps of Neill et al. (2015), I decided to run regressions on the scores across the five dimensions rather than the overall punitiveness score because I felt that the individual dimension scores would provide more meaningful results.

First and foremost, the political and symbolic dimension attempts to capture the political elements and symbolic nature of punitiveness. For the political aspect of punitiveness, Kutateladze is interested in capturing the “government’s reaction to what a convicted offender did, expressed through the political institutions of criminal justice” and how “penal practices often, especially around elections, become a vital part of a country’s life” (2008, p. 17). As for the symbolic nature of punitiveness, Kutateladze looks at how states “send a message of disapproval of certain acts (a penal code would be sufficient for this goal),” and Kutateladze looks at how the state “announces intolerance for disobedience” (2008, p. 17). The punishments being characterized as examples of political and symbolic punishment are “life imprisonment, the death penalty, mandatory sex offender registries, disenfranchisement, and three-strikes laws” (Kutateladze, 2008, p. 18).

Within the incarceration dimension, Kutateladze “includes five variables that measure incarceration rates,” and “variables on the average prison sentences imposed in state courts and the average prison terms actually served for six specific offenses as well as for all crimes combined” because plenty of scholarship has shown incarceration to be an important indicator of punitiveness (2008, p. 66). This dimension includes the variables that are most familiar to scholarship on punitiveness as these directly measure the amount of people being incarcerated, how many people are out of prison but still being supervised by the state through parole or probation, and how much time people are spending in prison.

For the punishing immorality dimension, Kutateladze includes variables pertaining to rape, prostitution, drug abuse, gambling, and public drunkenness—the crimes where "criminalization is justified or derived from the moral inappropriateness of the behaviors they are based upon," (2008, pp. 109 & 134). These are the crimes that society considers to be "be deviant and understandably unacceptable," even though "there are many other acts that, while being morally impermissible, are not criminalized" (Kutateladze, 2008, p. 109). Kutateladze includes these variables to show how "governments embrace one group's moral values and use criminal law to eliminate those of the other," and, recognizing that "states are by no means homogeneous" in how they criminalize different types of "immoral behavior"—if at all (2008, p. 109). The inclusion of these variables is meant to measure differences in state punitiveness by capturing the variation in which states choose to criminalize "immoral acts" and the extent to which they do so (2008, p. 109).

The conditions of confinement dimension includes prison overcrowding and "quality of prison services including food, mental and physical health," as well as the deaths of prisoners and the "deaths and sexual violence inside prisons culminating in lawsuits against prison administration and staff" (Kutateladze, 2008, pp. 138-139). Here, Kutateladze is interested in data that is able to illustrate the "severity of prison conditions" (2008, p. 137). This dimension is based on the research by James Whitman into how the prison conditions within the US compare to Germany and the overarching question, "'Which jurisdiction is more punitive based on the conditions in which it holds its prisoners?'" (Whitman, 2003, as cited in Kutateladze, 2008, pp. 137-138).

And finally, the juvenile justice dimension encompasses the following variables: "Age for juvenile court jurisdiction, Juvenile transfer laws, Juvenile inmates in adult prisons, Juvenile incarceration rate, Juveniles serving life without parole, and Overcrowding in juvenile facilities" (Kutateladze, 2008, p. 169). This dimension is included within the measure of state punitiveness because "states are permitted to develop juvenile justice practices as they wish," "nationwide changes…are unforseeable," and "juvenile justice systems have been strikingly diverse for quite some time" (Kutateladze, 2008, pp. 168-169).

As discussed in Appendix B, though this is not noted in the original research, when I replicated these measures, I found that a number of the dimensions are not measured reliably. The dimensions Punishing Immorality, Conditions of Confinement, and Juvenile Justice have Cronbach's Alpha scores that are below acceptable thresholds, which indicates that these measures have a lack of internal consistency; therefore, I am going to mostly disregard the values that I get for these dimensions in the regression models and focus my analysis on the dimensions Political and Symbolic Punishment and Incarceration.

Table 3.1 Descriptive Statistics for Numeric Variables

Variable	Description	Mean	Standard Deviation	Minimum	Maximum
Political and Symbolic Punishment	Measure for the punishments administered by states that have political and symbolic characteristics	1.767	0.798	0	4
Incarceration	Measure for how many people are incarcerated, the average amount of time that people spend in prison depending on the crime, how many people are admitted into jails and prisons versus how many are released, etc.	1.950	0.751	0	4
Punishing Immorality	Measure for the extent to which states punish people for committing acts traditionally regarded as "immoral"	1.909	0.830	0	4
Conditions of Confinement	Measure for the quality of life within prison for those incarcerated	1.988	0.667	0	4
Juvenile Justice	Measure for how punitive states are in dealing with juveniles who commit crimes	1.953	0.972	0	4
% Black	Percent of the population that identifies as Black (non-Hispanic)	9.893	9.415	0.260	37.350
% White Voter Turnout	Percent of the White population that voted in the most recent presidential election	51.342	8.705	29.700	71.100
% Voter Turnout	Percent of the voting eligible population that voted for the highest office in the most recent election--depending on the year, could be presidential, governor, or congressional votes.	35.816	25.684	0.327	69.500
% Poverty	Families living with an income beneath the poverty level	9.742	3.118	4.280	20.170
Median Income	Median household income	40,076.000	10,825.000	20,136.000	68,854.000
% Graduated High School	Educational attainment for population 25 years and over, specifically the percentage of people that identify as a high school graduate (or equivalent)	30.230	3.888	20.130	41.590
Welfare Payments	How much the state government spends per capita in welfare (in thousands of dollars)	5,377,221	8,434,156	110,000	63,848,655
Violent Crime Rate	Rate of violent crime arrests	0.038	0.020	0.006	0.131
Property Crime Rate	Rate of property crime arrests	0.131	0.310	0.066	0.274

Focal X Variables

The focal variable in all of my regression models is Percent Black. I'm interested in understanding the impact of percent Black on the different dimensions of punitiveness compared to the results of Neill et al (2015). I think the precision of my estimate for Percent Black increases because there are more observations overall with the addition of data for the three time periods. Following in the steps of Neill et al., I square root transformed the variable Percent Black—which Neill et al. did because of concerns about a right skew (2015). Plus, I confirmed with component plus residual plots that doing this improved the linear fit of the models.

When checking to see whether aggregated White voters' attitudes towards Black people mediate the relationship between Percent Black and punitiveness, I specifically am looking to see if there are any changes in the coefficients for Percent Black when I include those aggregated measures in the models. If the attitudes did mediate the relationship, then the coefficients would decrease in magnitude. I also confirmed that Percent Black residents plus the controls significantly predict the aggregated attitude measures, but I have not included those models within this chapter.

For this part of the thesis, I add in Thermometer – Blacks and Racial Resentment to the regressions—both being numeric variables that have been aggregated at the state-level from the ANES data.

For Thermometer — Blacks, I first filtered the respondents to include the feeling thermometer scores for only the respondents that identified as White. Then, I added in a column to represent which wave the data correlated with since I had to join the ANES data with the punitiveness data. To see how attitudes predict the impact of Percent Black on punitiveness, I filtered to include data from the years 1994, 2004, and 2014 and then added in a wave column which had the values 1995, 2005, and 2015. I already had this column for the punitiveness data. After creating the wave column for the ANES data, I grouped by wave and state and calculated the mean Thermometer — Blacks value for each of these, and then I joined the ANES data with the state-level punitiveness data.

For Racial Resentment, I followed the same steps—in fact, I calculated the means for both Thermometer — Blacks and Racial Resentment before joining the ANES data to the punitiveness data. The only difference is that, after I initially filtered to include only the responses of White respondents, I had to develop the racial resentment index. This entailed the same procedure I used back in Chapter 2. To recap, I essentially changed the values for two of the racial policy variables to ensure that the data all pointed in the same direction, where, as the values increased, racial resentment increased. Originally, for two of the responses, the values indicating the most racial resentment were 1 and 2, while the other two were 4 and 5, so I reversed the order of the values for the two with the most racial resentment being represented by 1 and 2 to 4 and 5. Afterwards, I went on to add the wave column to the ANES data, create the groups, calculate the mean racial resentment levels, and joined the ANES data to the state-level punitiveness data.

Covariates

The two categorical variables that I add to the regression models are Region and South. I included Region so that I could get more of a spatial understanding of the impact of racial-ethnic composition on different dimensions of punitiveness. The different levels for Region are Northeast, Midwest, South, and West, and, in the regression models, they are treated as dummy variables—with “South” being the reference group.

In regressions separate from the ones that included Region, I included the dummy variable South, coded differently such that it would take on the value of 1 if a state had been a part of the confederate South and a 0 if not. I created this variable because, in the conversation surrounding Percent Black and punitiveness, the states that historically made up the confederate South are often described as being distinctly more punitive than other states. This has a lot to do with how the confederate South, in the years before and after the civil war, enforced discriminatory criminal justice policies and practices in an effort to preserve the institution of slavery, restrict Black people’s freedom, and establish and maintain the racial caste system.

The variables that were measured numerically were Percent White Voter, Percent Voter Turnout, Percent High School Graduates, Percent Poverty, Welfare Payments, Violent Crime Rate, and Property Crime Rate. Following in the footsteps of Neill et al., I apply a square root transformation to Percent High School Graduates and Welfare Payments due to concerns about skewing (2015).

Percent White Voter measures the percentage of White voters that participated in the most recent presidential election. On the other hand, Percent Voter measures the overall voter turnout for the most recent presidential election. Percent High School Graduates was developed from Social Explorer's Decennial Census survey variable Educational Attainment for Population 25 Years and Over. Often, higher education is associated with less punitiveness for reasons that I discuss more in-depth in Appendix B.

Percent Poverty captures the percentage of families that were living beneath the poverty line. I included this because it's well-documented that people who are low-income tend to disproportionately make up the criminal justice systems and encounter the criminal justice system most often—and people's economic outcomes after having been incarcerated tend to be worse. The variable Welfare is a measure of how much the state government spends on welfare per capita. Violent crime rate and property crime rate were included to account for trends in crime being committed during each of the waves.

I added in another covariate: White Voter Participation. I added in the variable White Voter Participation because studies (Eitle et al, 2002) have indicated that the turnout of White voters in elections is a sensible measure of racial threat—if we believe the dominant group (White citizens) are using discriminatory practices and policies to ensure the subordination of the not-dominant group, it would make sense to expect that the turnout of White voters would be an effective measure of how threatened White voters feel.

Table 3.2 Descriptive Statistics for Categorical Variables

Variable	Description	N	%
Year	Year associated with the demographic variables and the beginning of the time period for the punitiveness measures		
1990		50	0.333
2000		50	0.333
2010		50	0.333
Census Region	Region that the state is in		
Northeast		9	0.180
Midwest		12	0.240
West		13	0.260
South		16	0.320
Confederate states	Dummy variable manually created to indicate the states that had been a part of the confederacy		
South	(includes Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, Virginia)	11	0.220
Non-South		39	0.780

Results

Hypothesis 4

My hypothesis is that, **net of appropriate controls, states with larger Black populations are likelier to be punitive across all of the dimensions than states with smaller Black populations**; therefore, if my hypothesis is correct, then the regressions should show that percent Black has a significant positive effect on the level of punitiveness.

Table 3.3 Adding More Years to the Neill et al. (2015) Regression Models (Region)

H4: Dimensions of State-Level Punitiveness

	Political and Symbolic Punishment			**Incarceration**			**Punishing Immorality**			**Conditions of Confinement**			**Juvenile Justice**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	8.03	5.13 – 10.94	**<0.001**	0.96	-3.22 – 5.14	0.650	7.03	3.02 – 11.03	**0.001**	-1.46	-5.13 – 2.21	0.434	-0.51	-5.44 – 4.43	0.839
Percent Black (Sqrt)	0.29	0.18 – 0.39	**<0.001**	0.09	-0.06 – 0.23	0.244	0.18	0.03 – 0.32	**0.015**	0.19	0.06 – 0.32	**0.005**	0.26	0.08 – 0.43	**0.004**
White Voter Participation	-0.03	-0.05 – -0.01	**0.001**	0.00	-0.02 – 0.02	0.993	-0.02	-0.05 – 0.00	0.060	-0.01	-0.03 – 0.01	0.553	-0.00	-0.03 – 0.03	0.958
Percent Voted	0.01	-0.01 – 0.03	0.370	-0.01	-0.05 – 0.02	0.371	-0.02	-0.05 – 0.01	0.128	0.01	-0.01 – 0.04	0.285	-0.01	-0.04 – 0.03	0.720
Percent Poverty	-0.15	-0.21 – -0.08	**<0.001**	0.02	-0.07 – 0.11	0.678	-0.06	-0.15 – 0.02	0.147	-0.06	-0.14 – 0.01	0.111	0.04	-0.07 – 0.14	0.497
Median Income	-0.00	-0.00 – -0.00	**<0.001**	0.00	-0.00 – 0.00	0.682	-0.00	-0.00 – 0.00	0.653	-0.00	-0.00 – 0.00	0.464	-0.00	-0.00 – 0.00	0.503
Percent High School Graduates (Sqrt)	-0.25	-0.58 – 0.09	0.147	0.37	-0.11 – 0.85	0.129	-0.32	-0.78 – 0.14	0.170	0.64	0.21 – 1.06	**0.003**	0.28	-0.29 – 0.85	0.331
Welfare Payments (Sqrt)	-1.23	-2.03 – -0.43	**0.003**	-1.29	-2.44 – -0.14	**0.028**	-0.31	-1.42 – 0.79	0.574	-0.79	-1.80 – 0.22	0.125	0.15	-1.21 – 1.51	0.826
Violent Crime Rate	3.53	-1.45 – 8.52	0.163	2.65	-4.54 – 9.83	0.468	6.12	-0.76 – 13.01	0.081	1.85	-4.46 – 8.15	0.563	14.12	5.64 – 22.60	**0.001**
Property Crime Rate	-0.63	-3.78 – 2.52	0.694	-2.19	-6.73 – 2.35	0.342	-4.08	-8.43 – 0.27	0.066	1.01	-2.97 – 4.99	0.617	-2.00	-7.36 – 3.35	0.461
Region [Midwest]	-0.37	-0.66 – -0.08	**0.014**	-0.21	-0.63 – 0.21	0.321	-0.05	-0.46 – 0.35	0.804	0.01	-0.36 – 0.38	0.965	0.67	0.17 – 1.16	**0.009**
Region [Northeast]	-0.45	-0.82 – -0.08	**0.019**	0.00	-0.54 – 0.54	0.998	-0.21	-0.73 – 0.30	0.413	0.14	-0.33 – 0.61	0.568	0.23	-0.40 – 0.86	0.474
Region [West]	0.17	-0.20 – 0.53	0.362	0.14	-0.38 – 0.67	0.589	-0.12	-0.62 – 0.39	0.646	0.75	0.29 – 1.21	**0.002**	0.71	0.09 – 1.32	**0.026**
Year 2000	1.45	1.05 – 1.85	**<0.001**	0.30	-0.28 – 0.89	0.304	0.25	-0.30 – 0.81	0.368	0.41	-0.10 – 0.92	0.118	0.42	-0.27 – 1.11	0.228
Year 2010	2.76	1.40 – 4.11	**<0.001**	-0.15	-2.11 – 1.80	0.877	-0.89	-2.76 – 0.98	0.349	1.65	-0.07 – 3.36	0.060	-0.38	-2.69 – 1.92	0.743
Observations	150			150			150			150			150		
R^2 / R^2 adjusted	0.644 / 0.607			0.167 / 0.080			0.373 / 0.308			0.186 / 0.101			0.307 / 0.235		

In accordance with my hypothesis, it appears that the size of the Black population has a significant positive effect on punitiveness—for all of the dimensions except Incarceration. Increases in the Black population are associated with increases in punitiveness across the different dimensions at the state-level.

The R-squared value for the Political and Symbolic Punishment is relatively high/acceptable, while the R-squared value for the Incarceration dimension suggests that we should be concerned about model fit—right now, it seems that the variance in the dependent variables isn't well explained by the independent variables in that particular dimension.

Still, looking at the first two dimensions, it looks like Percent Black, Region [Midwest], Region [East], Percent Poverty, Welfare Payments, and the different levels of year have noteworthy impacts on punitiveness. For Political and Symbolic Punishment, the size of the Black population and the state being located in the Midwest or the East has a negative effect on punitiveness (at least compared to the reference group, which would be states in the South). Interestingly enough, Percent Poverty, White Voter Participation, and Welfare Payments are associated with a negative change in the punitiveness level for the Political and Symbolic Punishment dimension.

The only significant variable for the Incarceration dimension model is Welfare Payments (Sqrt). The coefficient on this term is negative, specifically -1.29, which certainly makes sense. I would expect to see that states that are more generous with welfare are less punitive in different dimensions.

Overall, there is considerable support in this table for my hypothesis that states with larger Black populations tend to be more punitive. In the next table, I rerun the same regression model, except I use the dummy variable South in place of the dummies for all but one of the census regions.

Table 3.4 Adding More Years to the Neill et al. (2015) Regression Models (South)

H4: Dimensions of State-Level Punitiveness

	Political and Symbolic Punishment			**Incarceration**			**Punishing Immorality**			**Conditions of Confinement**			**Juvenile Justice**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	8.42	5.31 – 11.52	**<0.001**	1.72	-2.55 – 5.98	0.428	6.84	2.78 – 10.90	**0.001**	0.34	-3.57 – 4.26	0.863	1.81	-3.35 – 6.96	0.489
Percent Black (Sqrt)	0.19	0.09 – 0.29	**<0.001**	0.08	-0.06 – 0.22	0.259	0.18	0.05 – 0.31	**0.008**	0.05	-0.07 – 0.18	0.414	0.21	0.04 – 0.38	**0.015**
White Voter Participation	-0.03	-0.05 – -0.01	**0.003**	-0.00	-0.02 – 0.02	0.981	-0.02	-0.05 – 0.00	0.064	-0.00	-0.03 – 0.02	0.679	0.00	-0.03 – 0.03	0.855
Percent Voted	0.00	-0.02 – 0.02	0.959	-0.02	-0.05 – 0.01	0.202	-0.02	-0.05 – 0.01	0.118	0.01	-0.02 – 0.03	0.644	-0.00	-0.04 – 0.03	0.875
Percent Poverty	-0.10	-0.16 – -0.04	**0.001**	0.04	-0.04 – 0.12	0.351	-0.06	-0.14 – 0.02	0.126	-0.02	-0.10 – 0.06	0.578	0.02	-0.08 – 0.12	0.645
Median Income	-0.00	-0.00 – -0.00	**<0.001**	0.00	-0.00 – 0.00	0.559	-0.00	-0.00 – 0.00	0.607	0.00	-0.00 – 0.00	0.966	-0.00	-0.00 – 0.00	0.322
Percent High School Graduates (Sqrt)	-0.39	-0.73 – -0.04	**0.027**	0.23	-0.24 – 0.71	0.329	-0.30	-0.75 – 0.15	0.194	0.32	-0.11 – 0.76	0.141	0.03	-0.54 – 0.60	0.917
Welfare Payments (Sqrt)	-1.72	-2.48 – -0.96	**<0.001**	-1.34	-2.39 – -0.30	**0.012**	-0.47	-1.46 – 0.53	0.357	-1.11	-2.07 – -0.15	**0.023**	-0.27	-1.53 – 0.99	0.673
Violent Crime Rate	3.25	-1.96 – 8.46	0.220	2.60	-4.56 – 9.76	0.474	5.89	-0.92 – 12.71	0.089	1.91	-4.66 – 8.48	0.566	13.67	5.02 – 22.32	**0.002**
Property Crime Rate	1.58	-1.65 – 4.81	0.334	-1.58	-6.02 – 2.86	0.483	-3.88	-8.11 – 0.34	0.071	2.72	-1.35 – 6.80	0.188	-2.32	-7.69 – 3.04	0.393
South	0.30	-0.05 – 0.64	0.090	-0.16	-0.63 – 0.31	0.510	0.12	-0.33 – 0.56	0.613	-0.11	-0.54 – 0.32	0.619	-0.35	-0.92 – 0.22	0.224
Year 2000	1.53	1.13 – 1.94	**<0.001**	0.32	-0.23 – 0.88	0.254	0.32	-0.21 – 0.84	0.239	0.40	-0.11 – 0.91	0.123	0.55	-0.12 – 1.22	0.106
Year 2010	2.30	0.93 – 3.66	**0.001**	-0.51	-2.38 – 1.37	0.592	-0.76	-2.55 – 1.02	0.401	1.11	-0.61 – 2.83	0.205	0.23	-2.03 – 2.50	0.839
Observations	150			150			150			150			150		
R^2 / R^2 adjusted	0.602 / 0.568			0.152 / 0.078			0.371 / 0.316			0.096 / 0.017			0.261 / 0.197		

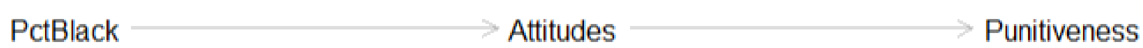
With the inclusion of the dummy variable South, representing the former confederate states, instead of the dummies for the census regions variable, it looks as though all of the trends stay mostly the same except Percent Black is no longer significant in the Conditions of Confinement dimension. Plus, South is not significant in a single model.

Nonetheless, these models largely also show support for my hypothesis that states with larger Black populations are more punitive—but less so than the other table for this hypothesis, which is something that I am certainly taking note of. The R-Squared also dropped across all of the models so I am again concerned about model fit.

Hypothesis 5

If White citizens' attitudes towards Black people mediates the relationship between Percent Black and punitiveness, then we should expect to see a decreased coefficient on Percent Black once added into the model (relative to our previous regressions, at least). Here, I attempt to test the idea that percent Black affects punitiveness through White voters' feelings of warmth or racial resentment towards Black people.

Figure 3.1 Schematic Diagram of Hypothesized Mediation



Hypothesis 5a

Net of appropriate controls, White voters' racial resentment towards Black people mediates the relationship between percent Black and punitiveness. I believe that changes in racial resentment explain why a state's level of punitiveness seems to change with the proportion of Black residents. I will focus only on models for Political and Symbolic Punishment and for Incarceration, since as previously mentioned, the measures for the other dimensions of punitiveness did not have sufficient internal consistency.

Table 3.5 Adding Aggregated Racial Resentment to the Neill et al. (2015) Regression Models: Political and Symbolic Punishment (Region)

Political and Symbolic Punishment

	Before			**After**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	8.79	5.26 – 12.32	**<0.001**	7.75	4.09 – 11.40	**<0.001**
Percent Black (Sqrt)	0.28	0.15 – 0.42	**<0.001**	0.26	0.13 – 0.39	**<0.001**
White Voter Participation	-0.04	-0.06 – -0.02	**<0.001**	-0.04	-0.06 – -0.02	**<0.001**
Percent Voted	0.00	-0.03 – 0.03	0.805	0.01	-0.02 – 0.04	0.698
Percent Poverty	-0.16	-0.24 – -0.09	**<0.001**	-0.17	-0.25 – -0.09	**<0.001**
Median Income	-0.00	-0.00 – -0.00	**<0.001**	-0.00	-0.00 – -0.00	**<0.001**
Percent High School Graduates (Sqrt)	-0.24	-0.65 – 0.17	0.247	-0.31	-0.72 – 0.10	0.140
Welfare Payments (Sqrt)	-0.90	-1.83 – 0.03	0.059	-0.83	-1.75 – 0.10	0.079
Violent Crime Rate	2.90	-2.91 – 8.71	0.324	2.22	-3.56 – 8.00	0.448
Property Crime Rate	0.67	-3.11 – 4.45	0.725	1.44	-2.38 – 5.26	0.456
Region [Midwest]	-0.48	-0.82 – -0.14	**0.006**	-0.48	-0.81 – -0.14	**0.006**
Region [Northeast]	-0.51	-0.95 – -0.07	**0.024**	-0.47	-0.91 – -0.03	**0.035**
Region [West]	0.08	-0.38 – 0.54	0.736	0.07	-0.39 – 0.52	0.772
Wave 2005	1.59	1.07 – 2.10	**<0.001**	1.61	1.10 – 2.12	**<0.001**
Wave 2015	2.34	0.49 – 4.19	**0.014**	2.42	0.59 – 4.25	**0.010**
Racial Resentment				0.39	-0.02 – 0.80	0.063
Observations	111			111		
R^2 / R^2 adjusted	0.672 / 0.624			0.684 / 0.634		

Though the evidence here is somewhat mixed, I certainly cannot say that these results make a strong case for my hypothesis about mediation, above all because the coefficient on Percent Black residents changes only marginally when we include racial resentment in the model. For Political and Symbolic Punishment, racial resentment is just shy of being significant and the coefficient is positive, as we'd expect. Not only that, but the coefficient on Percent Black has gone down by 0.02 and Percent Black continues to be significant. The R-squared value also slightly increases though the only significant terms for the Incarceration dimension are property crime rate and violent crime rate.

Now, as in the previous section, I re-specify the model with just the dummy variable for formerly confederate states rather than the full set of region dummies.

Table 3.6 Adding Aggregated Racial Resentment to the Neill et al. (2015) Regression Models: Political and Symbolic Punishment (South)

Political and Symbolic Punishment

	Before			After		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	9.10	5.42 – 12.77	**<0.001**	7.76	3.93 – 11.59	**<0.001**
Percent Black (Sqrt)	0.18	0.07 – 0.30	**0.002**	0.16	0.04 – 0.28	**0.010**
White Voter Participation	-0.04	-0.06 – -0.02	**<0.001**	-0.04	-0.06 – -0.02	**<0.001**
Percent Voted	0.00	-0.03 – 0.03	0.984	0.00	-0.03 – 0.03	0.874
Percent Poverty	-0.12	-0.20 – -0.05	**0.002**	-0.13	-0.21 – -0.06	**0.001**
Median Income	-0.00	-0.00 – -0.00	**<0.001**	-0.00	-0.00 – -0.00	**<0.001**
Percent High School Graduates (Sqrt)	-0.41	-0.80 – -0.02	**0.038**	-0.47	-0.86 – -0.08	**0.019**
Welfare Payments (Sqrt)	-1.18	-2.07 – -0.29	**0.010**	-1.04	-1.93 – -0.16	**0.021**
Violent Crime Rate	2.37	-3.56 – 8.30	0.430	1.65	-4.23 – 7.52	0.579
Property Crime Rate	2.65	-1.18 – 6.48	0.172	3.48	-0.37 – 7.33	0.076
South	0.45	0.07 – 0.84	**0.021**	0.46	0.08 – 0.83	**0.019**
Wave 2005	1.61	1.09 – 2.12	**<0.001**	1.60	1.09 – 2.11	**<0.001**
Wave 2015	2.12	0.30 – 3.94	**0.023**	2.14	0.35 – 3.93	**0.020**
Racial Resentment				0.44	0.02 – 0.85	**0.040**
Observations	111			111		
R^2 / R^2 adjusted	0.643 / 0.599			0.658 / 0.613		

Again, this model gives, at best, mixed results in relation to my hypothesis. With the addition of South instead of the Region variable, Racial Resentment is now significant and positive; however, it still does not appear to mediate the relationship between Percent Black and punitiveness for the Political and Symbolic Punishment dimension by much. The coefficient on Percent Black decreases after we've added Racial Resentment, but only by .02. Percent Black only changes marginally and clearly Percent Black affects the outcome but through other pathways.

Table 3.7 Adding Aggregated Racial Resentment to the Neill et al. (2015) Regression Models: Incarceration (Region)

Incarceration

	Before			**After**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	3.35	-1.27 – 7.96	0.153	4.37	-0.45 – 9.19	0.075
Percent Black (Sqrt)	0.14	-0.04 – 0.31	0.117	0.16	-0.01 – 0.34	0.070
White Voter Participation	-0.01	-0.04 – 0.01	0.318	-0.01	-0.04 – 0.01	0.304
Percent Voted	0.01	-0.02 – 0.05	0.457	0.01	-0.03 – 0.05	0.520
Percent Poverty	-0.02	-0.12 – 0.09	0.727	-0.01	-0.11 – 0.09	0.856
Median Income	-0.00	-0.00 – 0.00	0.590	-0.00	-0.00 – 0.00	0.644
Percent High School Graduates (Sqrt)	-0.11	-0.65 – 0.42	0.673	-0.05	-0.59 – 0.49	0.858
Welfare Payments (Sqrt)	-1.00	-2.21 – 0.22	0.108	-1.06	-2.28 – 0.15	0.086
Violent Crime Rate	8.41	0.81 – 16.01	**0.030**	9.08	1.46 – 16.71	**0.020**
Property Crime Rate	-4.40	-9.35 – 0.54	0.080	-5.15	-10.19 – -0.12	**0.045**
Region [Midwest]	-0.07	-0.52 – 0.37	0.742	-0.07	-0.51 – 0.37	0.744
Region [Northeast]	-0.02	-0.59 – 0.56	0.947	-0.06	-0.63 – 0.52	0.843
Region [West]	0.08	-0.52 – 0.69	0.787	0.09	-0.51 – 0.70	0.756
Wave 2005	0.57	-0.11 – 1.24	0.098	0.55	-0.13 – 1.22	0.111
Wave 2015	1.70	-0.72 – 4.12	0.167	1.61	-0.80 – 4.03	0.187
Racial Resentment				-0.38	-0.92 – 0.16	0.167
Observations	111			111		
R^2 / R^2 adjusted	0.214 / 0.099			0.229 / 0.108		

The Incarceration models don't really indicate that Racial Resentment serves as a mediator—if anything, the coefficient on Percent Black just increases by .02 when racial resentment is taken into account. However, as a more general note, the model of incarceration just doesn't seem very well specified, which can be seen in the low R-squared value and the fact that there are only a couple of significant variables altogether.

Now, I will see if the same remains true when I replace the census regions dummy variables with the former confederate South dummy variable.

Table 3.8 Adding Aggregated Racial Resentment to the Neill et al. (2015) Regression Models: Incarceration (South)

Incarceration

	Before			**After**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	4.26	-0.34 – 8.86	0.069	5.38	0.53 – 10.24	**0.030**
Percent Black (Sqrt)	0.15	0.00 – 0.30	**0.043**	0.18	0.02 – 0.33	**0.023**
White Voter Participation	-0.01	-0.04 – 0.01	0.298	-0.01	-0.04 – 0.01	0.291
Percent Voted	0.01	-0.03 – 0.05	0.553	0.01	-0.03 – 0.05	0.615
Percent Poverty	-0.01	-0.11 – 0.09	0.845	-0.00	-0.10 – 0.10	0.988
Median Income	-0.00	-0.00 – 0.00	0.490	-0.00	-0.00 – 0.00	0.508
Percent High School Graduates (Sqrt)	-0.23	-0.72 – 0.26	0.355	-0.18	-0.68 – 0.31	0.460
Welfare Payments (Sqrt)	-1.14	-2.25 – -0.02	**0.045**	-1.25	-2.37 – -0.13	**0.029**
Violent Crime Rate	8.43	1.00 – 15.86	**0.027**	9.03	1.59 – 16.48	**0.018**
Property Crime Rate	-4.40	-9.20 – 0.39	0.072	-5.10	-9.97 – -0.22	**0.041**
South	-0.19	-0.67 – 0.29	0.445	-0.19	-0.67 – 0.29	0.439
Wave 2005	0.66	0.01 – 1.31	**0.046**	0.66	0.01 – 1.31	**0.045**
Wave 2015	1.65	-0.62 – 3.93	0.153	1.63	-0.63 – 3.90	0.156
Racial Resentment				-0.37	-0.89 – 0.16	0.170
Observations	111			111		
R^2 / R^2 adjusted	0.215 / 0.119			0.230 / 0.127		

Percent Black became significant once we added in the former confederate states South dummy variable. Welfare Payments became significant in both of these regression models and appears to be negatively correlated with punitiveness.

Hypothesis 5b

Net of appropriate controls, White voters' feelings of warmth towards Black people mediates the relationship between percent Black and punitiveness. The feeling thermometer measures how much warmth voters feel towards a certain group, and I am imagining that the "opposite" of warmth in this case would be indifference. I believe that states with more Black people and White voters that feel indifferent towards those Black people would be more punitive than states with less Black people but more warmth from White voters. I would expect indifference to be just as important to the story of mass incarceration and why it's persisted as racial prejudice and racial resentment.

Table 3.9 Adding Aggregated Warmth to the Neill et al. (2015) Regression Models: Political and Symbolic Punishment (Region)

Political and Symbolic Punishment

	Before			**After**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	8.79	5.26 – 12.32	**<0.001**	9.52	5.46 – 13.57	**<0.001**
Percent Black (Sqrt)	0.28	0.15 – 0.42	**<0.001**	0.28	0.15 – 0.41	**<0.001**
White Voter Participation	-0.04	-0.06 – -0.02	**<0.001**	-0.04	-0.06 – -0.02	**<0.001**
Percent Voted	0.00	-0.03 – 0.03	0.805	0.00	-0.03 – 0.03	0.834
Percent Poverty	-0.16	-0.24 – -0.09	**<0.001**	-0.17	-0.25 – -0.09	**<0.001**
Median Income	-0.00	-0.00 – -0.00	**<0.001**	-0.00	-0.00 – -0.00	**<0.001**
Percent High School Graduates (Sqrt)	-0.24	-0.65 – 0.17	0.247	-0.24	-0.65 – 0.17	0.242
Welfare Payments (Sqrt)	-0.90	-1.83 – 0.03	0.059	-0.88	-1.81 – 0.05	0.065
Violent Crime Rate	2.90	-2.91 – 8.71	0.324	2.98	-2.84 – 8.81	0.312
Property Crime Rate	0.67	-3.11 – 4.45	0.725	0.65	-3.14 – 4.44	0.734
Region [Midwest]	-0.48	-0.82 – -0.14	**0.006**	-0.49	-0.83 – -0.15	**0.006**
Region [Northeast]	-0.51	-0.95 – -0.07	**0.024**	-0.51	-0.95 – -0.07	**0.024**
Region [West]	0.08	-0.38 – 0.54	0.736	0.09	-0.38 – 0.55	0.715
Wave 2005	1.59	1.07 – 2.10	**<0.001**	1.72	1.09 – 2.35	**<0.001**
Wave 2015	2.34	0.49 – 4.19	**0.014**	2.36	0.51 – 4.22	**0.013**
Thermometer - Blacks				-0.01	-0.03 – 0.02	0.470
Observations	111			111		
R^2 / R^2 adjusted	0.672 / 0.624			0.674 / 0.623		

There is no evidence that supports my hypothesis that warmth mediates the relationship between ethno-racial demography and punitiveness. If anything, more warmth seems to be associated with increased punitiveness, which does make me question the model specification for Incarceration and just how the variable is measured overall.

Table 3.10 Adding Aggregated Warmth to the Neill et al. (2015) Regression Models: Political and Symbolic Punishment (South)

Political and Symbolic Punishment

	Before			**After**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	9.10	5.42 – 12.77	**<0.001**	9.40	5.12 – 13.68	**<0.001**
Percent Black (Sqrt)	0.18	0.07 – 0.30	**0.002**	0.18	0.06 – 0.30	**0.003**
White Voter Participation	-0.04	-0.06 – -0.02	**<0.001**	-0.04	-0.06 – -0.02	**<0.001**
Percent Voted	0.00	-0.03 – 0.03	0.984	0.00	-0.03 – 0.03	1.000
Percent Poverty	-0.12	-0.20 – -0.05	**0.002**	-0.12	-0.20 – -0.05	**0.002**
Median Income	-0.00	-0.00 – -0.00	**<0.001**	-0.00	-0.00 – -0.00	**<0.001**
Percent High School Graduates (Sqrt)	-0.41	-0.80 – -0.02	**0.038**	-0.42	-0.81 – -0.02	**0.038**
Welfare Payments (Sqrt)	-1.18	-2.07 – -0.29	**0.010**	-1.18	-2.07 – -0.29	**0.010**
Violent Crime Rate	2.37	-3.56 – 8.30	0.430	2.40	-3.57 – 8.37	0.427
Property Crime Rate	2.65	-1.18 – 6.48	0.172	2.65	-1.19 – 6.50	0.174
South	0.45	0.07 – 0.84	**0.021**	0.45	0.07 – 0.84	**0.022**
Wave 2005	1.61	1.09 – 2.12	**<0.001**	1.66	1.01 – 2.31	**<0.001**
Wave 2015	2.12	0.30 – 3.94	**0.023**	2.12	0.29 – 3.95	**0.023**
Thermometer - Blacks				-0.00	-0.03 – 0.02	0.783
Observations	111			111		
R^2 / R^2 adjusted	0.643 / 0.599			0.643 / 0.595		

Again, there is no support for my hypothesis in this model. The coefficient for Percent Black and the R-squared value stay the same for the “Before” and “After” models. It appears that the aggregated measure for Thermometer – Blacks has no impact on the relationship between Percent Black and punitiveness (Political and Symbolic Punishment).

Table 3.11 Adding Aggregated Warmth to the Neill et al. (2015) Regression Models: Incarceration (Region)

Incarceration

	Before			**After**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	3.35	-1.27 – 7.96	0.153	1.84	-3.44 – 7.12	0.491
Percent Black (Sqrt)	0.14	-0.04 – 0.31	0.117	0.15	-0.03 – 0.32	0.095
White Voter Participation	-0.01	-0.04 – 0.01	0.318	-0.01	-0.04 – 0.02	0.445
Percent Voted	0.01	-0.02 – 0.05	0.457	0.02	-0.02 – 0.06	0.422
Percent Poverty	-0.02	-0.12 – 0.09	0.727	-0.01	-0.12 – 0.09	0.809
Median Income	-0.00	-0.00 – 0.00	0.590	-0.00	-0.00 – 0.00	0.686
Percent High School Graduates (Sqrt)	-0.11	-0.65 – 0.42	0.673	-0.11	-0.64 – 0.43	0.689
Welfare Payments (Sqrt)	-1.00	-2.21 – 0.22	0.108	-1.03	-2.24 – 0.19	0.097
Violent Crime Rate	8.41	0.81 – 16.01	**0.030**	8.24	0.65 – 15.84	**0.034**
Property Crime Rate	-4.40	-9.35 – 0.54	0.080	-4.36	-9.30 – 0.58	0.083
Region [Midwest]	-0.07	-0.52 – 0.37	0.742	-0.06	-0.50 – 0.39	0.803
Region [Northeast]	-0.02	-0.59 – 0.56	0.947	-0.02	-0.59 – 0.56	0.955
Region [West]	0.08	-0.52 – 0.69	0.787	0.07	-0.54 – 0.67	0.821
Wave 2005	0.57	-0.11 – 1.24	0.098	0.29	-0.54 – 1.12	0.487
Wave 2015	1.70	-0.72 – 4.12	0.167	1.65	-0.77 – 4.07	0.179
Thermometer - Blacks				0.02	-0.01 – 0.05	0.250
Observations	111			111		
R^2 / R^2 adjusted	0.214 / 0.099			0.225 / 0.102		

The results here are mostly consistent with what happened when I regressed punitiveness (Incarceration) on Percent Black and added in racial resentment for Hypothesis 5a: little to no change in the coefficient on Percent Black. The little change there is implies that greater warmth is associated with more punitiveness, which doesn’t make the most theoretical sense to me and, in any case, the estimate is not significant. Again, as mentioned earlier, it seems as though the Incarceration models simply aren’t well-specified, which is why most of the variables are not showing up as significant. It does certainly make sense that Violent Crime Rate is positive and significant here.

Table 3.12 Adding Aggregated Warmth to the Neill et al. (2015) Regression Models: Incarceration (South)

Incarceration

	Before			After		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	4.26	-0.34 – 8.86	0.069	2.63	-2.69 – 7.95	0.329
Percent Black (Sqrt)	0.15	0.00 – 0.30	**0.043**	0.16	0.01 – 0.31	**0.031**
White Voter Participation	-0.01	-0.04 – 0.01	0.298	-0.01	-0.04 – 0.02	0.429
Percent Voted	0.01	-0.03 – 0.05	0.553	0.01	-0.03 – 0.05	0.497
Percent Poverty	-0.01	-0.11 – 0.09	0.845	-0.01	-0.10 – 0.09	0.904
Median Income	-0.00	-0.00 – 0.00	0.490	-0.00	-0.00 – 0.00	0.576
Percent High School Graduates (Sqrt)	-0.23	-0.72 – 0.26	0.355	-0.21	-0.70 – 0.28	0.401
Welfare Payments (Sqrt)	-1.14	-2.25 – -0.02	**0.045**	-1.16	-2.27 – -0.05	**0.041**
Violent Crime Rate	8.43	1.00 – 15.86	**0.027**	8.25	0.83 – 15.67	**0.030**
Property Crime Rate	-4.40	-9.20 – 0.39	0.072	-4.40	-9.19 – 0.38	0.071
South	-0.19	-0.67 – 0.29	0.445	-0.17	-0.65 – 0.30	0.471
Wave 2005	0.66	0.01 – 1.31	**0.046**	0.37	-0.43 – 1.18	0.361
Wave 2015	1.65	-0.62 – 3.93	0.153	1.63	-0.64 – 3.90	0.158
Thermometer - Blacks				0.02	-0.01 – 0.05	0.231
Observations	111			111		
R^2 / R^2 adjusted	0.215 / 0.119			0.227 / 0.123		

These results still do not support my hypothesis and are actually confusing considering they seem to imply that greater warmth of feeling towards Black neighbors is associated with more punitiveness—though it's not really even suggesting that since the difference in the coefficients is very slight (0.01). Welfare payments have once again become significant with the inclusion of the former confederate states dummy variable South—and Welfare Payments remain negatively correlated with punitiveness.

Discussion

In this section, I focused on understanding the results of the regression models I ran to investigate whether White voters' attitudes towards Black people mediate the relationship been Percent Black and punitiveness.

There are mixed results at best because the coefficient on Percent Black barely ever changed when racial resentment was added to the regression models and there was absolutely no support provided when the feeling thermometer was added to the models. If anything, the feeling thermometer presented me with results that contradict what I expected and believed to be the case because the coefficient on Percent Black actually increased (very slightly) when I added in the feeling thermometer. Plus, even when there were significant results and some change after the addition of racial resentment, these changes were very small (as far as magnitude).

Ultimately, the lack of conclusive results for any of the mediation models shows me that there has to be some other mechanism through which Percent Black is impacting punitiveness at the state-level. Now, it's just a matter of identifying and testing out theories to better understand what other mechanisms might be operative here—I consider these things and more in the Conclusion.

Conclusion: Reviewing the Implications of the Past and Planning for the Future

Ultimately, this thesis is about understanding the relationship between group threat and punitiveness at the state-level. In Chapter 1, I began by giving an account of the history of racialized mass incarceration and how it's been especially harmful for the Black community. Then, I discussed group threat theory and how it relates to White voters' attitudes concerning Black people and states' levels of punitiveness.

In Chapter 2, I explored how changing racial demographics at the state-level and district-level impact White voters' attitudes towards Black people and police at the individual-level. One way I measured White voters' attitudes was by using the Thermometer — Blacks variable from ANES, which captures respondents' feelings of warmth towards members of the Black community. Another way I measured White voters' attitudes towards Black people was by using a racial resentment index, which captures racial policy attitudes. I measured White voters' attitudes towards police by using the ANES variable Thermometer — Police.

When running regressions with individual-level ANES attitude measures and state-level demographic variables, I found that there was significant support provided for most of my hypotheses. White individuals in places with larger Black populations on average tend to have lower feelings of warmth towards Black people, more racial resentment, and more warmth towards police compared to their counterparts in places that have fewer Black people. The same was true when I ran regressions with individual-level ANES attitude measures and Congressional district-level demographic variables.

From here, I transitioned to Chapter 3, where I took a step back from the local level and I looked at how punitiveness at the state-level varies with racial demographic differences. To connect state-level punitiveness with White voters' attitudes towards Black people, I aggregated the variables Thermometer – Blacks and Racial Resentment at the state-level and ran regressions to see how White voters' attitudes mediate the relationship between Percent Black and punitiveness.

In Chapter 3, when I extended the studies of Kutateladze (2008) and Neill et al. (2015) to include more observations covering a range of years, I discovered that there were issues with internal consistency for the measure of punitiveness developed by Kutateladze.

Therefore, I focused my analyses on the Political and Symbolic Punishment and Incarceration dimensions. Upon adding additional years, it appeared that, in accordance with my hypothesis, the size of the Black population has a significant positive effect on punitiveness—for all of the dimensions except Incarceration. Increases in the Black population are associated with increases in punitiveness across the different dimensions at the state-level. When I added in the dummy variable for the formerly confederate states, in place of the dummy variables for the census regions variable, it looked as though all of the trends stayed mostly the same.

Then, as mentioned previously, I aggregated the White voters' attitudes from Chapter 2 and ran more regressions to investigate whether White residents' attitudes towards Black people mediate the relationship been Percent Black and punitiveness, specifically the Political and Symbolic Punishment and Incarceration dimensions. As mentioned in previous chapters, I focused on those two dimensions because they were the only ones that were somewhat reliably measured—that is, had an acceptable level of internal consistency.

The results for the hypothesis that racial resentment mediates the relationship between Percent Black and punitiveness were negative—none of the models were conclusive enough to actually provide support. There was no support for the hypothesis that warmth towards Black people mediates the relationship between Percent Black and punitiveness, at least when aggregated at the state-level. Plus, even for racial resentment, the coefficient on Percent Black barely changed when the mediator was added to the model.

Why might this be?

First and foremost, one reason behind the lack of support for my hypotheses is that there may be some other reason for which demographics predict punitiveness at the state-level. Ultimately, from the results of Chapter 3, it appears that the attitudes I focused on do not mediate the relationship between Percent Black and state-level punitiveness through warmth, and it's not clear that mediation occurs through racial resentment either. Though I don't have the necessary variables now, I remain confident that motivations and perceptions are central to the relationship between Percent Black and punitiveness at the state-level.

Michelle Alexander says that politicians produced racist narratives about criminality and depicted social disorder as being linked to behavior—behaviors they made sure to racialize (2010). But why do people believe those types of narratives? Perhaps the best avenue for future exploration is how changing demographics impact people's willingness to believe narratives about race and crime through group threat. The more threatened that a dominant group may feel, the more susceptible that members of that group are to believing in harmful narratives about the people they perceive to be threatening their status within society. The willingness to believe in harmful narratives surrounding race and crime would then translate to a willingness to support the politicians advocating for tough-on-crime policies that increase state-level punitiveness. Therefore, in a subsequent research project, I hope to examine perceptions of race and criminality and how group threat might predict the tendency to adopt certain beliefs, which in turn might impact state-level punitiveness. I'm interested in examining what makes people receptive to the racist narratives discussed by Alexander (2010).

In the future, I would still want to carry this work forward—that is, carry forward the work of investigating the link between group threat and state-level punitiveness. I would either dedicate more time to finding more ways of measuring racial attitudes, or dedicate time towards improving the internal consistency for the different dimensions of Kutateladze's (2008) measure for punitiveness. As for the first option, I am already looking at using the General Social Survey as a source for measuring racial prejudice. And for Kutateladze's measure, I have begun looking into even more literature on the ways in which states can be punitive—I am especially interested in understanding different localities' willingness to burden the low-income population with fines and fees as they navigate the criminal justice system. The benefit of looking at the courts would be the opportunity to get more localized data, which would provide a lot more variation in Black population size over the years and across space than state-level data.

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Appendix A: Using Kutateladze's Measure for Punitiveness

Kutateladze defines punitiveness at the state level as referring to "a combination of an official political state's ideologies, policies and programs of dealing with 'objects' of the criminal justice system," with objects referring to the people that have been "suspected of the commission of a crime, then charged or discharged, convicted or acquitted, incarcerated or punished…released from custody after finishing sentence or released on parole" (2008, p. 11). Because there is really no one variable that would fully and accurately encompass punitiveness, Kutateladze's measure of punitiveness involves evaluating the punitiveness of states by their performance across five different dimensions: political and symbolic punishment, incarceration, punishing immorality, conditions of confinement, and juvenile justice. There are different ways that a state can demonstrate punitiveness and these five dimensions capture a lot of the story of punitiveness.

To gather the data for the 44 variables that make up the measure for punitiveness, I mainly depended on the sources that Kutateladze cites in the 2008 study "Introducing a new measurement of state punitiveness and testing it across the United States" because there weren't any specific data sources that I could use for the state punitiveness variables from the 2015 study by Neill, Yusuf, and Morris. Therefore, I ended up gathering the data from "Bureau of Justice Statistics, Uniform Crime Reporting Program, Office of Juvenile Justice and Delinquency Prevention, National Corrections Reporting Program, National Judicial Reporting Program, Corrections Yearbook, Death Penalty Information Center, Human Rights Watch, Amnesty International" and many other sources (Kutateladze, 2008, p. 14).

There were times where there was missing data in the tables and other times where tables were simply missing overall. In these instances, data was substituted from previous years whenever possible, and it has been acknowledged later on within this paper which variables are missing entirely.

Furthermore, the 2015 study by Neill, Yusuf, and Morris focused on the years 2002-2007, while Kutateladze's study encompassed the years 1995-2006. I made the choice to include the years 1995-2007, in hopes of increasing the accuracy of the measurements for state punitiveness since I did not consider it sufficient to include just 2002-2007—especially given that a great deal of the variables draw upon data from the earlier years and some of these data were apart of series that were discontinued prior to 2001.

Now, I will discuss the actual process through which I collected the data for each of the variables and any of the math that needed to be done. Table A.1 shows the different dimensions and the variables that make up those dimensions.

Table A.1 Dimensions and Variables

Political and Symbolic Punishment	Incarceration	Punishing Immorality	Conditions of Confinement	Juvenile Justice
Life without the possibility of parole	Stock incarceration	Statutory rape & age of consent	Prison overcrowding	Age of juvenile court jurisdiction
Life with the possibility of parole	Flow incarceration	Arrests for prostitution & commercialized vice	Operating cost per inmate	Juvenile transfer laws
Prison sentence of 20 years to life	Prison admission rates	Arrests for drug abuse	Food service cost per inmate	Juvenile inmates in adult prisons
Death penalty application	Prison release trends	Arrests for gambling	Medical care cost per inmate	Juvenile incarceration rate
Frequency of executions	Ratio of imprisonment to probation	Arrests for drunkenness	Inmate deaths	Juveniles serving life without parole
Death row population	Avg. incarceration terms for all offenses		Inmate-on-inmate & staff-on-inmate sexual violence	Overcrowding in juvenile facilities
Use of sex offender registries	Avg. time served for voluntary/nonnegligent manslaughter		Lawsuits filed against agencies & staff	
Application of felon disenfranchisement laws	Avg. time served for vehicular & nonvehicular manslaughter			
Size of disenfranchised populations	Avg. time served for forcible rape			
Three-strikes laws' application and sentence	Avg. time served for armed robbery			
Number of three strikes prisoners	Avg. time served for burglary			
	Avg. time served for auto theft			
	Avg. time served for the possession & use of marijuana			
	Avg. total maximum term imposed for all offenses			
	Avg. prison term expected to be served for all offenses			

For variable 1, I was unable to get the Camp (2003) book that Kutateladze used within their study because my library could only locate and request Corrections Yearbook 2001, which was published by Camp & Camp in 2002, and Corrections Yearbook: Everything Anyone Wants to Know About Jails, which Camp & Camp published in 1999. I obtained the data pertaining to those serving life without possibility of parole for 2001 since that was all I had available. I calculated the average number of murders and non-negligent manslaughter by using FBI's UCR "Persons Arrested" tables from 1995-2007. I then calculated the ratio for those serving life without possibility of parole in 2001 to the "average annual number of arrests for murder and non-negligent manslaughter" (p. 26). For variable 2, I followed mostly the same procedure, except I found the data for those serving life with the possibility of parole for 2001. Variable 3 had to do with those serving 20 years or more than that. Like I did with variables 1 and 2, I obtained this data from Camp (2002). This time, though, I divided the number of inmates who were serving 20+ years (all the way up to life) by the "average annual number of arrests for violent offenses," which I again calculated using the data from the UCR for the years 1995 to 2002--I multiplied that number by 100 and got the imprisonment rate for each state.

I was able to get the information for the death penalty application variable (4) by consulting the Death Penalty Information Center to get information on which states continue to apply the death penalty (Death Penalty Information Center, n.d.).

For variable 5, I calculated the frequency of executions by consulting the same source that Kutateladze did, which was the Capital Punishment series reports that are put out by the Bureau of Justice Statistics. We got the total number of executions across the years 1996-2006, divided by the average annual arrests (for murder and non-negligent manslaughter across 1995-2006), and then multiplied by 1,000 to get the execution rate.

I got the Death Row Population (variable 6) data by consulting the Death Penalty Information Center's end-of-year report for 2007 where they released statistics on the size of each state's death row population. Then, I divided that by the average annual arrests (for murder and non-negligent manslaughter across 1995-2006), and then multiplied by 1,000 to get the death row rate.

I was not able to get data for variable 7 because the Family Watchdog database is constantly being updated with new information, and there is no archive where they keep older sex offender counts by states.

I found the data on disenfranchisement laws' application in the 2007 Sentencing Project report that Kutateladze references (2008). I used the same source for variable 9.

Variable 10 was made up of the combined score of 3 elements--"Strike Zone," "Number of Strikes Needed," and "Life Sentences Requirement" (Kutateladze, 2008, pp. 58-59). I used the data from Schiraldi et al. (2004) for each of these elements.

For variable 11, I got the data from Schiraldi, Colburn & Lotke (2004) just like Kutateladze (2008) did. I also brought in the data from Harrison & Beck (2004) to create the rate of three-strikes prisoners per 1,000 state prisoners.

I obtained the data for variables 12, 13, 14, 15 from Sabol, Minton, & Harrison (2007) like Kutateladze (2008) did. When average annual arrests were needed for constructing the variables, I brought in data from the FBI's UCR "Persons Arrested" table--variable 12 only needed arrests data for 1995-1997 and 1999-2005, variable 13 only needed arrests data for 2004 and 2005, and variable 14 needed arrests for the years 2005 and 1999 (2008, pp. 72-75).

For variable 16, I used data from Harrison & Beck (2006) and "Persons Arrested" data from the FBI's UCR 2004 table. I divided the number of inmates by arrests and multiplied by 1,000 to get the incarceration rate. I divided the number of people on probation by the number of arrests and multiplied by 1,000 to get the probation rate. Then, I calculated the ratio between the incarceration rate and the probation rate for 2005.

For variable 17, I used Camp (2002) to get the average time served for all offenses by state.

Before beginning to work with variables 18-25, I set up a case_when so that I could get more easily digestible values for the time served by each inmate--the data was binned by categories because the specific number of months/years that a person spent incarcerated was restricted-access only. Originally the sentence length variable was made up of the following categories: "(0) < 1 year," "(1) 1-1.9 years," "(2) 2-4.9 years," "(3) 5-9.9 years," and "(4) >=10 years." I settled on dividing the sentence lengths by half and then assigned those new numeric variables values to each of the binned values: 0.5 assigned to category (0), 1.45 assigned to (1), 3.45 assigned to (2), 7.45 assigned to (3), and 10 assigned to (4)--since there is a much larger range for that bin and this is still likely lowballing the estimate. The dataframe was in the form of states (rows) by years (columns). Then, for each of those variables, I calculated the means across the columns to get the mean sentence length for the years 1998-2007. Following Kutateladze's steps, I put the scores for the states from variable 17 into any places where there was missingness.

Variable 19 is missing because I am not able to break down the manslaughter category to vehicular and non-vehicular manslaughter -- there are only the types of offenses that we combined to create variable 18, which was "murder (including non-negligent manslaughter" and "Negligent manslaughter". I also could not obtain data for the variables 25 and 26, but this was due to the data being in a format that I couldn't work with in RStudio.

For Statutory Rape and Age of Consent, which is variable 27, I followed Kutateladze's lead and used the Lewin Group report to record the information pertaining to the four elements that Kutateladze combines to give each state a score: "Age of Consent," "Minimum Age of a Victim," "Age Difference," and "Mistake of Age Defense" (2008, pp. 117-118). For "Age of Consent," states are grouped 0 to 2 where states with 16 as the minimum age are 0 (least punitive), states with 17 as the minimum age are 1, and states with 18 as the minimum age are 2 (most punitive) (2008, p. 117). For "Minimum Age of a Victim," states are given a 0 if the minimum age of a victim is "lower than the Age of Consent," and a 1 if the minimum age isn't lower (2008, p. 117). The "Age Difference" element looks at the "presence or absence of age-gap requirements between the perpetrator and underage partner to group jurisdictions" (2008, pp. 116-117). States with such requirements are given a 0 (least punitive), while states without these requirements are rate 1 (most punitive). And finally, the "Mistake of Age Defense" just looks at "whether or not [states] allow the mistake-of-age defense (element scores = 0 and 1, respectively)" (2008, p. 116). The variable 27 score overall was then computed by "adding the [four] elements' scores and then subtracting 1 from the sum...negative scores were assigned zero" (2008, p. 119).

I collected data for variables 28, 29, 30, and 31 at the same time since I gathered the arrests data from the FBI's UCR reports--the data for each of the variables was from 2005. The 2005 population estimates came from the same report. I divided the arrests rate for each variable by the state populations and then multiplied by 1,000,000 to get the rate per 1,000,000 residents.

For variable 32, I used the same data sources as Kutateladze (2008), which was data from the Bureau of Justice Statistics's *Prisoners* series, and this entailed combining information from 11 different documents because I needed to record the prison overcrowding data for the years 1995-2006. Then, I took the average of those population counts.

For variable 33, I got the data for operating costs from Stephan (2004, June). I also obtained medical care costs and food service costs (variables 34 and 35) from Stephan (2004, June) instead of Camp (2003) since I couldn't access Camp (2003). I divided the cost by the median family income for 2006, which I got from the ACS 2006 (1-Year Estimates).

When it came to recording the amount of inmate deaths by type (suicide or homicide) for variable 36, I took the data from Mumola (2005, p.3) like Kutateladze does (2008, p. 156).

For variable 37, I used the same source as Kutateladze (2008), which was Beck, Harrison, & Adams (2007) and recorded the amount of allegations of inmate-on-inmate sexual violence and the allegations of staff-on-inmate sexual violence reported by State or Federal prison authorities for 2006.

For variable 38, I had to use the table "Lawsuits filed by inmates and court orders" in Camp & Camp (2002, p. 74) because, as mentioned earlier, my library was not able to get ahold of the Camp (2003) corrections yearbook. I divided the lawsuits filed by the number of inmates in prison 6/30/01.

For variable 39, I obtained the data from Snyder & Sickmund (2006), and didn't have to do much besides adding the ages together. For variable 40, I used Snyder & Sickmund (2006) to populate the data pertaining to juvenile transfer laws. I added together what Kutateladze refers to as the punitiveness aggravators and then subtracted the punitiveness mitigators to get the punitiveness score.

For variable 41, I used Sabol, Minton, & Harrison (2007) to get the number of incarcerated juveniles for mid-year 2006. Then, I got the population count from the Decennial Census data available on Social Explorer for 2000. I divided the number of incarcerated juveniles by the overall general juvenile population and multiplied by 100,000 to get the rate of juvenile inmates in adult prisons per 100,000.

Following Kutateladze's lead, I created the juvenile incarceration rate (variable 42) by taking the number of incarcerated juveniles (Sickmund, Sladky, & Kang, 2005), dividing that by the number of juveniles that were arrested in 2003 according to FBI's UCR report--specifically the "Persons Arrested" table--and then multiplying by 1,000.

I used the same Human Rights Watch (2005) document that Kutateladze used to create variable 43 and was able to get all of the necessary information. The dissertation has the LWOP per 100,000 14-17 year olds listed as 12.54; however, according to the Human Rights Watch "State population data table," the LWOP rate is 132.94. I went with 132.94. For variable 44, I easily obtained the data from Snyder & Sickmund's Juvenile offenders and victims: 2006 National report (2006, March). At the end of the process of collecting the data, I joined all of the variables together to create one large table in which states were rows and columns were variables. And, from here, I went on to run the regressions that Neill et al. run in their 2015 study, before proceeding with my own analyses as reported in Chapter 3.

In Table A.2, I present the scores I obtained for each of the dimensions after replicating Kutateladze’s study.

Table A.2 Scores for Each Dimension

State	Political and Symbolic Punishment	Incarceration	Punishing Immorality	Conditions of Confinement	Juvenile Justice
Alabama	3.00	2.33	1.4	2.43	3.17
Alaska	0.90	1.42	0.8	1.43	2.50
Arizona	2.00	1.75	1.6	1.00	2.17
Arkansas	3.00	1.75	2	2.14	2.17
California	2.50	1.25	3.6	1.71	1.50
Colorado	2.00	2.08	1.8	2.29	2.00
Connecticut	1.70	1.67	1.8	2.29	2.67
Delaware	2.80	1.00	2.4	2.14	3.00
Florida	3.10	2.42	2.6	1.43	2.67
Georgia	3.10	2.67	3	1.57	2.33
Hawaii	0.60	2.33	1.6	2.00	1.33
Idaho	1.80	2.75	1.4	2.86	1.33
Illinois	1.30	1.83	3	2.71	2.83
Indiana	2.10	1.58	2.2	2.14	2.83
Iowa	1.20	1.50	1	2.29	2.17
Kansas	1.90	1.25	1	2.14	2.33
Kentucky	2.00	1.75	2.6	2.00	1.33
Louisiana	2.10	2.08	2.8	2.57	2.67
Maine	0.50	2.25	0.4	0.57	0.83
Maryland	2.30	2.33	2.6	2.14	1.67
Massachusetts	0.90	2.75	1.2	2.57	2.67
Michigan	0.70	2.83	1.6	0.86	3.00
Minnesota	0.60	0.50	1.6	1.43	1.83
Mississippi	2.90	2.58	2.8	2.00	2.17
Missouri	1.80	1.58	3	2.14	2.33
Montana	2.10	3.25	0.4	2.57	1.83
Nebraska	2.00	1.17	1.8	1.86	2.33
Nevada	3.10	2.58	2.4	1.57	2.17
New Hampshire	1.30	2.25	1.6	2.14	1.17
New Jersey	1.20	1.58	2	1.86	1.00
New Mexico	1.40	2.83	1.4	1.00	1.33
New York	1.30	2.17	1.8	2.14	2.33
North Carolina	1.90	1.25	1.8	1.57	2.50
North Dakota	1.60	0.50	1.2	1.14	1.83
Ohio	2.10	3.25	2.2	1.71	2.50
Oklahoma	2.50	3.17	2	1.57	1.83
Oregon	1.60	2.08	1.6	1.86	1.50
Pennsylvania	1.80	2.33	2.2	1.29	2.50
Rhode Island	1.00	0.58	1	1.00	2.50
South Carolina	2.70	2.42	2.6	2.14	3.00
South Dakota	1.80	1.67	1	1.86	2.00
Tennessee	2.90	1.67	3.4	1.71	1.67
Texas	2.30	2.92	2.8	1.86	1.83
Utah	1.40	1.25	1.6	2.14	1.83
Vermont	0.70	1.00	0.6	2.29	1.33
Virginia	2.90	2.67	2.4	2.00	2.50
Washington	2.40	1.42	1	2.00	1.50
West Virginia	1.00	2.00	1	1.29	1.50
Wisconsin	1.20	1.50	1.4	2.29	1.00
Wyoming	1.80	2.00	2.2	1.71	1.83

I calculated the Overall Punitiveness Score (OPS) for each state by taking a mean of the scores that states got for the five dimensions, and those results can be seen in the table below. The most punitive states are South Carolina, Georgia, Virginia, Mississippi, Alabama, Louisiana, Florida, Nevada, Ohio, and Texas—the majority of those states are located within the South, interestingly enough. The least punitive states are Maine, Vermont, Minnesota, Rhode Island, North Dakota, West Virginia, Alaska, Wisconsin, New Jersey, and Hawaii. Though this information is helpful for getting a sense of how states compare overall, I don't run regressions with the OPS score because of the issues with internal consistency across the five dimensions—I present Cronbach's Alpha scores for the measures over the years in Appendix B.

Table A.3 Overall Punitiveness Scores

State	Overall Punitiveness Score
Maine	0.91
Vermont	1.18
Minnesota	1.19
Rhode Island	1.22
North Dakota	1.26
West Virginia	1.36
Alaska	1.41
Wisconsin	1.48
New Jersey	1.53
Hawaii	1.57
New Mexico	1.59
Iowa	1.63
Utah	1.65
Washington	1.66
South Dakota	1.66
New Hampshire	1.69
Arizona	1.70
Kansas	1.73
Oregon	1.73
Michigan	1.80
North Carolina	1.80
Nebraska	1.83
Wyoming	1.91
Kentucky	1.94
New York	1.95
Massachusetts	2.02
Connecticut	2.02
Pennsylvania	2.02
Idaho	2.03
Montana	2.03
Colorado	2.03
California	2.11
Indiana	2.17
Missouri	2.17
Maryland	2.21
Arkansas	2.21
Oklahoma	2.21
Delaware	2.27
Tennessee	2.27
Illinois	2.34
Texas	2.34
Ohio	2.35
Nevada	2.36
Florida	2.44
Louisiana	2.44
Alabama	2.47
Mississippi	2.49
Virginia	2.49
Georgia	2.53
South Carolina	2.57

Appendix B: Initial Replication of Neill et al.

As I discussed in the main text, Chapter 3 builds on the foundations of this paper, and here I will report the results of that replication.

To determine what variables might predict increased punitiveness in states, Neill et al. (2015) explored the relationships between various social, economic, and cultural factors and state-level punitiveness across five dimensions: political and symbolic punishment, incarceration, punishing immorality, conditions of confinement, and juvenile justice—these dimensions being the ones I discussed in further detail in Appendix A.

They ultimately found that "poverty rate and welfare spending are the dominant negative drivers of state punitiveness in terms of political and symbolic punishment" and, "for the incarceration dimension, citizen engagement and property crime have a statistically significant and negative impact on state punitiveness, while the percent of population that is Black and the percent of population with a high school diploma have a significant and positive effect" (Neill et al., 2015, p. 763).

Moreover, "violent crime rate was a significant and positive driver of the punishing immorality dimension of state punitiveness" and, "for juvenile justice, violent crime rate and the percent of the population that is Black are positive and statistically significant" (2015, p. 763). From their analysis, it seems that, while different factors predict different forms of punitiveness, one of the most consistently important factors is the racial makeup of a population.

Variables

I used mostly the same variables for my regressions building on Neill et al.'s 2015 results, and I've already discussed those in Chapter 3. However, now, I will provide more explanations for the inclusion of different variables but this time with the explanations given by Neill et al. (2015).

As far as racial threat, social control, and cultural explanations, the general belief is that "white citizens may be more likely to support punitive crime policies if they think they will be more likely to target a population they fear or dislike," which tends to be the Black population (Neill et al., 2015, p. 756). Therefore, states with higher amounts of Black people will be more punitive than states with less Black people. The authors also hypothesize that there is a negative relationship between "education and support for punitiveness," which would manifest as states being less punitive when their citizens are more educated (Neill et al., 2015, p. 757). This could be due to the citizens being "more open to new information regarding various issues, including crime policy," or even that "with education comes a greater tolerance for difference" (Bobo & Johnson, 2004 as cited by Neill et al., 2015, p. 757).

Furthermore, Neill et al. believe there should be a "positive relationship between poverty rates and punitiveness" but a negative relationship between median income and punitiveness (2015, pp. 757-758). Neill, Yusuf, and Morris hypothesize that people with lower incomes might feel they need to commit crime in order to make a living and the state may be using criminal justice as a way to both respond to the increased crime and exert social control (2015). If this is the case, they say that it would then make sense for people in states with higher median incomes to be less likely to commit crime, resulting in states not feeling the need to be as punitive.

With regard to political explanations, the authors believe that there is a negative relationship between citizen engagement and state punitiveness, where states with really civically engaged citizens tend to be less punitive (Neill et al., 2015). When people are more involved politically, they tend to steer the state away from repressive policies. Another important aspect of the story to consider though is that “At the state level, a conservative citizenry has been a significant predictor of state imprisonment rates” (Jacobs & Carmichael, 2001 as cited by Neill et al., 2015, p. 758). Violent crime rate and property crime rate were included to control for how state punitiveness could’ve party been in response to these increases in these variables.

Unlike my work in Chapter 3, Neill et al. (2015) did not control for regional differences or White voter participation. They also did not include data for multiple time periods, instead carrying out a single cross-sectional analysis.

Table B.1 Cronbach's Alpha Scores for the Replication and Extension Measures of Punitiveness

Year	Dimension	Cronbach's Alpha	Internal Consistency Rating
1995	Political and Symbolic Punishment	0.4013316	Unacceptable
1995	Incarceration	0.867066	Good
1995	Punishing Immorality	0.5752569	Poor
1995	Conditions of Confinement	-0.1791045	Unacceptable
1995	Juvenile Justice	(only one column)	NULL
2005	Political and Symbolic Punishment	0.7220491	Acceptable
2005	Incarceration	0.6605827	Questionable
2005	Punishing Immorality	0.4458896	Unacceptable
2005	Conditions of Confinement	-0.2047138	Unacceptable
2005	Juvenile Justice	0.1836828	Unacceptable
1995-2007	Political and Symbolic Punishment	0.6974811	Questionable
1995-2007	Incarceration	0.7877517	Acceptable
1995-2007	Punishing Immorality	0.4458896	Unacceptable
1995-2007	Conditions of Confinement	-0.3654591	Unacceptable
1995-2007	Juvenile Justice	0.2103193	Unacceptable
2015	Political and Symbolic Punishment	0.7353003	Acceptable
2015	Incarceration	0.6021356	Questionable
2015	Punishing Immorality	0.5210353	Poor
2015	Conditions of Confinement	0.1655172	Unacceptable
2015	Juvenile Justice	0.1203324	Unacceptable

Results

Neil et al.

In the study, Neill, Yusuf, and Morris regressed the scores for the five dimensions of state level punitiveness on eight independent variables "representing racial, social control, cultural, political, and economic factors" (2015, p. 763). They ran seemingly unrelated regressions in an effort to see the entire picture of state level punitiveness because "all five dependent variables are measures of the same underlying construct (punitiveness)" (Neill, Yusuf, and Morris, 2015, p. 763). The seemingly unrelated regression method was used because this approach "estimates the parameters of all equations simultaneously, so…the parameters of each single equation also take the information provided by the other equations into account" (Cadavez & Henningsen, 2011, p. 2).

Regarding the results of their regression, for political and symbolic punishment, Neill, Yusuf, and Morris found that only percent poverty and welfare payments had coefficients that were statistically significant (2015, p. 764). Both of these variables had negative effects on punitiveness, which means that, as the percentage of the population that is in poverty and the amount of welfare payments decreases, the indicators of political and symbolic punishment increase.

With the incarceration dimension, however, Neill, Yusuf, and Morris discovered that percent voted, percent Black, percent high school graduates, and property crime rate all had statistically significant coefficients (2015, p. 764). Percent voted and property crime rate both had negative values, meaning, as the percentage of the population that voted and the property crime rate decreased, states became more punitive with respect to incarceration. On the other hand, percent Black and percent high school graduates had positive coefficients, which means that increases in these variables are associated with increases in the incarceration dimension of state level punitiveness.

For the punishing immorality dependent variable, Neill, Yusuf, and Morris did not get any statistically significant results (2015, p. 764).

Conditions of confinement had one significant predictor: percent Black (2015, p. 764). As percent Black increased, state level punitiveness as far as conditions of confinement increased too.

For juvenile justice, there were only two predictors with statistically significant coefficients and they were percent Black and violent crime rate (2015, p. 764). States with a higher percentage of Black people and higher violent crime rates tended to have higher levels of punitiveness regarding juvenile justice.

Replication

Instead of running the seemingly unrelated regressions model at first, I decided to run five separate regressions and look at those coefficients—later, I compared these coefficients with the coefficients I obtained from the seemingly unrelated regressions. The results of these five separate regressions differed greatly from the results of the original study.

Similar to Neill, Yusuf, and Morris, I regressed variables representing state level punitiveness on eight independent variables that essentially captured states' racial, social, cultural, political, and economic composition (2015). The variables representing the state level punitiveness came from the scores that states received for each of the five dimensions: political and symbolic punishment, incarceration, punishing immorality, conditions of confinement, and juvenile justice. The eight independent variables were percent of the population that voted, percent living below the poverty level, median income, percent of the population that is Black, percent high school graduates, welfare payments, violent crime rate, and property crime rate.

As mentioned before, I initially ran five separate regressions representing each of the five dimensions instead of using seemingly unrelated regression like Neill, Yusuf, and Morris did (2015). This decision was spurred by a desire to see whether there were any changes in the coefficients if I went from regressing on the independent variables separately to using a seemingly unrelated regression model to run all of the equations simultaneously—I wanted to see if the values themselves would change or whether there would be any changes in which of the coefficients were statistically significant.

Table B.2: Replication Results

Dimensions of State-Level Punitiveness

	Political and Symbolic Punishment			**Incarceration**			**Punishing Immorality**			**Conditions of Confinement**			**Juvenile Justice**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	3.01	-8.26 – 14.28	0.593	-8.67	-22.38 – 5.03	0.209	10.09	-2.58 – 22.76	0.115	0.33	-11.57 – 12.23	0.956	-2.32	-13.34 – 8.70	0.673
Percent Black (Sqrt)	0.28	0.15 – 0.41	**<0.001**	0.09	-0.06 – 0.25	0.231	0.22	0.08 – 0.36	**0.004**	0.07	-0.06 – 0.21	0.277	0.26	0.14 – 0.39	**<0.001**
Percent Voted	-0.01	-0.05 – 0.02	0.334	-0.03	-0.07 – 0.01	0.124	-0.02	-0.06 – 0.01	0.220	0.01	-0.02 – 0.05	0.442	0.01	-0.02 – 0.04	0.532
Percent Poverty	-0.04	-0.12 – 0.04	0.286	0.13	0.03 – 0.22	**0.009**	-0.02	-0.11 – 0.06	0.613	0.03	-0.05 – 0.11	0.481	-0.05	-0.13 – 0.02	0.159
Median Income	-0.00	-0.00 – -0.00	**0.019**	0.00	-0.00 – 0.00	0.540	0.00	-0.00 – 0.00	0.427	0.00	-0.00 – 0.00	0.354	-0.00	-0.00 – 0.00	0.079
Percent Graduated High School (Sqrt)	0.34	-0.95 – 1.63	0.596	1.27	-0.29 – 2.84	0.108	-0.81	-2.26 – 0.64	0.263	0.05	-1.31 – 1.41	0.937	0.56	-0.70 – 1.82	0.375
Welfare Payments (Sqrt)	-2.15	-3.73 – -0.58	**0.009**	-1.58	-3.50 – 0.33	0.103	-1.05	-2.82 – 0.72	0.238	-1.10	-2.77 – 0.56	0.188	-0.17	-1.71 – 1.37	0.824
Violent Crime Rate	0.02	-0.22 – 0.26	0.883	-0.05	-0.34 – 0.24	0.733	0.03	-0.24 – 0.30	0.818	-0.07	-0.33 – 0.18	0.572	0.20	-0.04 – 0.43	0.100
Property Crime Rate	0.05	-0.04 – 0.14	0.256	-0.10	-0.21 – 0.01	0.076	0.03	-0.07 – 0.14	0.545	-0.00	-0.10 – 0.09	0.951	0.01	-0.08 – 0.10	0.797
Observations	50			50			50			50			50		
R^2 / R^2 adjusted	0.642 / 0.572			0.388 / 0.268			0.570 / 0.486			0.107 / -0.067			0.450 / 0.343		

As far as the results of the regressions I ran, for political and symbolic punishment I found that median income, percent Black, and welfare payments had statistically significant coefficients. Median income had a very small negative coefficient (0.00005) which is interesting because it's a relatively minimal effect. Welfare payments had a coefficient of -2.15 indicating that as welfare payments increase, Political and Symbolic punishment decreases by quite a bit.

Regarding the incarceration regression, only the coefficient for percent poverty was statistically significant. This model tells us that an increase in the amount of people living below the poverty level is associated with an increase in how punitive states are with respect to the incarceration dimension.

For the punishing immorality and juvenile justice regressions, percent Black was the only statistically significant coefficient. Given that both coefficients were positive, we know the model thinks that increases in the percentage of the population that is Black are associated with increases in state level punitiveness, specifically where punishing immorality and juvenile justice are concerned.

In the conditions of confinement regression, I did not get any statistically significant results.

When comparing my results to those of Neill, Yusuf, and Morris, it is immediately apparent that the coefficients our models consider statistically significant are different. For political and symbolic punishment, my statistically significant coefficients were median income, percent Black, and welfare payments, while Neill, Yusuf, and Morris had percent poverty and welfare payments (2015). Regarding incarceration, the only coefficient that was statistically significant in my model was percent poverty. In this model, Neill, Yusuf, and Morris found that the coefficients for percent voted, percent Black, percent high school graduates, and property crime rate were all statistically significant (2015).

For punishing immorality, percent Black was statistically significant in my model, but there were no statistically significant coefficients in the model by Neill, Yusuf, and Morris (2015). Where the dependent variable for conditions of confinement was concerned, my model did not obtain any statistically significant results, while the model by Neill, Yusuf, and Morris found that percent Black was statistically significant (2015). And finally, for juvenile justice, I got a statistically significant coefficient for percent Black, but Neill, Yusuf, and Morris found that percent Black and violent crime rate were both statistically significant (2015).

As far as the most prominent trend, my model and the model by Neill, Yusuf, and Morris show that percent Black is significant to the overall picture of state punitiveness (2015). In my model, the percent Black variable was statistically significant in political and symbolic punishment, punishing immorality, and juvenile justice, and in the model by Neill, Yusuf, and Morris this variable was statistically significant in incarceration, conditions of confinement, and juvenile justice (2015). Both models showed that percent Black was important in at least three of the five dimensions of state level punitiveness, which shows that the racial makeup of states is especially crucial to the patterns of state level punitiveness that we see.

These results are interesting with regard to my theory of the role of racial threat and punitiveness because it appears that the results from Neill et al. and my replication show that percent Black is a significant predictor for punitiveness—across the majority of the five punitive dimensions. With the addition of more variables within the extension section, we will be better able to examine whether aggregated citizens' attitudes towards Black people have any impact on state punitiveness.

Seemingly Unrelated Regressions

Following the five separate regressions I ran earlier, I decided to run seemingly unrelated regressions to see whether those results more closely resembled the results of the original study. As for the results, the political and symbolic regression equation revealed statistically significant coefficients for median income, percent Black, and welfare payments. In the incarceration model, only the coefficient for percent poverty was statistically significant, but the coefficient for property crime rate was almost statistically significant. For punishing immorality, only the coefficient on percent Black was statistically significant. The conditions of confinement regression did not have any statistically significant coefficients. The regression for juvenile justice had a statistically significant coefficient for percent Black and almost statistically significant coefficients for median income and violent crime rate.

There are some small changes in the variables that the model thinks are statistically significant. In my earlier regressions, for political and symbolic punishment, percent high school graduate was included alongside median income and percent Black, but the seemingly unrelated regression model included welfare payments instead of percent high school graduate. The incarceration model had the same result as my earlier regression, which is that percent poverty is statistically significant. For punishing immorality and juvenile justice, it was once again apparent that only percent Black was statistically significant. Same as before, I did not get any statistically significant coefficient for conditions of confinement. Overall, the only change that increased the similarities between my results and those of Neill, Yusuf, and Morris was the inclusion of welfare payments instead of percent high school graduates in the political and symbolic punishment model.

Similar to before, the results imply that percent Black plays a huge role in the punitiveness of states, especially with regard to punishing immortality and juvenile justice for both models. The continued importance of percent Black to the story of states' punitiveness only furthers my determination to better understand whether it's racial threat that has a large impact on states' punitiveness.

Discussion

The implications of the study by Neill, Yusuf, and Morris reveal interesting trends in how social control is exerted within states—and who that control is primarily intended for. The implications of percent poverty and welfare payments being statistically significant in the political and symbolic punishment model are that "blacks are perceived as a potential threat requiring coercive controls" and states with "a less generous welfare system are more likely to make use of symbolic forms of punishment" (Neill et al, 2015, pp. 764-765).

As far as incarceration, increased political participation, number of Black people, and amount of high school graduates are correlated with an increase in how punitive states are. These trends indicate that it's likely "the social control argument holds and that for states with large black populations, the white citizenry may be more likely to support policies that will adversely affect blacks as a way to control and contain this population" (2015, p. 766). For punishing immorality, there aren't many implications to glean as none of the coefficients are statistically significant.

One of the implications for conditions of confinement is that these conditions were "more a product of state corrections budgets and administrative decisions within individual prisons than a result of socioeconomic factors" (2015, p. 767). In regard to juvenile justice, both percent Black and violent crime rate were statistically significant, which points towards the idea that harsher crime policies are the states' way of controlling the Black population as well as handling crime altogether.

Assuming my regressions are accurate, one of the main implications would be that group threat seems to transcend all of the different dimensions of punitiveness. Across the five models, three of the models had statistically significant coefficients for percent Black. These three models were political and symbolic punishment, punishing immorality, and juvenile justice. The coefficients for percent Black within these models are 0.28, 0.22, and 0.26, respectively. These coefficients indicate that percent Black has a substantial positive effect on how punitive a state is as far as political and symbolic punishment, punishing immorality, and juvenile justice. The implications of the regressions I ran justify further examination into whether the relationship between various social, economic, cultural, and political factors and state punitiveness is mediated by the racial makeup of the states. The goal of my extension is to determine the extent to which the other factors' correlation with state punitiveness is affected by the percentage of the population that is Black. Another trend is that, in regards to incarceration, the coefficient for percent poverty is both positive and statistically significant.

I'm not too sure why my results differ from theirs, but it may be due to some of the missing data as described in the previous appendix. In any case, in Chapter 3, I built my own models on these foundations and developed them in relation to my own ideas, which is why I added in elements like time, regions, and aggregated attitudes towards Black people.

Appendix C: Addressing the Low Cronbach's Alpha Scores

As seen previously in Table B.1, the internal consistency for several of the dimensions of punitiveness analyzed in Chapter 3 were unacceptably low. For most of my analyses, I focused only on response variables that did have high internal consistency; however, here I report on one other strategy I tried in addressing the low Cronbach's Alpha scores.

One of the techniques I used to address the low Cronbach's Alpha scores is simply decreasing the number of variables I'm including to measure each dimension. Ideally, I'd include as many variables as possible to get an accurate gauge of how states compare to each other across these categories of punitiveness; however, when the Cronbach's Alpha scores end up being as low as they were in the previous section, then it makes sense to cut down on the variables being used.

In cutting down on the number of variables I've included in each dimension, I tried to initially keep the variables that have typically been used in previous studies as measures of punitiveness and, of these variables, I kept the ones that were consistently available over the years (or mostly consistently given how difficult it was to locate reliable data for the 1990-1999 wave). However, as there were still issues with internal consistency for all of the dimensions except the incarceration dimension, I decided to keep only one variable for each category—the variable that appeared to be the most reliable across the years and seemed to be the best measure for each dimension.

Table C.1 Using One Variable to Measure Each Dimension

Political and Symbolic Punishment	Incarceration	Punishing Immorality	Conditions of Confinement	Juvenile Justice
Death Row Population	Average Time Served for Drug-Related Arrests	Arrests for Drug Abuse Violations	Inmate Deaths	Juvenile Incarceration Rate

Now, we're going to look at the same hypothesis from Chapter 3, but this time we are including only one variable for punitiveness in each dimension instead of multiple variables making up the measures.

Results

Hypothesis 1

Like in Chapter 3, the hypothesis I am investigating here is that, **net of appropriate controls, states with larger Black populations are likelier to be more punitive across all of the dimensions**. If my hypothesis is correct, then the regressions should show that percent Black has a significant positive effect on the level of punitiveness.

Table C.2 Results of the Regressions After Selecting One Variable for Each Dimension (Region)

H1: Dimensions of State-Level Punitiveness

	Political and Symbolic Punishment			**Incarceration**			**Punishing Immorality**			**Conditions of Confinement**			**Juvenile Justice**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	5.84	0.03 – 11.64	**0.049**	-2.77	-9.76 – 4.23	0.435	8.88	2.17 – 15.58	**0.010**	2.06	-4.76 – 8.88	0.552	-0.62	-7.83 – 6.58	0.864
Percent Black (Sqrt)	0.39	0.18 – 0.59	**<0.001**	0.26	0.02 – 0.50	**0.038**	0.20	-0.04 – 0.44	0.096	-0.05	-0.29 – 0.19	0.669	0.12	-0.13 – 0.37	0.348
White Voter Participation	-0.03	-0.06 – 0.01	0.099	0.01	-0.03 – 0.05	0.692	-0.02	-0.06 – 0.02	0.327	-0.02	-0.06 – 0.02	0.247	-0.03	-0.07 – 0.01	0.205
Percent Voted	0.04	-0.01 – 0.08	0.091	0.01	-0.04 – 0.06	0.717	-0.04	-0.09 – 0.01	0.098	0.01	-0.04 – 0.06	0.805	-0.02	-0.07 – 0.04	0.549
Percent Poverty	-0.10	-0.22 – 0.03	0.123	0.00	-0.14 – 0.15	0.964	-0.11	-0.26 – 0.03	0.116	-0.08	-0.22 – 0.06	0.272	0.11	-0.04 – 0.26	0.161
Median Income	-0.00	-0.00 – -0.00	**<0.001**	0.00	-0.00 – 0.00	0.488	-0.00	-0.00 – 0.00	0.276	-0.00	-0.00 – 0.00	0.415	-0.00	-0.00 – 0.00	0.650
Percent High School Graduates (Sqrt)	-0.21	-0.87 – 0.46	0.544	0.84	0.04 – 1.64	**0.040**	-0.26	-1.04 – 0.51	0.500	0.38	-0.41 – 1.16	0.345	0.38	-0.45 – 1.21	0.368
Welfare Payments (Sqrt)	-2.93	-4.53 – -1.33	**<0.001**	-2.33	-4.26 – -0.40	**0.019**	-0.59	-2.43 – 1.26	0.531	1.73	-0.15 – 3.61	0.071	2.19	0.20 – 4.18	**0.031**
Violent Crime Rate	11.74	1.77 – 21.72	**0.021**	4.47	-7.48 – 16.41	0.461	3.11	-8.40 – 14.63	0.594	4.35	-7.37 – 16.07	0.464	20.69	8.31 – 33.07	**0.001**
Property Crime Rate	4.79	-1.51 – 11.10	0.135	-8.18	-15.73 – -0.62	**0.034**	-1.25	-8.53 – 6.02	0.734	-5.61	-13.01 – 1.79	0.136	-5.74	-13.56 – 2.08	0.149
Region [Midwest]	-0.47	-1.06 – 0.12	0.114	-0.50	-1.21 – 0.21	0.163	-0.36	-1.03 – 0.32	0.298	-0.71	-1.40 – -0.03	**0.042**	1.03	0.30 – 1.75	**0.006**
Region [Northeast]	0.03	-0.71 – 0.77	0.938	0.50	-0.40 – 1.39	0.275	-0.51	-1.37 – 0.35	0.239	-0.08	-0.95 – 0.80	0.860	-0.20	-1.12 – 0.73	0.672
Region [West]	0.60	-0.13 – 1.33	0.105	0.58	-0.29 – 1.45	0.188	-0.41	-1.25 – 0.43	0.342	0.80	-0.05 – 1.66	0.066	0.89	-0.01 – 1.79	0.053
Year 2000	2.47	1.66 – 3.28	**<0.001**	0.02	-0.95 – 1.00	0.961	0.85	-0.08 – 1.78	0.074	-0.13	-1.08 – 0.81	0.780	-0.01	-1.01 – 0.99	0.985
Year 2010	5.97	3.26 – 8.68	**<0.001**	1.39	-1.87 – 4.66	0.400	-1.02	-4.15 – 2.11	0.521	-0.20	-3.39 – 2.98	0.900	-1.98	-5.34 – 1.39	0.248
Observations	150			147			150			150			150		
R^2 / R^2 adjusted	0.478 / 0.424			0.183 / 0.097			0.251 / 0.173			0.189 / 0.104			0.306 / 0.234		

It appears that there is some support for my hypothesis given that Percent Black was significant to both the Political and Symbolic Punishment and Incarceration dimensions. It's interesting that none of the other dimensions have significant coefficients for Percent Black but given the low R-Squared values all around, I think there are just issues with model specification.

Welfare payments are negative and significant for Political and Symbolic Punishment and Incarceration, but positive and significant for Juvenile Justice.

Table C.3 Results of the Regressions After Selecting One Variable for Each Dimension (South)

H1: Dimensions of State-Level Punitiveness

	Political and Symbolic Punishment			**Incarceration**			**Punishing Immorality**			**Conditions of Confinement**			**Juvenile Justice**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	6.81	0.69 – 12.93	**0.030**	-3.27	-10.64 – 4.09	0.381	9.33	2.50 – 16.15	**0.008**	3.47	-3.84 – 10.79	0.349	4.66	-2.97 – 12.28	0.230
Percent Black (Sqrt)	0.22	0.02 – 0.42	**0.030**	0.04	-0.20 – 0.28	0.725	0.31	0.09 – 0.53	**0.006**	-0.28	-0.52 – -0.04	**0.021**	0.18	-0.07 – 0.42	0.161
White Voter Participation	-0.03	-0.06 – 0.01	0.110	0.01	-0.04 – 0.05	0.749	-0.02	-0.06 – 0.02	0.318	-0.02	-0.06 – 0.02	0.279	-0.02	-0.06 – 0.02	0.366
Percent Voted	0.02	-0.02 – 0.07	0.317	-0.01	-0.06 – 0.05	0.834	-0.05	-0.09 – 0.00	0.069	-0.02	-0.07 – 0.04	0.556	-0.01	-0.06 – 0.04	0.717
Percent Poverty	-0.03	-0.15 – 0.09	0.672	0.07	-0.07 – 0.22	0.318	-0.11	-0.24 – 0.02	0.107	0.02	-0.12 – 0.17	0.768	0.08	-0.07 – 0.23	0.312
Median Income	-0.00	-0.00 – -0.00	**0.012**	0.00	-0.00 – 0.00	0.072	-0.00	-0.00 – 0.00	0.147	0.00	-0.00 – 0.00	0.771	-0.00	-0.00 – 0.00	0.154
Percent High School Graduates (Sqrt)	-0.49	-1.16 – 0.19	0.159	0.74	-0.07 – 1.54	0.074	-0.31	-1.07 – 0.44	0.411	-0.03	-0.84 – 0.78	0.949	-0.17	-1.01 – 0.67	0.693
Welfare Payments (Sqrt)	-3.11	-4.61 – -1.61	**<0.001**	-1.93	-3.74 – -0.12	**0.037**	-0.88	-2.55 – 0.79	0.301	1.38	-0.41 – 3.17	0.131	0.93	-0.94 – 2.80	0.329
Violent Crime Rate	12.17	1.90 – 22.44	**0.021**	6.12	-6.12 – 18.35	0.324	2.26	-9.18 – 13.70	0.697	4.79	-7.48 – 17.06	0.442	18.58	5.78 – 31.37	**0.005**
Property Crime Rate	7.61	1.24 – 13.98	**0.020**	-5.59	-13.22 – 2.04	0.150	-1.27	-8.37 – 5.82	0.723	-1.49	-9.10 – 6.12	0.699	-6.78	-14.71 – 1.16	0.094
South	0.11	-0.57 – 0.78	0.757	0.31	-0.50 – 1.12	0.452	-0.15	-0.91 – 0.60	0.693	0.18	-0.63 – 0.99	0.667	-0.92	-1.76 – -0.07	**0.033**
Year 2000	2.36	1.57 – 3.16	**<0.001**	-0.38	-1.34 – 0.57	0.430	1.08	0.20 – 1.97	**0.017**	-0.24	-1.19 – 0.71	0.619	0.58	-0.41 – 1.57	0.247
Year 2010	4.72	2.03 – 7.41	**0.001**	-0.46	-3.68 – 2.76	0.777	-0.78	-3.78 – 2.22	0.608	-1.92	-5.13 – 1.30	0.240	-0.17	-3.52 – 3.18	0.920
Observations	150			147			150			150			150		
R^2 / R^2 adjusted	0.434 / 0.385			0.121 / 0.042			0.243 / 0.177			0.089 / 0.009			0.241 / 0.175		

Here again we see mostly the same pattern, but this time the Percent Black variable is significant in the Political and Symbolic Punishment, Punishing Immorality, and Conditions of Confinement dimensions. Welfare Payments, Violent Crime Rate, Property Crime Rate, Year 2000, and Year 2010 are significant for the Political and Symbolic Punishment dimension. Only Welfare is significant in the Incarceration model.