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Racial bifurcation and social control: Toward a general group conflict theory

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Abstract

Research linking racial demographics to punishment yields inconsistent results, suggesting conceptual limitations of compositional measures of racial threat (e.g., percentage Black). This study introduces a structural measure of racial demographic threat: the Racial Bifurcation (RB) Index. Unlike compositional measures, the RB index aligns with conflict theories by peaking when two groups approach demographic parity (a 50:50 demographic split)—the theoretical point of maximum group tension. Using Poisson Pseudo-Maximum Likelihood fixed-effects regression on panel data from 1,739 U.S. counties (1993-2023), we compare the effects of compositional threat (percentage Black) and structural threat (Racial Bifurcation) on both targeted (Black-specific) and diffuse (overall) jail and prison outcomes. Findings strongly support the diffuse effects hypothesis: racial threat measures better predict overall, rather than Black-specific, incarceration. Crucially, Racial Bifurcation outperformed Percentage Black as a measure of racial threat: it remains a significant, positive predictor of overall incarceration rates when controlling for Percentage Black, whereas the effects of Percentage Black are null or negative when controlling for Racial Bifurcation. By employing a measure (RB) and outcome (overall incarceration) that are agnostic to specific group identities, this study supports a more generalizable theory of intergroup conflict.

KEYWORDS
racial threat, group conflict, polarization, incarceration

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Abbreviations: RB, racial bifurcation.

1 INTRODUCTION

There are no plausible shortcuts away from the problem of bifurcation. Its origins lie deep in the tendency to group comparison...reinforced by the exigencies of attempting to form electoral majorities. (Horowitz 2000, p. 681)

Jail and prison populations were extraordinarily consistent for the first half of the 20th century, leading some researchers to develop a theory of the "stability of punishment" (Blumstein & Cohen, 1973). Beginning around 1975, however, U.S. prison populations began growing dramatically. By 2003, there were 2.1 million people in prison or jail (Western, 2006). The U.S. incarceration rate now exceeds that of all other developed nations, at 629 prisoners per 100,000 (Fair & Walmsley, 2024). Troubling as the aggregate figure is, there is significant jurisdictional variation in incarceration within the United States, both between and within states. Incarceration rates in 2022 varied from a high of 661 pcm (per cent mille; prisoners per 100,000 residents) for Mississippi to a low of 94 pcm for Massachusetts; the state average was 300 pcm (World Population Review, n.d.). Nonetheless, the 21st century has been characterized by modest declines, particularly among men of color (Robey et al., 2023).

These variations reflect the accumulated decisions of lawmakers, law enforcement officers, judges, juries, and even the citizens who invoke the law. Each of these decisions reflects an act of power, which accumulates to account for the stock and flow of local jails and state prisons. Political scientists and conflict theorists have long noted that power—how it is perceived, exercised, and (re)negotiated—is deeply connected to group identity. Because group identity is so frequently based on racial/ethnic identity, and because a group's size substantially corresponds to power, it is unsurprising that scholars have frequently explored the relationships between racial composition and formal social control (for reviews, see Feldmeyer & Cochran 2018; Dollar 2014).

This research, however, has often produced inconsistent results. For example, research findings have varied across different crime control measures (e.g., police expenditures, arrests, sentencing, incarceration; Dollar 2014; Feldmeyer & Cochran 2018) as well as based on the racial/ethnic group that is the source or target of minority threat (e.g. Feldmeyer & Ulmer 2011; Zane 2018). In this paper, we advance an alternative approach that recognizes (1) an appreciation for diffuse (rather than targeted) effects of racial animus, which can raise the incarceration rates of all (not just minoritized groups); and (2) an alternative, structural measure of racial demographics that better captures conflict dynamics outlined by theory and, unlike compositional measures, applies in multi-group settings irrespective of the specific groups involved.

In the sections that follow, we provide an overview of conflict and group threat theories to underscore the relevance of group conflict and group size on punishment (including incarceration). Next, we discuss how group conflict theories relate to trends of increasing political factionalism—a landscape where groups with differing beliefs, interests, or ideologies compete for power, influence, or policy. In turn, we discuss "drained pool politics"—observing that racial conflict often leads to expressions of power that harm *everybody* in any effort to punish the "other" (McGhee, 2022). Given this pattern, we propose a measure of racial bifurcation to explore the association between group conflict and mass incarceration. We illustrate the ways in which this measure is conceptually and analytically suited to describing the maximum possible tension between groups, a key characterization of group conflict theories. In a series of Poisson fixed-effects regression models, we demonstrate that racial bifurcation strongly predicts variation in population-adjusted jail and prison rolls and admissions in over 1,700 U.S. counties between 1993-2023. Given these insights, we call for researchers to consider racial bifurcation as a key construct when evaluating group threat theories.

2 | CONFLICT & THREAT THEORIES

Incarceration is often understood as a reflection of conflict. For consensus criminologists, formal punishment like incarceration is a form of conflict resolution, reflecting underlying interpersonal conflicts that must be remedied. For conflict criminologists, incarceration is not merely an outcome of conflict but represents a manifestation of conflict itself, as a tool used to assert or maintain group hierarchies (Vold, 1958). Two theories are especially salient to explaining racial/ethnic conflict: Blalock's racial threat theory, and Horowitz's theory of ethnic group conflict.

2.1 | Blalock and Racial Threat Theory

Blalock's 1967 racial threat theory, primarily examining White/Black relations in the United States, is a macrosocial approach to examining and explaining intergroup conflict. Blalock rejects normative theories of prejudice that focus primarily on socialization and norms without considering the roles of group identity and power dynamics. Understanding why many prejudices are socially acceptable requires analyzing the interests served by those prejudices. Power relations and perceptions of threatened group position play key roles in shaping interactions between minority and majority groups. Blalock's racial threat theory is most well-known for its proposition that a minority group's increase in size (strongly related to power) leads to perceptions of threat by the majority group, provoking responses such as discrimination, exclusion, or outright hostility. A central theme of racial threat theory is competition: groups may compete for both economic and political resources, which contribute to the acquisition of financial, political, and social capital. The intensity of discrimination and the forms it takes are tied to the level of competition between groups.

Liska and colleagues (Liska et al., 1981; Liska & Chamlin, 1984) explicitly extended group threat theories to the domain of formal social control. According to them, minority populations present not only economic and political threats, but also *symbolic* threats that social norms, customs, and even physical safety are threatened by large or growing minority groups. Since then, a substantial body of work has explored the role of minority group threat in policing (e.g., Kent & Jacobs 2005; DAlessio et al. 2005; Stults & Baumer 2007; Jackson & Carroll 1981), capital punishment and lynching (e.g., Jacobs & Carmichael 2002, 2004; Jacobs et al. 2005; Baumer et al. 2003), criminal sentencing (e.g., Britt 2000; Johnson et al. 2008; Ulmer & Johnson 2004), and incarceration (e.g, Greenberg & West 2001; Jacobs & Carmichael 2001; Myers 1990).

Studies of racial threat theory frequently use a measure of racial composition as a proxy for racial threat, or as the source of racial threat perceptions. As racial and ethnic demographics shift, the dynamics of social control also change. The majority group makes efforts to maintain its dominance and address perceived threats from minority populations, while minority groups become emboldened and more assertive about their interests. Thus, racial composition contributes to conflict—including through the justice system and the use of formal control—given how often it corresponds to group hierarchy and societal power dynamics.

2.2 | Horowitz and Ethnic Group Conflict

Another key contribution to the study of intergroup conflict is Donald Horowitz's *Ethnic Groups in Conflict* 2000. While Blalock primarily focused on White/Black relations in the US, Horowitz provides a comprehensive examination of ethnic conflict across the world, describing the social conditions that facilitate or restrain ethnic conflict, including group status, collective fears, historical memory, and the hierarchical structure of social systems.

Groups are acutely aware of their status relative to others, often producing status anxiety. When groups perceive their status as unjustly low, they may symbolically, politically, or literally fight for higher status. In response, higher-status groups witnessing the rise of others may take preemptive or defensive actions to protect their privileged position. Thus, group status can produce collective fears. Especially in winner-take-all, majority-rule political systems, minority groups may fear domination, exclusion, marginalization, and irrelevance. Further, when under pressure to assimilate, minority groups may fear the loss of their cultural heritage or language. Conversely, majority groups may fear losing privileges or superordinate status due to a shifting demographic and political context. Therefore, collective fears affect both privileged and underprivileged groups, fostering social tension which can escalate into conflict.

Historical memory facilitates conflict because meaning-making from past events contributes to the contextualization of present-day action. Groups often remember historical events in ways that can either underscore their own perceived victimization or glorify past valor. Collective myths often arise from historical memories, which serve to solidify group identity but can also entrench enmity between groups. Past massacres, forced migrations, or economic exploitations become central to a group's identity and narrative, hindering reconciliation. In turn, leaders exploit historical grievances politically to galvanize group solidarity and justify new conflicts. Both high-status and low-status groups may use historically accurate, distorted, or even completely fictional narratives in ways that contribute to ongoing conflict.

Conflict arises in both ranked and unranked social structures. In ranked systems, there is a clear hierarchy of ethnic groups, where group identity and social class (or economic role) coincide. Examples include caste systems or apartheid states (e.g., pre-genocide Rwanda, where the Hutu/Tutsi distinction also aligned with a perceived socio-economic hierarchy, or apartheid South Africa). In ranked systems, conflict is typically vertical, a revolutionary struggle by the subordinate group against the dominant group over the very structure of the hierarchy itself. While ranked systems produce struggles for equality or subordination, unranked systems produce struggles for dominance. In unranked systems, two or more ethnic groups exist in parallel, competing for control of the same political and economic system. In this system, groups have their own internal class structures (e.g., rich and poor Malays, rich and poor Chinese in Malaysia; or different groups in Nigeria). Conflict here is a competition between parallel groups for power, resources, and, most importantly, control of governance. Fear of domination intensifies as each group fears the other will capture the state and use its power to marginalize them.

We propose that this framework is also able to contextualize the shifting contours of racial conflict in the United States. The eras of slavery and *de jure* Jim Crow represented a clear ranked system, with a legally enforced and rigid social, political, and economic hierarchy. However, the post-Civil Rights era has arguably transitioned the U.S. toward an unranked system. Lynching and plainly discriminatory justice policies have decreased since the mid-20th century, but formal social control has ironically expanded significantly. Once formal subordination ends, conflict does not disappear; it becomes reciprocal, competitive, and often politically intense. Social groups now vie for control of government, representation, and symbolic recognition in a shared political arena. The decline of formal racial hierarchy has not eliminated racial conflict, but transformed it into a political competition between nominally equal groups. Racial politics thus shifts from challenging subordination to contesting relative advantage—representation, resource distribution, policy benefits, and moral legitimacy. American ideologies and mythologies regarding the "American Dream," meritocracy, and equal opportunity actually heighten conflict: because groups are legally and nominally "equal," grievances are framed as struggles over merit and political power.

Democracy can intensify group conflict, especially in winner-take-all systems like the U.S., because subordination and domination can be achieved by mobilizing a simple majority of voters. The following section explores the process of factionalism and the ways that democratic processes have ironically been used to advance autocratic governance, often to address perceived threat.

2.3 | Factionalism

Factionalism is a potential mechanism through which racial/ethnic composition contributes to conflict, including formal social control and criminal sentencing. Political scientists warn that factionalism is increasing both domestically and globally. Factionalism is characterized by "identity-based political parties" (Walter 2023, p. 35). Partisanship is increasingly organized around racial, ethnic, and religious identity rather than political belief, leading to open—and often violent—ethnic conflict. Worldwide, for instance, most civil wars fought in the 20th century were organized along ethnic divisions (Fearon & Laitin, 2003; Horowitz, 2000).

Racial and ethnic identity can be potent forces for political mobilization. Factionalism intensifies when one group perceives another as a threat, either culturally, economically, or politically. These perceptions can be based on actual events, but are just as often exaggerated or manipulated for political purposes. For instance, nationalists have successfully manipulated social media algorithms to stoke hate against Rohingyas in Myanmar, Kurds in Turkey, indigenous peoples in Brazil, Latin Americans in the U.S., or non-European immigrants in Hungary. In each of these cases, misinformation campaigns contributed to the election of authoritarians promising to preserve an ethnic hierarchy (Walter, 2023). Factionalism can lead to increased social and political polarization, where moderate voices are drowned out, and more extreme or radical rhetoric gains prominence. This polarization can result in dehumanization of the "other," facilitating acts of violence, violation of basic human rights, or permitting an excess of judicial or extrajudicial punishment (Walter, 2023).

Factionalism is especially potent where nations slip from liberal democracy to anocracy—and, eventually, autocracy (Walter, 2023). In the U.S. (as elsewhere), faith in democracy is eroding, perceptions of public institutions are at their lowest ever recorded, and populism is increasing (Funk, 2022). Some scholars have claimed that in 2020 the U.S. technically slipped from "democracy" to "anocracy" (Masaru, 2021), and that the U.S. has not yet regained the "full democracy" status it held from 1976-2016 (*Center for Systemic Peace*, n.d.).

No country is immune from factionalism. The history of the U.S. is marked by a long history of racial and ethnic divisions, from Native American displacement, to African slavery, to periodic waves of European, Asian, and Latin American immigration. This racial tension often translates into political factionalism, ironically facilitated by their enfranchisement. As Black populations grew in Louisiana parishes, White voters, especially those of lower socioeconomic status, systematically defected from the Democratic party to the Republican party, demonstrating that political reorganization is frequently a response to out-group political gains and strongly connected to racial identity (Giles & Hertz, 1994). Parties and political movements sometimes coalesce around racial or ethnic identities or issues, leading to ideological divides and polarization. Past injustices or perceived slights can be embedded in the collective memory of a faction. Over time, these grievances can be passed down generations and serve as a rallying cry for mobilization. Historical events, if not reconciled or addressed, can be manipulated or weaponized by leaders to galvanize support and justify aggression. Contemporary political rhetoric surrounding "replacement theory" (National Immigration Forum, n.d.), "criminal aliens" (Rose, 2025) and a racially diverse government workforce as "dumb" (Schwartz, 2025) illustrate the ways group identity, power threat, and status loss inform identity-based politics and motivate political factionalism in the U.S. today.

2.4 Synthesizing Theory

It is possible to make some generalizations about intergroup conflict by synthesizing the foregoing review. First, social identity, particularly racial/ethnic identity, contributes to group cohesion, enables factionalism, and drives group-based behaviors. Second, group status and stratification are social realities that contribute to the way individuals and groups interact, producing the contours for conflict, as groups attempt to either improve or preserve their relative social position. Third, threats and fears contribute to the emotional volatility that enables group conflict. According to Blalock, majority groups may perceive economic, political, and symbolic threats to their position of privilege. Horowitz agrees, and further describes how minority groups' fears of domination, eradication, or assimilation contribute to social tensions that facilitate conflict. Fourth, competition for financial, social, and political capital is a driving force for conflict. Finally, racial/ethnic demographics will often correspond to intergroup conflict because relative group size so frequently corresponds to group position, power, and tension, especially in horizontal power structures where groups share the same legal and democratic process.

Taken together, these theories suggest that an ideal measure of racial threat should reflect a demographic reality in which two groups are poised for competition, not simply when minority size increases. Such a measure should capture demographic *structure*, rather than a raw indication of demographic composition. An ideal measure should capture bipolar tension, provide generalizability across multiracial contexts, and distinguish contexts of diffuse power from those marked by dominance of a single group relative to minority opposition. While Blalock focuses explicitly on the subordination of African Americans in the U.S.—as the "threatening" group subjected to discrimination from a "threatened" group—Horowitz's cross-national historical evidence illustrates that group conflict is dynamic, reciprocal, and often affects multiple parties.

Recent assessments of the group threat literature note that traditional group threat models often fail to specify exactly *who* feels threatened and *why* this threat manifests as generalized, rather than group-specific, social control (Vogel & Messner, 2024). Although the goal may be to subordinate a specific minority group, mechanisms of control are often expanded in ways that capture members of the majority group as well, such as criminal sentences. We argue that this ambiguity stems from a narrow theoretical and measurement focus on a unidirectional threat from a minority to a majority, and a unidirectional response from majority to minority. Shifting the focus to *structural* threat (e.g., Racial Bifurcation) may better explain how intergroup power parity fuels a factionalism that results in diffuse, punitive consequences for all. We therefore turn to a brief discussion of targeted vs. diffuse effects in racial threat theory.

2.5 Targeted vs. Diffuse Effects: Drained Pool Politics

The effects of racial threats on formal social control can be either “targeted” or “diffuse.” (Zane, 2018). Targeted effects refer to specific and directed responses aimed at the minority group perceived as the threat. This can be seen in policies or actions that disproportionately affect the threatening group.

Diffuse effects, in contrast, impact a wide segment of the population, not necessarily confined to the minority group perceived as the threat (Zane, 2018). This can manifest as general policies or practices that increase social control universally across social groups. For example, an entire state might see increases in prison populations, not just the incarceration of minoritized groups (e.g., Greenberg & West 2001; Jacobs & Carmichael 2001; Myers 1990). While the reaction might be sparked by the perceived threat from a particular group, the diffuse nature means even individuals outside the “threatening” group are affected. In fact, some research has found that racial composition predicts White, but not Black, incarceration rates (Bridges & Crutchfield, 1988).

Heather McGhee (2022) argues that racial threat can lead to diffuse effects that negatively impact all members of society beyond the members of a threatening minority. The idea that society is a zero-sum contest is deeply entrenched in American society. This mentality is, in fact, at the genesis of the feelings of “threat” that characterize group threat theories—the fear of eroding economic, political, and symbolic advantages as other groups make gains on these fronts. For instance, “great replacement theory” has circulated in U.S. politics, arguing that immigration of Black and Brown people is part of a broader political effort to dilute the power and culture of White people (National Immigration Forum, n.d.).

One of McGhee’s most useful examples is the history of public pools. In the mid-20th century, rather than integrate public swimming pools, many towns opted to drain them entirely, ensuring that no one, Black or White, could use them. This decision punished the very citizens that the policy sought to “protect” from Black “threat.” The draining of these pools is emblematic of the broader diffuse effects of racism. Although the goal is to block Black users to maintain White exclusivity, the entire community suffers, including Whites who are collateral damage in the wider symbolic racial conflict. An examination of political realignment in the American South revealed lower-status Whites were most sensitive to Black population growth and most likely to abandon the Democratic party as Black political power increased (Giles & Hertz, 1994). By prioritizing racial hierarchy over the party that historically championed their economic interests, these voters demonstrated a willingness to incur personal or collective loss to prevent an out-group from gaining status—a broader exercise of ’drained pool politics.’

Although we do not dismiss the racial disparities in the U.S. criminal justice system, efforts to sanction Black Americans may have contributed to collective harms and diffuse effects. The War on Drugs is the quintessential example. As Michelle Alexander (2010) and Bruce Western (2006) have demonstrated, the war on drugs and the era of mass incarceration are products of control designed to subordinate Black people. Nonetheless, the imperative that these laws and policies be written and applied in race-neutral, “colorblind” language helps to explain why the incarceration rate nearly tripled for *White* men between 1980 and 2000 (Western, 2006). Particularly in a context of universal laws such as in the U.S., statutes enacted in response to racial threat ultimately apply to individuals of all races. Although disparities may arise in their enforcement, stricter laws in principle extend to all offenders, regardless of group membership. In turn, once prison capacity is expanded, those beds can be filled by individuals from any group, even if the initial impetus for the buildup was rooted in perceived threats associated with specific populations. Furthermore, we might expect diffuse effects to emerge where racialized stereotypes about crime are incorrect or exaggerated. For instance, White voters support harsher punishment for drug offenders, believing that drug crimes are disproportionately committed by African Americans (Meier, 2016). Nonetheless, illicit drug use is nearly identical between White and Black Americans (SAMHSA, n.d.). To the extent that a social group supports punitive sanctions for behaviors it errantly believes is primarily or exclusively conducted by another social group, we can expect collateral consequences for all social groups engaging in those behaviors, leading to diffuse effects.

Feldmeyer et al. have argued that “the key question for racial/ethnic and immigrant threat is not whether racial, ethnic, and immigrant context shapes overall sentencing patterns for all defendants...but whether it specifically increases *punishment for racial and ethnic minorities*” (Feldmeyer et al. 2015, p. 81, italics in original). Although we agree that targeted discrimination is true to Blalock’s original theoretical propositions, a broader reading of conflict theories and empirical evidence provides good reasons to move beyond theoretical “originalism.” Economists have argued that conflict is frequently a form of rent-seeking behavior characterized by “social groups with opposed interests [who] incur losses in order to increase the likelihood of obtaining their preferred outcomes” (Esteban & Ray 1999, p. 380). It is therefore unsurprising that punitive legal policy should produce harms across all segments of society.

Ultimately, “drained pool politics” illustrates the rationale for diffuse effects, even in ranked systems with specific sources of racial threat. That example, however, is rooted in mid-20th-century racial politics, and characteristically posits broad harms from *specific* demographic threats. In the following section, we discuss alternative measures of racial composition, and argue that demographic *structure*—not just the relative size of one minority group—may best reflect group conflict theory and the dynamics of group conflict in modern, multiethnic democracies like the U.S.

3 | MEASURING RACIAL COMPOSITION

If theories of racial threat and group conflict emphasize competition, status, and parity as sources of widespread conflict and broad harm, then our measurement strategy must reflect these conditions. In this section we evaluate the extent to which commonly used racial threat measures align with this theoretical foundation and suggest a novel alternative, racial bifurcation, which is designed to reflect these elements.

We argue that an ideal measure in the context of group threat theories should satisfy three key properties:

1. Peak Value Corresponds to Peak Group Tension:
   (a) Its value would peak at precisely the point of parity, where the most conflict would be theoretically expected.
   (b) In highly diverse areas where no single group is large enough to pose a threat, the measure should reflect reduced tension.
   (c) In majority-minority contexts, where no group holds a clear dominance, the measure should reflect lower racial conflict.
2. Parsimony: It should consist of a single indicator, eliminating the need for multiple racial/ethnic group variables, while remaining comprehensive enough to consider such contexts. It should describe demographic *structure*—its characteristics or distribution rather than mere composition.
3. Applicable to Multiracial Contexts: Could summarize ethnic distribution even if the groups themselves were different. In the U.S., a single measure might capture Black/White tension in the South, or White/Hispanic tension in the Southwest. An ideal measure could also capture demographic distribution across racial/ethnic categories, irrespective of which and how many categories there are (including those that are relevant in other nations).

The next sections explore how well commonly-used measures of racial threat satisfy these properties, then propose an index of racial bifurcation as a compelling alternative. These measures can be categorized into two camps. *Compositional demographic threats* reflect the longstanding idea that threat increases (linearly or non-linearly) with the simple demographic composition of a single or combined "minority group" (e.g., percentage Black; percentage minority). *Structural demographic threats*, on the other hand, suggest that threat is a product of the demographic *structure*, such as population heterogeneity (e.g., the diversity index) or the balance between sizable groups (e.g., racial bifurcation).

3.1 | Compositional Demographic Threat

Seventy percent of studies which include a measure of racial threat rely on a measure of racial composition (Feldmeyer & Cochran, 2018). Most commonly, this is done using the percentage of the population that belongs to a specific racial or ethnic minority group, or to the percentage of the population that is non-majority (e.g., non-white).

3.1.1 | Percentage Black (or another racial/ethnic group)

Researchers oftentimes use uncombined operationalizations of threat by measuring how, for instance, the relative size of the Black or of the Latino population affects criminal justice outcomes. It is the most-used measure in racial threat literature (Feldmeyer & Cochran, 2018). Figure 1 illustrates low and high values of percentage Black. In which of these contexts would we expect the most conflict—at 2% Black, as on the left, or at 98% Black, as on the right? Theoretically, neither is expected to have substantial racial conflict. In fact, percentage black does not satisfy any of the three ideal properties identified previously. First, the measure peaks at 100% Black, where racial conflict would be absent because there is only one racial group (Property 1). Other values may also be substantively ambiguous. For example, a value 33% Black could describe a 33:67 split, a 33:33:34 split, or a 33:20:20:17:10 split, wherein Black people are a minority, equal, or majority depending on the prevalence of other groups—despite equivalent values on this measure. Percentage Black is also specific to a single race, meaning that any attempt to incorporate other socially defined groups would require separate measures for each (e.g., percentage Hispanic), which reduces parsimony (Property 2). As such, the measure also lacks applicability to other contexts, as it does not consider any race other than Black (Property 3).

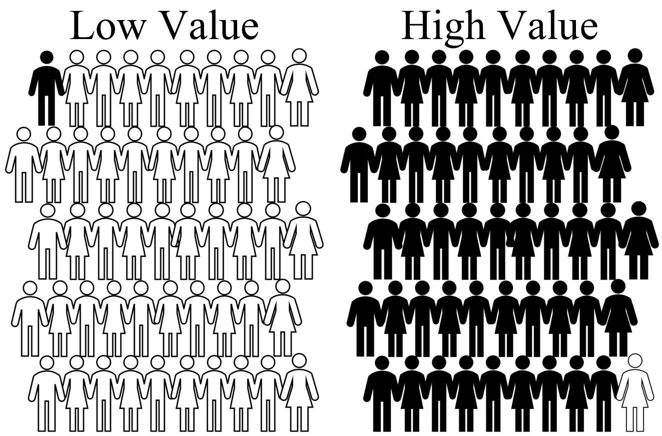

FIGURE 1 Percentage Black Measure

To be sure, compositional measures such as percentage Black have their advantages. It is straightforward, easy to operationalize, and has an intuitive interpretation. The measure is also adequate for researchers interested in studying a unique history of racial subordination focused upon one group, such as African Americans, or in contexts that are completely (or nearly) split into two primary groups (such as Black and White). However, such contexts are increasingly rare. The U.S., for instance, is an increasingly pluralistic nation, forecast to be majority-minority by 2046 (US Census Bureau, 2012), and racial animus is directed at multiple groups, such as Latin Americans. Measures such as "percentage Black" or "percentage Hispanic" either ignore other groups or require multiple measures to comprehensively measure racial composition, at a cost of parsimony.

Most troubling, however, is the fact that this measure's peak value does not correspond to theoretical peak racial tension. As Blalock (1967) originally explicated, formal social control always increases with the Black population size. This is true even for Blalock's hypothesized curvilinear relationships, which predict, in some circumstances, increasing or decreasing slopes in a positive relationship between percentage Black and discrimination—but never a reversal in direction. But what should we expect when Black people reach a substantial majority? In fact, more than 100 U.S. counties are majority Black, and several in the South are more than 80% Black. Existing theoretical propositions and mathematical models—those that assume punishment continues to increase with the Black population size—appear facially invalid in these circumstances. Some research has found evidence of nonlinear relationships between minority group size and various criminal justice outcomes. For instance, Kent & Jacobs (2005) find that police strength is associated with quadratic transformations of percentage Black and percentage Hispanic, as the relationship turns negative after a tipping point . Keen & Jacobs (2009) similarly observed a nonlinear, inverted-U-shaped relationship between Black population size and racial disparities in prison admissions. These studies suggest that minority groups may grow large and powerful enough that threat effects give way to social and political power. As we discuss in a later section, however, these curvilinear relationships and tipping points are inherent to an alternative measure that is more parsimonious and theoretically consistent.

3.1.2 | Percentage Minority

Researchers oftentimes combine multiple minority groups into a single "percentage minority" variable, which satisfies Property 2 (parsimony—a single summary statistic summarizing racial composition) and Property 3 (applicability to multiracial contexts—although crudely). However, this measure treats "minorities" as a monolithic category, ignoring the relative size and power distribution among groups. As illustrated in Figure 2, an identically high value of "percentage minority" can describe very different contexts. Specifically, percentage minority would peak either in a place where a minoritized group has majority status (such as majority-Black counties in the American South), or in extremely diverse, majority-minority places. That the same exact value of percentage minority results from two wildly different compositions undermines the measure's validity. A county that is 40% minority could be 60% White and 40% Black, leading to significant tension and conflict, or 60% White, 10% Black, 10% Latino, 10% Asian, and 10% American Indian, which would theoretically limit tensions between any two groups. Especially in diverse areas, a crude binary distinction (majority vs. minority) obscures the complex interplay of multiple racial and ethnic groups. In summary, the percentage minority variable does not satisfy several of our ideal properties. Foremost, its peak value does not correspond to theoretical peak group tension (Property 1). As illustrated in Figure 2, neither low nor high values necessarily reflect a circumstance where a minority group is large enough to "threaten" some majority.

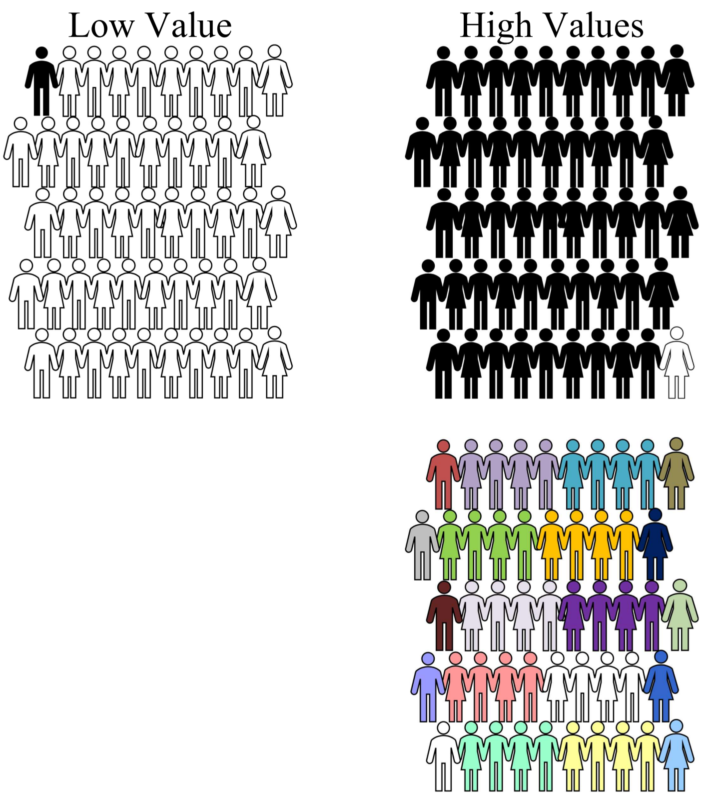

FIGURE 2 Percentage Minority Measure

In fact, much like the measure of percentage black, very high values can indicate a context where the minoritized group is hegemonic. Concurrently, in multiracial cases, there may be no clear majority group to exercise dominance, or to threathen a established majority.

3.2 | Structural Demographic Threat

Structural demographic threat extends beyond racial composition measures in describing the *nature* of demographic arrangements. They may describe, for instance, the extent to which places are fragmented into multiple social groups, or to which places are bifurcated into similarly-sized groups.

3.2.1 | Ethnic Diversity

In cross-national group conflict research in political science, economics, and a handful of studies in criminology, a measure of diversity is commonly used: the ethnic heterogeneity index, also known as the ethnic fractionalization index. The measure is both intuitive and consistent with evidence that regions low in diversity (such as Japan) experience lower levels of conflict. One common measure, presented by Alesina et al. (2003), is expressed as:

$$P = 1 - \sum_{i=1}^{N} s_{ij}^2 \tag{1}$$

where s_{ij} is the share of group i ($i = 1 \ldots N$) in region j. This measure has the intuitive interpretation of being the probability that two randomly chosen individuals are from the same ethnic group. As we did with the previous measures, we illustrate its range of values in Figure 3. While low ethnic diversity may inhibit group conflict, there is no compelling theoretical reason

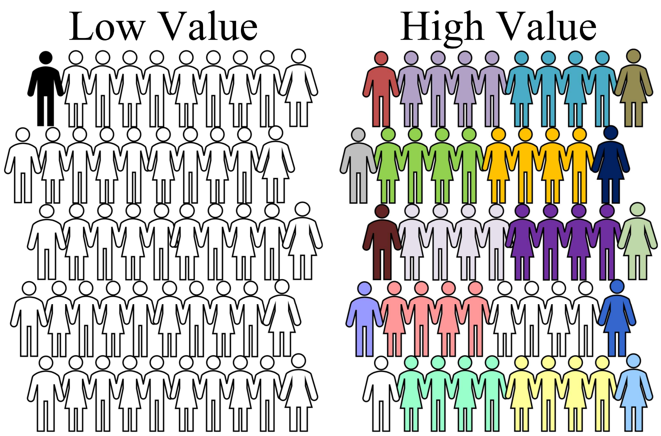

FIGURE 3 Ethnic Diversity Measure

or empirical evidence that very high diversity, in itself, facilitates group conflict. In places that are extremely diverse—such as Nigeria, boasting over 250 different ethnic groups (CIA, 2021)—no group numerically holds majority status, minimizing the role of group status and power differentials. In such contexts, political mobilization hinges on other dimensions of group affiliation rather than ethnic identity or factionalism. As Horowitz explains:

> Some groups are so small in size and so geographically concentrated that it makes little sense for them to devote energy to political activity much beyond their locality. Other groups, however, may be large and influential enough to make plausible claims to power at the center... Several Asian and African states embrace a large number of dispersed ethnic groups, none of them large or powerful enough to threaten to dominate the center... [T]here are incentives in dispersed systems against carrying ethnic extremism too far. (Horowitz 2000, p. 37).

Indeed, research has rather consistently demonstrated that diversity is unrelated to conflict and social control (Ruddell 2005; Ruddell & Urbina 2004; Montalvo & Reynal-Querol 2002; cf. Marier & Cochran 2023). While the U.S. uses fewer categories of racial and ethnic identity than nations like Nigeria, these theoretical principles nonetheless apply. Where fragmented into several subgroups, fear, threat, and competition are less acute and more dispersed, rather than being focused upon a singularly powerful, threatening, and identifiable "enemy." In turn, group power is distributed rather than concentrated into a dominant majority.

A measure of ethnic diversity satisfies Property 2 (parsimony), since it is a summative measure that comprehensively describes racial composition, and it can be used no matter how many (or which) racial/ethnic groups are present (Property 3). However, the diversity does not peak alongside group tension, and very diverse places see little racial conflict because there is no majority group with hegemonic power, and/or no identifiable source of group threat (Property 1).

3.2.2 | Racial Bifurcation

A measure of racial bifurcation, such as the RQ ethnic polarization index (Montalvo & Reynal-Querol, 2005),[2] can be measured as:

$$RQ = 1 - \sum_{i=1}^{N} \left(\frac{0.5 - s_{ij}}{0.5} \right)^2 s_{ij} \tag{2}$$

where s_{ij} is the share of group i ($i = 1 \dots N$) in region j. This index of ethnic bifurcation was derived from Esteban & Ray (1994) index of income polarization and reflects the distance from a bipolar (50:50) distribution, where conflict is theoretically at its peak. Again, we illustrate its range of values in Figure 4. The bifurcation index satisfies all five ideal properties. First,

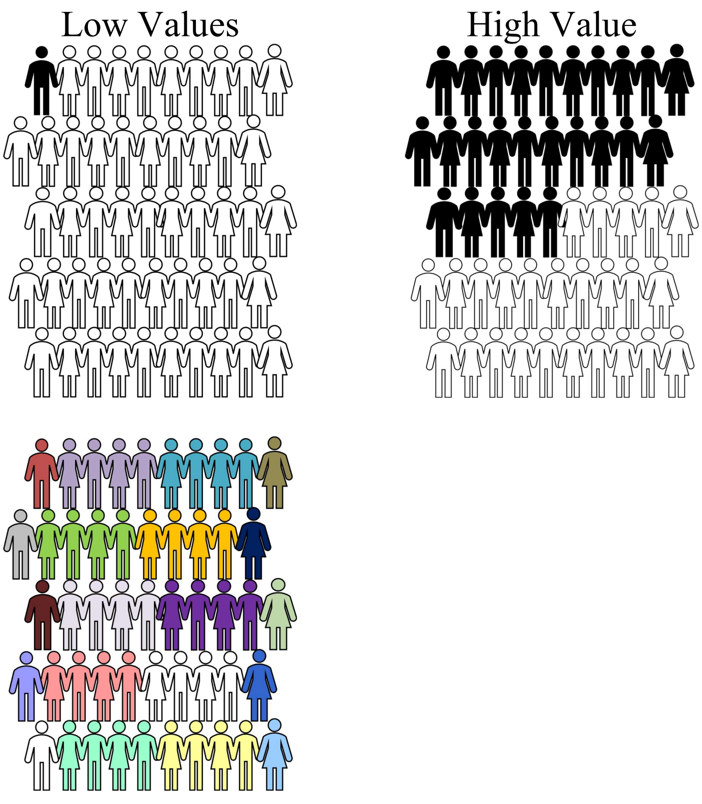

FIGURE 4 Racial Bifurcation Measure

[2] The ethnic polarization index comes from the field of economics. However, because the term "polarization" often refers to polarized *sentiment* in many social sciences, rather than the distributional composition of social groups, we have chosen to use the term "bifurcation index" to reduce misunderstandings or misinterpretation. Although we explicitly assume that bifurcation contributes to sentimental polarization and factionalism, and is an underlying assumption of racial threat theories, we recognize these as distinct concepts.

the index's peak value corresponds to the theorized peak group tension (Property 1). Conflict often arises when there are two dominant groups in opposition, especially if they are of substantial size. A bifurcation index peaks (at 100%) when there's a 50:50 distribution of the population, indicating evenly distributed power and, hence, heightened tension.

The index has a low value where diversity is so significant that it precludes a "threatening" group, as illustrated in the bottom-left portion of Figure 4. In places where there's little bifurcation, even if the absolute minority percentage is high—diverse areas where power and resources are diffused among many smaller groups—the potential for conflict is low because there's no particularized target or source of threat.

Conversely, the index also has a low value where diversity is so significant that it precludes the concentration of power in a majority group. This is true in majority-minority regions, again illustrated in the bottom-left portion of Figure 4. In such circumstances, no group is large enough to exercise dominance. In many areas, the traditional notion of "majority" and "minority" ceases to apply, as no single group holds an absolute majority. Although once-dominant groups may resent their loss of status and still express animus toward out-group members, the relative lack of political and social capital theoretically reduces their power and, therefore, the potential for conflict.

Second, the racial bifurcation index is parsimonious (Property 2), because a single measure can be used in a one-group context (where it is zero), a two-group context (where it is 100% if the two groups are equal in size), and in any other multi-group context (where it falls between these points). By precluding the need for multiple indicators in multi-group contexts, the index preserves degrees of freedom and parsimony. Third, the racial/ethnic bifurcation index is appropriate to multiracial/multiethnic contexts (Property 3), because it measures the degree of two-group tension regardless of which specific groups are present. Areas with similar bifurcation scores, regardless of their specific racial or ethnic makeup, might have comparable dynamics in terms of potential conflict. For example, Latino threat may be particularly acute in the American Southwest, Black threat in the old South, and Asian threat in the Pacific Northwest. Furthermore, these groups may be primarily in conflict with each other, residing in counties with few White residents. Perceptions of competitive threat are not limited to a dominant White majority; rather, they are multidirectional and can occur between any distinct racial communities (Bobo & Hutchings, 1996). Regardless of context or of the specific groups in question, the racial bifurcation index summarizes threat into a single metric that avoids the pitfalls of the "percentage minority" measure.[3]

In the two-group case, the bifurcation index is a linear function of the ethnic fractionalization index (Montalvo & Reynal-Querol, 2002). Furthermore, in the two-group case, the bifurcation index inherently accounts for the curvilinear relationships proposed by Blalock (1967) and identified in prior studies of racial/ethnic threat (e.g. Kent & Jacobs 2005; Keen & Jacobs 2009), since the index increases more slowly at more extreme values of percentage minority. Therefore, in two-group contexts, the

[3] Admittedly, it is an empirical question whether these different forms or sources of threat operate similarly, or whether, for instance, bifurcation between Latin Americans and Black Americans are similarly conflict-evoking as bifurcation between Whites and others.

bifurcation index is consistent with percentage minority measures but offers the additional advantage of also being applicable to multi-group contexts. Figure 5 illustrates the relationship between minority group size and the bifurcation index in the two-group context. In short, the racial/ethnic bifurcation index provides a more nuanced and theoretically aligned operationalization

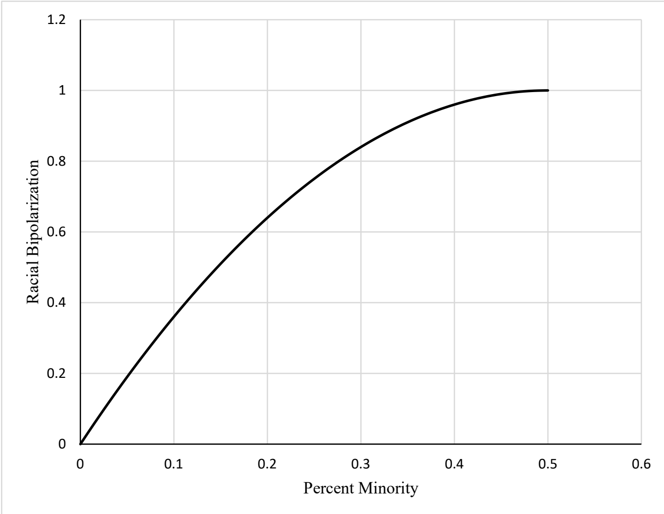

FIGURE 5 Bivariate Relationship Between %Minority and Racial Bifurcation in a two-group context

for conflict theories. Importantly, the bifurcation index is agnostic to the sources or targets of threat, describing, more generally, the potential conditions for conflict in various settings. It is also more consistent with factionalism as a key mechanism through which racial composition contributes to conflict, because identity-based politics, and the machinery of law tend to be more polarized where racial groups cluster into distinct sizable blocks rather than being dispersed across many smaller groups.

In these ways, the bifurcation index contributes to the generalizability of conflict theory. While recognizing the tragic peculiarities of Black slavery and subordination in the U.S., group conflict theories may describe more general sociological phenomena beyond. While scholars have noted the tension between targeted and general *effects* of racial threat (Feldmeyer et al., 2015), our review of theory and measurement suggests that compositional vs. structural *sources* of racial threat deserve equal attention. Demographic *structure* may matter more than demographic *composition*. Specifically, bipolar, two-group tension can predict group conflict irrespective of which groups are opposed. As such, a single measure could simultaneously operationalize conflict across locales throughout the United States (and even globally), irrespective of their specific demographic makeup.

While it has yet to be applied within the U.S.—remedied by the present study—cross-national evidence suggests that racial/ethnic bifurcation is a strong predictor of group conflict, even in nations with very different histories and sociopolitical arrangements. The measure has been used to predict civil wars (Montalvo & Reynal-Querol, 2010, 2005), genocides (Montalvo & ReynalQuerol, 2008), and domestic terrorism (Danzell et al., 2019). Most salient to the present study, cross-national research finds that racial/ethnic bifurcation is a significant predictor of incarceration rates throughout the world. In their cross-sectional examination of incarceration rates, Marier & Cochran (2023) found that ethnic bifurcation was a significant predictor of overall incarceration rates internationally, despite the very different forms of racial and ethnic differentiation around the world. In contrast, the most homogeneous *and* the most diverse nations demonstrated the lowest incarceration rates.

4 | CURRENT STUDY

This study makes two primary contributions to the literature on racial threat, group conflict, and formal social control. First, we advance the field by introducing and applying a novel, *structural* measure of demographic racial threat: the Racial Bifurcation (RB) Index. While traditional measures such as percentage minority, percentage Black, or indices of ethnic diversity have been used in prior literature, they fail to capture the relative group size and power (im)balances that are foundational to conflict criminology and group threat theory. These measures either ignore important intergroup dynamics (e.g., by collapsing multiple minority groups into a single category), misrepresent conditions for maximum threat (e.g., by increasing monotonically, even in majority-minority regions), or are too abstracted from the mechanisms of power, competition, and factionalism emphasized in theories of conflict.

Racial bifurcation, by contrast, captures the demographic conditions that theories such as Blalock's racial threat theory and Horowitz's ethnic conflict theory propose are most conducive to tension: when sizable and competing groups approach parity. This measure peaks when two groups near a 50:50 distribution, a condition that reflects the greatest potential for competition, symbolic threat, and punitive reactions. Unlike other measures, the RB index is equally effective in two-group or multi-group contexts, can be represented by a single measure regardless of context, and it is empirically consistent with the nonlinear and context-dependent associations that have been observed in prior studies. To date, however, this index has not been applied to criminal justice outcomes in the United States—a gap this study aims to fill. We examine compositional vs. structural *sources* of "threat" by comparing the explanatory power of the (structural) RB Index to the more commonly used (compositional) measure of percentage Black.

Second, we examine whether racial threat produces diffuse *effects*, in addition to targeted ones. While much of the racial threat literature has focused on the disproportionate impacts of criminal justice policy on specific minoritized populations, recent scholarship suggests that the mechanisms of threat and punishment also harm those outside the target group (Vogel & Messner, 2024; Zane, 2018; Feldmeyer et al., 2015). We examine this possibility in the context of incarceration, asking whether increases in compositional or structural racial threats predict overall or race-specific increases in incarceration. In the case of structural racial threat (bifurcation) and diffuse targets of racial threat (overall incarceration), this study therefore contributes to general theory by examining both an independent and dependent variable that are agnostic to any specific racial group(s) and emphasizing the underlying sociological processes at play, rather than the specific group identities involved. Ultimately, we compare four types of relationships:

1. Compositional racial threat → Targeted effects (i.e., %Black → Black incarceration)
2. Compositional racial threat → Diffuse effects (i.e., %Black → overall incarceration)
3. Structural racial threat → Targeted effects (i.e., racial bifurcation → Black incarceration)
4. Structural racial threat → Diffuse effects (i.e., racial bifurcation → overall incarceration)

Furthermore, to assess whether each measure captures distinct sources of demographic tension, we also examine whether bifurcation has an effect after accounting for the size of the Black population and whether the size of the Black population has an effect after accounting for bifurcation. The first pattern would suggest bipolar tension among other social groups, and the second would suggest that Black populations are *uniquely* threatening. We investigate both targeted and diffuse effects:

5. Compositional *and* structural demographic threats → Targeted effects (i.e., racial bifurcation and %Black → Black incarceration)
6. Compositional *and* structural demographic threats → Diffuse effects (i.e., racial bifurcation and %Black → Overall incarceration)

To evaluate these relationships, this study uses sets of fixed effects regressions to model jail and prison incarceration rates and admissions rates across U.S. counties using measures of racial bifurcation and percentage Black, after accounting for crime rates and several socioeconomic covariates.

5 | METHODS

This study uses a combination of sources with longitudinal data about U.S. counties between 1993 and 2023. The analytic sample consists of up to 58,686 countyyear observations nested within 1,739 counties. These represent 53.6% of all U.S. counties and approximately 80% of the U.S. population, offering substantial coverage and supporting the generalizability of the findings. We limited all analyses to the same core set of counties to ensure cross-model comparisons were not confounded by differences in sample composition. Because our fixed-effects models predict incarceration counts with population size included as an offset (see Analytic Strategy), counties in the analytic sample were required to have at least one Black resident (so that the offset remains positive) and at least two non-missing observations.

5.1 Dependent variables: Incarceration Trends

To examine targeted vs. diffuse *effects*, we consider measures of both overall and race-specific prison and jail populations and admissions. In models testing diffuse effects, we use the overall number of incarcerated persons in jail and prison and the overall number of jail and prison admissions; in models testing targeted effects, we use race-specific counts for Black prisoners and admissions (except jail admissions, which does not include racially disaggregated data). This results in seven dependent variables, allowing us to evaluate the robustness of targeted vs. diffuse effects and compositional vs. structural racial threat across a variety of indicators:

1. Black prison population
2. Black prison admissions
3. Black jail population
4. Overall prison population
5. Overall prison admissions
6. Overall jail population
7. Overall jail admissions

Vera assembles it from multiple Bureau of Justice Statistics sources (including the Annual Survey of Jails, Census of Jails, and National Corrections Reporting Program) and supplements these with data collected directly from state and local agencies to fill gaps in federal reporting (Kang-Brown et al., 2020; Vera Institute of Justice, 2025).[4]. To address inconsistencies and data quality, Vera employs a cleaning protocol which includes manually reviewing data anomalies and replacing erroneous or missing data with linear interpolation or omission rather than treating them as zeros. Critically for our analysis, prison data is aggregated by the county of commitment (i.e., the county where a person was sentenced), which correctly aligns with our theoretical focus on the decisions of county-level officials (e.g., prosecutors, judges). The methodology also accounts for regional jails, apportioning incarcerated populations from 162 "receiving" jurisdictions back to the 467 "sending" counties to avoid mismeasurement in counties that contract for jail beds. The jail population is defined by Vera as "the average daily number of people held in jail though December 31 of a given year" (Kang-Brown et al. 2020, p. 8), while the prison population measures the number of individuals held on December 31 of each year. Where quarterly data was collected, the annual mean value was used. Values were rounded where non-integers were found in the data (e.g., due to calculation of average inmates

[4] Available at https://github.com/vera-institute/incarceration-trends

per anum). The use of count regression models with population exposure terms (overall, or race-specific, as appropriate) means these prisoner counts are population-adjusted and represent per capita incarceration or admission *rates*.[5]

5.2 | Independent Variables: Percentage Black and Racial Bifurcation

To examine compositional vs. structural demographic threats, we evaluate a measure of each: percentage Black and racial bifurcation. *Percentage Black* measures the proportion of Black residents aged 15 to 64 relative to the overall county population. We also incorporate a squared term to model nonlinear effects, guided by theory, substantial prior research, and empirical evidence of improved model fit. *Racial Bifurcation* reflects the degree of approximation of racial group distributions to a bipolar (50:50) scenario. Montalvo & Reynal-Querol (2005) modified the Esteban & Ray (1994) polarization index of income disparities to apply it to ethnic groups, as it appears in Equation 2 above. The resulting value is multiplied by 100, where a value of 0 reflects complete homogeneity and a value of 100 reflects 100% bifurcation (a 50:50 racial distribution). We refer to this measure as the Racial Bifurcation (RB) Index. The underlying demographic data used come from the Vera dataset, but were originally produced through a collaboration between the U.S. Census Bureau and the National Center for Health Statistics to generate county-level population estimates disaggregated by age and race. These are primarily based on decennial national censuses and on the American Community Survey (ACS), which happens yearly.

5.3 | Controls

Analyses also accounted for other dynamic predictors of correctional populations. A measure of *Population density* (thousand people per square mile) and the proportion of the adult population (ages 15 to 64) who are males (*Percentage Male*) were calculated from Vera's data. A *Poverty rate* is from the Small Area Income and Poverty Estimates (SAIPE), which is maintained by the U.S. Census Bureau. The rate measures the proportion of each county's population who fall under certain family income thresholds, determined by the household size and the number of children.[6] For example, in 2016 a family of three people with one child would need to earn at least $19,318 to be out of poverty. We collected the *Gini Index* from Census Bureau, which reflects income inequality.[7] Finally, a *Property crime rate* and a *Violent crime rate* are from the U.S. Federal Bureau of Investigations and reflect the index offenses detected and documented by law enforcement. Data were collected from files compiled and published by Kaplan (2024, 2025). The rates represent aggregated crime counts from the reporting agencies within each county, adjusted for missing months (12 / months reported), and divided by the population covered by reporting

[5] Given some race-specific population estimate discrepancies and implausible/inaccurate values in some very small counties, (e.g., race-specific estimates larger than the total population estimates, race-specific sums greater than the total) we excluded those observations, which constituted far less than 1% of all observations.
[6] Details can be found at: https://www.census.gov/topics/income-poverty/poverty/guidance/poverty-measures.html
[7] Census Gini estimates are drawn from both the decennial census and 1-year or 5-year American Community Surveys, based upon availability. Missing values were linearly interpolated by year.

agencies. Those adjustments implicitly assume that uncovered months and uncovered populations experience the same rates as covered ones.[8]

5.4 | Analytic Strategy

We predict our dependent variables using a set of Poisson count regression models with high dimensional fixed effects for each county and year (Guimaraes & Portugal, 2010). Fixed effects analysis takes advantage of the multiple time-observations for each county to estimate the longitudinal association between changes in the independent variables on changes on each respective dependent variable (Allison, 2009). These effects estimates cannot be biased by any characteristics of counties which are time stable (e.g., geographical location, historical past), or exogenous temporal shocks that influence incarceration across all counties (e.g., omnimbus crime bills, terrorist attacks, COVID-19) even if those characteristics are not included as covariates in the models. Thus, estimates are less prone to omitted variable bias than those of models without fixed effects. Count models, such as Poisson regression, are appropriate for estimating discrete count outcomes, such as the number of prisoners, which are often right-skewed and do not satisfy key assumptions required for OLS regression (Cameron & Trivedi, 2013). Specifically, we employ the Poisson Pseudo Maximum Likelihood (PPML) estimator proposed by (Silva & Tenreyro, 2006, 2011). We select this method over log-linear OLS or conventional Poisson regression for three primary reasons. First, log-linearizing the dependent variable in the presence of heteroskedasticity leads to inconsistent estimates due to Jensens inequality. PPML addresses this by estimating the multiplicative equation in levels. Second, PPML allows for the inclusion of zero-valued observations, avoiding biases introduced by truncating the sample or adding arbitrary constants (e.g., $\ln(y + 1)$). Finally, as a pseudo-likelihood estimator, PPML does not require the data to follow a strict Poisson distribution; it yields consistent estimates even under overdispersion or variance misspecification, provided the conditional mean is correctly specified.

The PPML models estimate the *incidence rate* of incarceration by including an exposure term to account for total population aged 15 to 64 (for race-specific models, the total Black population aged 15 to 64). Thus, they model *incarceration rates*—the probability that a resident between the ages of 15 and 64 was incarcerated in a jail or prison each year. We report coefficients as incident rate ratios, which here reflect incarceration rate ratios. Analyses were performed in Stata 18 with cluster-robust standard errors.[9] We also illustrate estimates by plotting the outcomes predicted in each model across levels of the independent variables.

[8] The shortcomings of county-level crime data are substantial, and well documented (e.g., Maltz & Targonski 2002; Kaplan 2025). Nonetheless, modeling incarceration trends without an estimate for crime, however imperfect, would likely bias estimates, and the use of fixed effects helps account for time-invariant sources of bias. That we find significant, positive associations between incarceration and violent crime provides some reassurance.

[9] We also explored several alternative model specifications. For instance, we examined OLS regression models on log-transformed incarceration rates, and both the substantive patterns and the magnitude of effects were similar. We also explored fixed effects negative binomial models, which account for overdispersion with an extra dispersion parameter, and the results were remarkably consistent with the Poisson models reported herein. We have chosen not to report the fixed effects negative binomial regression models because they are not considered true fixed effects models (Wooldridge, 2010)

TABLE 1 Descriptive Statistics

Variables	Counties	Obs.	Mean	SD	Min	Max
Dependent Variables						
Black Prison Population	1,739	33,219	359.39	1,314.64	0	24,888
Black Prison Admissions	1,739	30,101	180.07	697.56	0	17,339
Black Jail Population	1,739	45,407	163.44	494.39	0	13,144
Total Prison Population	1,739	48,405	632.43	2,180.63	0	58,387
Total Prison Admissions	1,739	49,111	307.52	1,149.00	0	40,098
Total Jail Population	1,739	49,510	402.26	956.21	1	23,467
Total Jail Admissions	1,739	49,515	6,480.23	13,356.34	2	307,178
Independent Variables						
%Black (percentage points)	1,739	58,686	12.84	15.75	0.006	88.56
Racial Bifurcation	1,739	58,667	52.73	28.72	0.53	99.78
Control Variables						
Pop. density (thousands p/ square mile)	1,739	58,667	0.29	1.42	0.001	73.66
Male (percentage points)	1,739	58,686	50.54	2.70	38.95	74.65
Poverty Rate (percentage points)	1,739	50,207	15.03	5.84	1.86	50.46
Median Income ($thousands)	1,739	50,207	44.81	15.22	11.30	159.67
Gini coefficient of inequality	1,739	58,686	44.15	3.61	31.10	70.70
Property crime rate	1,739	56,129	2,653.65	2,067.35	0	293,656.90
Violent crime rate	1,739	56,129	348.96	302.35	0	7,387.39
Exposure Terms						
Total Population 15 to 64	1,739	58,686	100,392	293,558	888	6,980,934
Black Population 15 to 64	1,739	58,686	13,320	54,422	1	1,385,394

6 | RESULTS

6.1 | Descriptive Statistics

Table 1 presents the descriptive statistics of the analytic sample. An observation (year within county) has, on average, 632 prison inmates, of which 359 are Black. They also have an average of 402 jail inmates, of which 163 are Black. Ranges for all variables are very wide, particularly above the average, reflecting right-skewed distributions which justify the use of the Poisson model. Bifurcation has a mean of 52.73, and ranges between 0.53 and 99.78, reflecting extensive variability across U.S. counties. Black individuals represented an average of 12.84% of the population of county-years in the analytical sample, ranging from nearly 0% to nearly 89%. Regarding the controls, an average county in the analytic sample has 290 people per square mile, is 50.54% male, has a 15.03% poverty rate, a median income around $44,810, a Gini coefficient of 44.81, a property crime rate of 2,654 per 100,000 residents and a violent crime rate of 349 per 100,000 residents. In the regression models crime rates were re-scaled to crimes per 1,000 residents , given very small coefficients.

Figure 6 demonstrates the geographic variation in racial bifurcation. The index is highest in the South, where Black populations are higher, and in the Southwest, where Latino populations are higher. Note that bifurcation is moderate, not highest, in major urban centers like Chicago and New York, where there is more diversity, reducing two-group bifurcation. Figure 7 illustrates the national trends in racial bifurcation between 1993 and 2023, including the trends by urbanicity. As expected, bifurcation is highest in urban counties and lowest in rural counties. Bifurcation increased gradually in most places, although it is leveling off in urban counties as they gradually become more racially diverse.

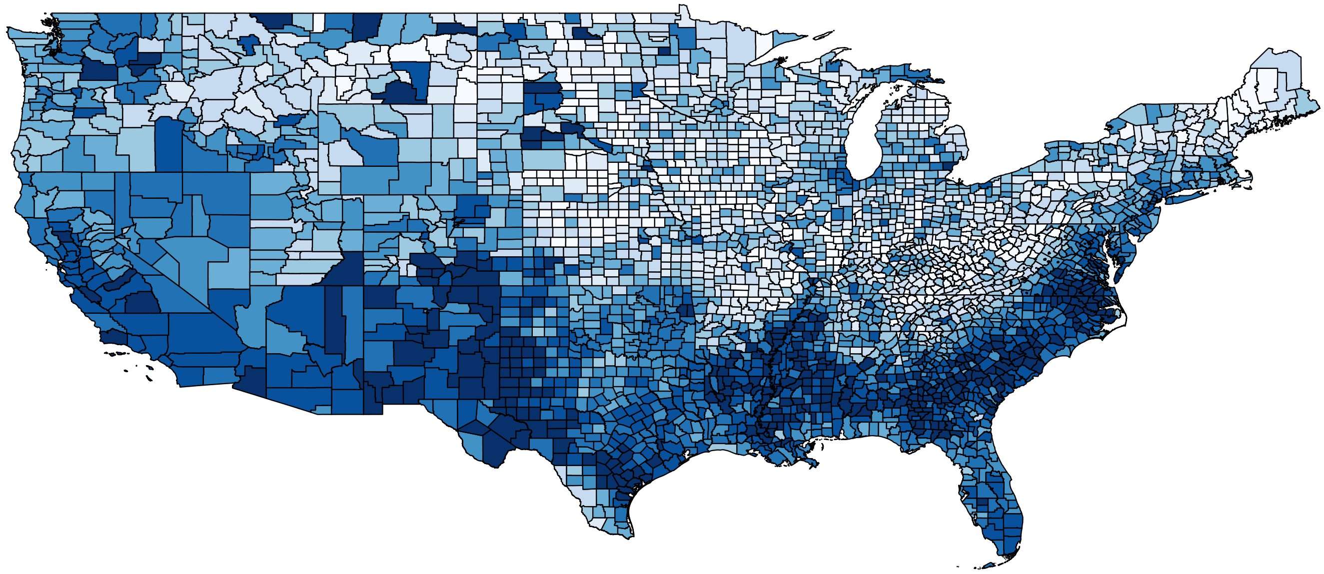

FIGURE 6 Geographic Variation of Racial Bifurcation

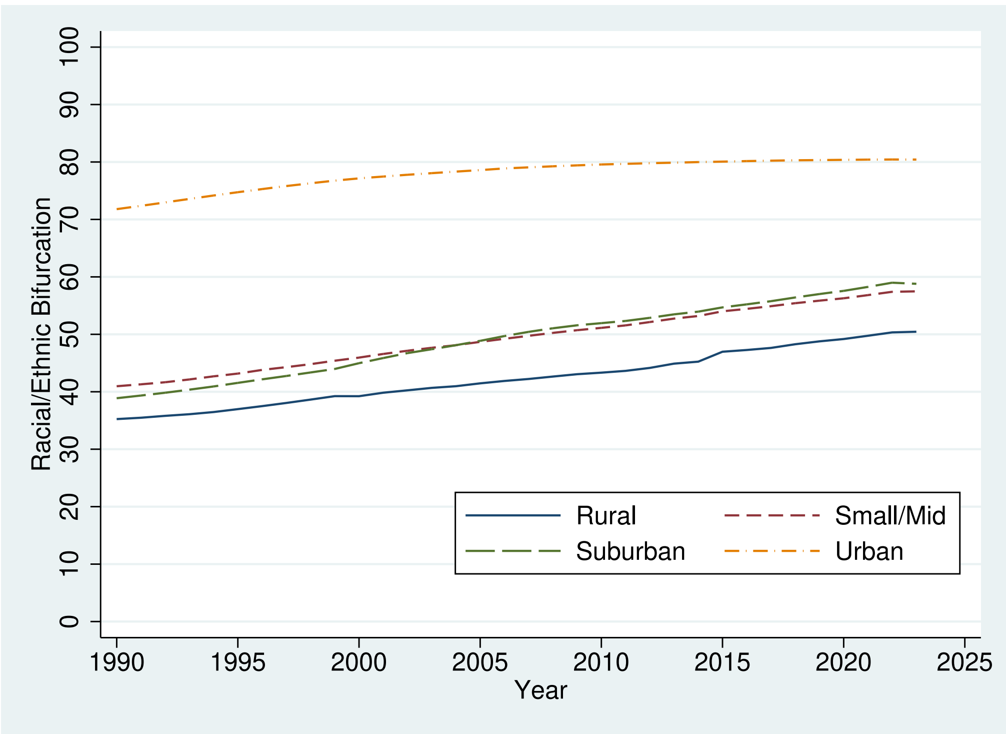

FIGURE 7 Temporal Trends of Racial Bifurcation (1990-2023)

6.2 | Regression Models

Table 2 operationalizes racial threat using its traditional measure: *Percentage Black* (and its squared term). Models 1-3 are targeted-effects models, examining the relationship between Black composition and Black jail/prison outcomes. Models 4-7 are diffuse-effects models, examining the relationships with the *overall* jail and prison outcomes. Across these seven models, *Percentage Black* predicts a statistically significant effect in the hypothesized (positive) directions in just 3 models—and in just *one* of the targeted-effects models. Specifically, *Percentage Black* predicts an increase in the *Black Prison Admissions Rate*, with a decreasing and then reversing slope (Model 2; $IRR_{\%Black} = 1.0284$, $p = .092$; $IRR_{\%Black^2} = .9996$, $p < .01$), in an inverted-⋃-shaped relationship. Similarly, *Percentage Black* predicts positive linear and negative curvilinear relationships with the *Total Prison Population Rate* (Model 4; $IRR_{\%Black} = 1.0403$, $p < .001$; $IRR_{\%Black^2} = .9995$, $p < .001$) and *Total Prison Admissions Rate* (Model 5; $b_{\%Black} = 1.110$, $p < .001$; $b_{\%Black^2} = .9988$, $p < .001$). However, *Percentage Black* demonstrates null relationships with the *Total Jail Population Rate* and the *Total Jail Admissions Rates*, and predicts a *negative* association with the *Black Prison* and *Jail Population Rates*. Thus, the associations are mixed, and evidence indicates inconsistent effects of *Percentage Black* across incarceration outcomes.

TABLE 2 Poisson Pseudo Maximum Likelihood Models: Compositional Threat Measure (Percentage Black)

	Targeted Effects			Diffuse Effects			
	(1) Black Prison Pop	(2) Black Prison Adm	(3) Black Jail Pop	(4) Total Prison Pop	(5) Total Prison Adm	(6) Total Jail Pop	(7) Total Jail Adm
Percentage Black	0.9698***	1.0284	0.9396***	1.0403***	1.1096***	0.9990	1.0030
	(.0084)	(.0171)	(.0095)	(.0090)	(.0235)	(.0100)	(.0089)
Percentage Black^2	1.0002*	0.9996**	1.0007***	0.9995***	0.9988***	1.0001	1.0000
	(.0001)	(.0002)	(.0002)	(.0001)	(.0002)	(.0002)	(.0001)
Population Density	0.9374	0.9383	0.9130	0.8440*	0.8183	0.8257***	0.7487***
	(.0460)	(.0556)	(.0440)	(.0704)	(.0869)	(.0470)	(.0615)
Percentage Male	0.9935	1.0175	1.1023***	1.0232*	1.0703***	1.0868**	1.0548**
	(.0109)	(.0203)	(.0190)	(.0103)	(.0179)	(.0304)	(.0173)
Poverty Rate	0.9974	0.9998	1.0069	0.9945	0.9873	1.0047	1.0015
	(.0030)	(.0077)	(.0050)	(.0030)	(.0074)	(.0045)	(.0036)
Median Income	0.9884***	0.9781***	0.9895***	0.9856***	0.9721***	0.9847***	0.9900***
	(.0017)	(.0031)	(.0019)	(.0018)	(.0028)	(.0016)	(.0018)
Gini Index	0.9919*	0.9861*	0.9885**	0.9791***	0.9729***	0.9840***	0.9904**
	(.0033)	(.0054)	(.0035)	(.0030)	(.0045)	(.0035)	(.0031)
Property Crime Rate	0.9993	0.9981	1.0007*	1.0004	1.0000	1.0009*	1.0010*
	(.0005)	(.0017)	(.0003)	(.0003)	(.0011)	(.0004)	(.0004)
Violent Crime Rate	1.0026	1.0034	1.0046	1.0151***	1.0228**	1.0135***	1.0145***
	(.0023)	(.0071)	(.0034)	(.0025)	(.0084)	(.0037)	(.0035)
Counties	1,739	1,739	1,739	1,739	1,739	1,739	1,739
Observations	27,777	24,750	40,132	38,951	39,559	44,012	44,015
AIC	366899	391564	665804	966030	1242712	1257905	23045682
BIC	366973	391637	665881	966107	1242789	1257983	23045760

Incident Rate Ratios. Cluster robust standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 3 operationalizes racial threat using the Racial Bifurcation Index. *Racial Bifurcation* demonstrates a null relationship with the *Black Prison Population Rate* (Model 8), a significant positive association with the *Black Prison Admission Rate* (Model 9; $IRR = 1.0108$, $p < .001$), and a significant *negative* association with the *Black Jail Population Rate* (Model 10; $IRR = .9929$, $p <$ 001). Thus, the evidence for *Racial Bifurcation* on targeted (Black-specific) incarceration outcomes is also mixed.

On the other hand, there is strong, consistent support for the relationship between *Racial Bifurcation* and diffuse effects, which is always positive and significant at an alpha level of $p < .001$. A one percentage-point increase in *Racial Bifurcation* is associated with a 1.62% increase in the *Total Prison Population Rate* (Model 11); a 2.99% increase in the *Total Prison Admissions Rate* (Model 12); a 0.9% increase in the *Total Jail Population Rate* (Model 13); and a 0.93% increase in the *Total Jail Admissions Rate* (Model 14).

TABLE 3 Poisson Pseudo Maximum Likelihood Models: Structural Threat Measure (Racial Bifurcation)

	Targeted Effects			Diffuse Effects			
	(8) Black Prison Pop	(9) Black Prison Adm	(10) Black Jail Pop	(11) Total Prison Pop	(12) Total Prison Adm	(13) Total Jail Pop	(14) Total Jail Adm
Racial Bifrucation	0.9982	1.0108***	0.9929***	1.0162***	1.0299***	1.0090***	1.0093***
	(.0020)	(.0032)	(.0019)	(.0015)	(.0033)	(.0016)	(.0015)
Population Density	0.9273	0.9388	0.9110	0.8869	0.8955	0.8600*	0.7748***
	(.0490)	(.0604)	(.0625)	(.0570)	(.0770)	(.0532)	(.0579)
Percentage Male	1.0000	1.0252	1.1035***	1.0201*	1.0647***	1.0787**	1.0487**
	(.0116)	(.0207)	(.0196)	(.0091)	(.0186)	(.0286)	(.0153)
Poverty Rate	0.9963	0.9954	1.0080	0.9879***	0.9751**	1.0001	0.9960
	(.0031)	(.0077)	(.0063)	(.0026)	(.0079)	(.0046)	(.0034)
Median Income	0.9898***	0.9769***	0.9905***	0.9818***	0.9650***	0.9823***	0.9881***
	(.0019)	(.0033)	(.0017)	(.0017)	(.0030)	(.0017)	(.0017)
Gini Index	0.9911**	0.9874*	0.9853***	0.9795***	0.9749***	0.9823***	0.9885***
	(.0033)	(.0057)	(.0038)	(.0030)	(.0044)	(.0035)	(.0032)
Property Crime Rate	0.9995	0.9979	1.0008*	1.0003	0.9994	1.0008*	1.0010*
	(.0006)	(.0017)	(.0003)	(.0003)	(.0017)	(.0004)	(.0004)
Violent Crime Rate	1.0003	1.0009	1.0043	1.0106***	1.0168	1.0113***	1.0113***
	(.0021)	(.0075)	(.0035)	(.0023)	(.0100)	(.0034)	(.0031)
Counties	1,739	1,739	1,739	1,739	1,739	1,739	1,739
Observations	27,777	24,750	40,132	38,951	39,559	44,012	44,015
AIC	371280	389818	677535	907343	1177154	1239642	22706428
BIC	371346	389883	677604	907412	1177223	1239711	22706498

Incident Rate Ratios. Cluster robust standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Finally, both *Percentage Black* and *Racial Bifurcation* are simultaneously included in the same models in Table 4. After controlling for Racial Bifurcation, *Percentage Black* displays a null or negative linear relationship with jail and prison outcomes in *every* model. On the other hand, after controlling for Percentage Black, *Racial Bifurcation* demonstrates a significant, positive association with jail and prison outcomes in 5 of seven models—one targeted-effects model and all four diffuse-effects models. Specifically, a one-percentage-point increase in *Racial Bifurcation* is associated with a 1.1% increase in the *Black Prison Admissions Rate* (Model 16), a 1.9% increase in the *Total Prison Population Rate* (Model 18), a 2.9% increase in the *Total Prison Admissions Rate*, a 1.5% increase in the *Total Jail Population Rate*, and a 1.4% increase in the *Total Jail Admissions Rate*.

TABLE 4 Poisson Pseudo Maximum Likelihood Models: Compositional and Structural Threat Modeled Simultaneously

	Targeted Effects			Diffuse Effects			
	(15)	(16)	(17)	(18)	(19)	(20)	(21)
	Black Prison Pop	Black Prison Adm	Black Jail Pop	Total Prison Pop	Total Prison Adm	Total Jail Pop	Total Jail Adm
Percentage Black	0.9537***	0.9922	0.9257***	0.9775*	1.0130	0.9523***	0.9608***
	(.0128)	(.0202)	(.0142)	(.0101)	(.0218)	(.0134)	(.0104)
Percentage Black^2	1.0004**	1.0000	1.0009***	1.0003*	0.9999	1.0007**	1.0005***
	(.0002)	(.0002)	(.0002)	(.0001)	(.0002)	(.0002)	(.0001)
Racial Bifurcation	1.0050	1.0113**	1.0049	1.0190***	1.0285***	1.0153***	1.0140***
	(.0029)	(.0038)	(.0031)	(.0019)	(.0036)	(.0024)	(.0020)
Population Density	0.9441	0.9475	0.9199	0.8966	0.8892	0.8656**	0.7895***
	(.0439)	(.0593)	(.0438)	(.0543)	(.0788)	(.0395)	(.0533)
Percentage Male	0.9941	1.0184	1.1010***	1.0219*	1.0652***	1.0848**	1.0505**
	(.0111)	(.0209)	(.0189)	(.0093)	(.0182)	(.0284)	(.0160)
Poverty Rate	0.9961	0.9961	1.0054	0.9874***	0.9752**	0.9978	0.9949
	(.0028)	(.0081)	(.0044)	(.0027)	(.0079)	(.0039)	(.0032)
Median Income	0.9873***	0.9756***	0.9886***	0.9812***	0.9656***	0.9821***	0.9874***
	(.0017)	(.0031)	(.0018)	(.0017)	(.0027)	(.0018)	(.0017)
Gini Index	0.9924*	0.9870*	0.9889**	0.9806***	0.9743***	0.9840***	0.9902**
	(.0034)	(.0055)	(.0035)	(.0029)	(.0043)	(.0034)	(.0031)
Property Crime Rate	0.9991	0.9978	1.0006*	1.0003	0.9995	1.0008*	1.0010*
	(.0005)	(.0017)	(.0003)	(.0003)	(.0015)	(.0004)	(.0004)
Violent Crime Rate	1.0021	1.0022	1.0038	1.0105***	1.0163	1.0104**	1.0107***
	(.0023)	(.0072)	(.0035)	(.0023)	(.0096)	(.0034)	(.0032)
Counties	1,739	1,739	1,739	1,739	1,739	1,739	1,739
Observations	27,777	24,750	40,132	38,951	39,559	44,012	44,015
AIC	365799	389226	664807	903837	1176617	1220049	22549083
BIC	365881	389308	664893	903923	1176703	1220136	22549170

Incident Rate Ratios. Cluster robust standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

These relationships are visualized in Figure 8. The top panels illustrate models predicting targeted effects, while the bottom panels depict diffuse effects. Blue lines represent *Percentage Black*, red lines represent *Racial Bifurcation*, and dashed lines without confidence intervals indicate non-significant associations. These figures, which report the predicted values of our seven outcome variables, illustrate and reinforce several of the relationships reported in the tables.[10] First, across nine models and

[10] Confidence intervals are at 95%. To avoid predicting beyond what our data permit, we do not predict outcomes beyond 85% Black, the upper limit of our county sample.

twelve substantive relationships, targeted effects models perform quite poorly, where only three significant relationships in the hypothesized directions are observed (Models 2, 9, and 16). In contrast, across twelve models and 15 relationships, diffuse effects models perform much better, with ten significant relationships consistent with threat theory. Second, *Racial Bifurcation* consistently displays stronger associations relative to *Percentage Black*, demonstrating a strong, positive association with overall jail and prison outcomes (as well as *Black Prison Admissions*), whether it is modeled alone or in conjunction with *Percentage Black*. On the other hand, *Percentage Black* demonstrates rather poor predictive power, especially after accounting for *Racial Bifurcation*, where the effects apparent when modeled alone *reverse direction* after controlling for *Racial Bifurcation*. The wide confidence intervals for *Percentage Black* also reveal its imprecision, in contrast to the much narrower confidence intervals for *Racial Bifurcation*. Overall, these illustrations provide evidence for (a) diffuse rather than targeted effects, and (b) superior predictive power of *Racial Bifurcation* over *Percentage Black*.

7 | DISCUSSION

The United States is peculiar for its extraordinarily high levels of incarceration compared to other developed democracies. Moreover, there are enormous disparities across jurisdictions within the U.S. in terms of their incarceration rates. Among the proposed explanations for these disparities are those that link racial composition, group power dynamics, and formal social control. Conflict theorists, including Blalock (1967) and Horowitz (2000), note that relative group size often corresponds to social capital and political power. Furthermore, racial composition signals social “threats,” such as to longstanding hegemonic power, to a national identity, or to economic security. In response to these anxieties, groups may move to institutionalize more social control—hiring more police (Kent & Jacobs, 2005), supporting more punitive policies (Ousey & Unnever, 2012), and incarcerating more people (Jacobs & Carmichael, 2001).

Horowitz (2000) describes ranked and unranked societies, and how each contributes to different types and scales of conflict. A ranked system closely aligns with Blalock’s descriptions in his theory of minority group relations in the U.S., in which a “subordinate” social group—African Americans—“threaten” a superordinate group—White Americans. Under his propositions, a lower social group is both the the source and the target of social anxieties and conflict. But this theory has been challenged in several ways. First, racial threat research has produced inconsistent findings (Vogel & Messner, 2024; Feldmeyer & Cochran, 2018), and broad research suggests that racially discriminatory criminal justice outcomes have narrowed over several decades (Walker et al., 2018). Second, the Civil Rights Movement dismantled an explicit racial hierarchy and further enfranchised Black Americans. Third, the scale of the incarceration has nonetheless increased dramatically since then. Fourth, the U.S. has become increasingly multiethnic, producing conditions for racial conflicts beyond Black and White. Fifth, similar anxieties, conflicts,

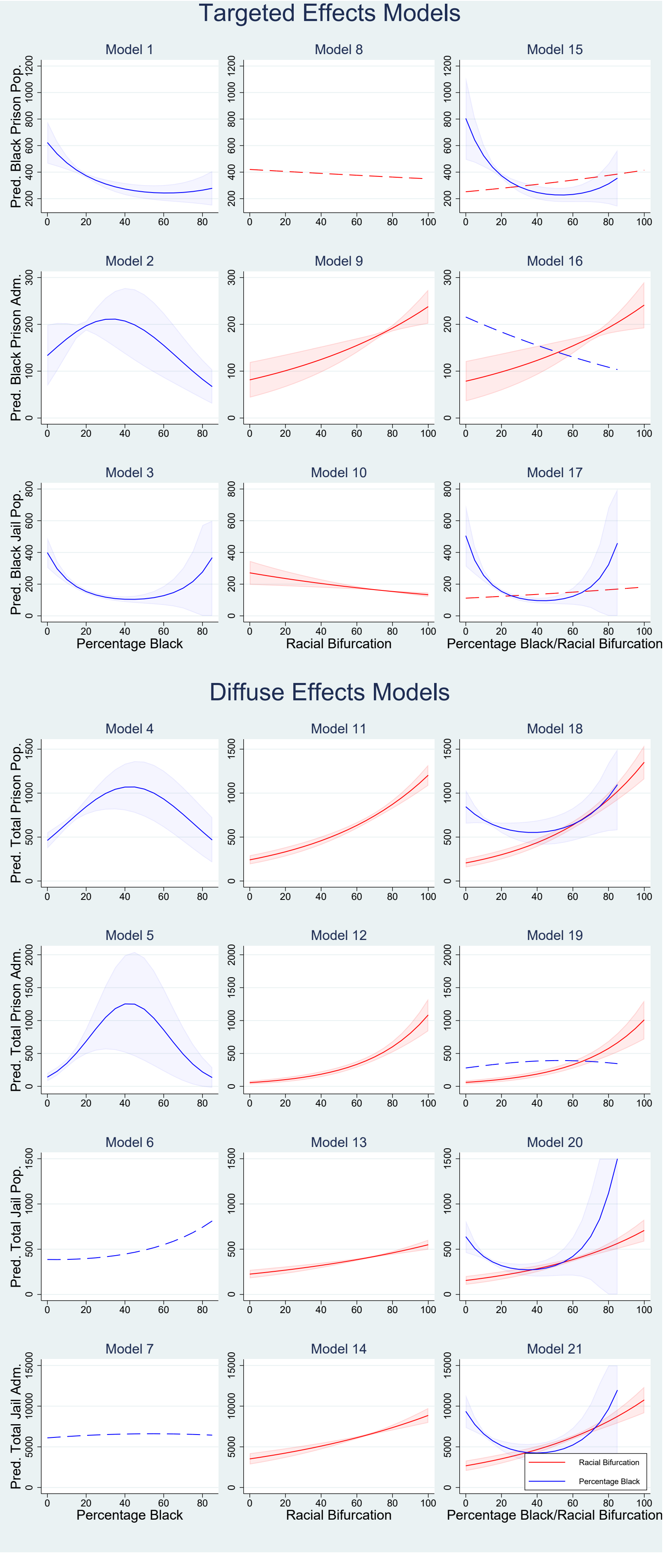

FIGURE 8 Predicted Values for All Outcomes and Models

and criminal justice responses should manifest across varied social contexts, both within and beyond the U.S., even as the specific groups involved differ. And finally, mass incarceration has indiscriminately affected many social groups, including Whites. This pattern of facts suggests that group conflicts produce broad (i.e., diffuse) harms, and that it may be simplistic to delineate specific groups as "threatening" and "threatened."

Therefore, this study sought to address parallel issues of both theory and measurement in the context of group conflict theory. To do so, we examined targeted vs. diffuse effects, as well as compositional vs. structural demographic threats. We advocated for the use of Racial Bifurcation which, we argued, is best suited to operationalize the group dynamics outlined by theory, and which addresses key shortcomings of measures used by the existing literature, such as percentage Black or percentage minority/non-white. We argued that measures of racial composition such as percentage Black are overly simplistic, failing to describe demographic *structure*. A measure of Racial Bifurcation, however, reflects the racial/ethnic composition theorized to maximize group tension, namely where one large group coexists with another sizable group. In contrast, the index retains low values in contexts where no minority group is large enough to be perceived as a threat, or where the presence of multiple groups precludes the concentration of antagonistic power. The measure maintains parsimony, as it consists of a single variable, and can be used to describe multiracial contexts, regardless of the designation of specific groups. Beyond merely advocating for a measure of Racial Bifurcation, we used the measure in a test of group threat using data 1,739 U.S. counties between 1993 and 2023. Specifically, we estimated the association between Racial Bifurcation and trends in jail and prison outcomes, and compared it to *percentage Black*, which is the most traditional measure used in the racial threat literature.

Across 21 models predicting seven carceral outcomes, our findings provided consistent evidence for (1) diffuse rather than targeted effects and (2) the salience of Racial Bifurcation. The models provided no consistent evidence for targeted effects. Although percentage Black and Racial Bifurcation independently predicted higher Black Prison Admissions, only Racial Bifurcation remained significant when both measures were included simultaneously in the model; neither measure predicted other Black-specific outcomes. Conversely, we found overwhelming support for diffuse effects. Although percentage Black demonstrated a classic Kuznets curve for Total Prison Admissions and Populations, this effect fell away after accounting for Racial Bifurcation. In turn, Racial Bifurcation was a stronger, more consistent predictor than percentage Black, and remained both significant and substantively large even when controlling for it. To the extent that Black populations contribute to more racial threat, these effects appear to be driven primarily via their contribution toward Racial Bifurcation, which is both theoretically and methodologically more appropriate. Though our findings generally endorse the theories, they challenge traditional operationalizations of racial threat and suggest that U.S. punitiveness is driven less by simple "minority threat" and more by the *structural dynamics of intergroup competition* in liberal, democratic, multiethnic society, a dynamic that contributes to factionalism, drained pool politics, and diffuse harms for all groups.

We found a modest association between violent crime rates and overall incarceration trends. The most generous explanations are that incarceration is an exceptionally lagging indicator, or that we reached the maximum marginal utility of incarceration at the turn of the century, when rates were already extraordinarily high. The least generous explanation is that incarceration is a tool of social control, but not necessarily crime control. Given the enormous economic and human costs of incarceration, other potential strategies may be more productive in most contexts, such as policing, justice reinvestment, and prevention programs (Biglan et al., 2005; Kaplan & Chalfin, 2019; Sabol & Baumann, 2020). However, given the substantial problems with county-level crime data, these results may also be a limitation of the data (Maltz & Targonski, 2002; Kaplan, 2025).

A key theoretical contribution of this study is its generalizability. Unlike much of the existing literature on racial threat—which often focuses on specific racial dyads (e.g., Black-White or Latino-White relations)—this study finds robust evidence for both an independent variable (the Racial Bifurcation index) and dependent variables (overall incarceration rates) that are agnostic to the specific racial or ethnic identities of any group. This agnosticism is a strength: it supports both theoretical propositions and models that account for the social conditions under which group conflict and its consequences are most likely to manifest, regardless of which groups are involved. In doing so, the analysis supports a more general theory of intergroup conflict—one that can account for the dynamics of punishment across various group configurations and diverse sociopolitical contexts. The Racial Bifurcation index captures not the identity of conflicting groups but the relational structure of competition and punitive response, making it broadly applicable across counties, regions, and even nations with different demographic compositions. Similarly, by focusing on population-level incarceration metrics, our outcomes reflect the system-wide effects of group tension, rather than presuming group-specific victimization or culpability. Together, these properties advance a more generalizable and parsimonious framework for exploring group-based power dynamics, answering previous calls for a more generalized theory of social structure and control (Vogel & Messner, 2024).

Moreover, we tested and found this framework to be more predictive of the criminal justice outcomes anticipated by theory. When social groups compete horizontally for power, resources, and control of the government within a shared democratic and legal framework, the imperative that policy and law be applied in race-neutral ways contributes to widespread consequences. The greatest tension occurs at demographic parity (a 50:50 split), especially if political factions form along ethnic lines. Undoubtedly, this often describes Black/White tensions in the U.S., and to that extent remains consistent with Blalock's theory. Just as often, however, this describes tensions between other groups. The U.S. is an increasingly multiracial, multiethnic society, but this diversity is unevenly distributed; demographic structure varies widely across counties. It has been said that "all politics is local," reflected in how informal norms and customs, decentralized justice systems, and formal criminal justice responses are ultimately shaped by local demographic and social characteristics. Racial Bipolarization accommodates this variability by enabling researchers to simultaneously assess threat dynamics among different dyads as they exist across diverse locales.

The results also provide a theoretical rationale for 21st century decarceration, resolving what some have called a problem or paradox for group threat theory (Vogel & Messner, 2024). After decades of growth, incarceration has begun to decline, especially among minority men (Robey et al., 2023; Muller & Roehrkasse, 2022). Urban areas are responsible for the largest share of total prisoners and are also responsible for the largest drop in incarceration (Simes, 2021). As evidenced in Figure 7, these urban counties are seeing racial bifurcation level off, on average, and even decline in many places. These counties are becoming more diverse, moving from bifurcated to fragmented or multi-polar arrangements. The recent 21st-century decarceration trend may be partially driven by a demographic dividend in major urban centers: as increasing diversity reduces structural bifurcation, it reduces the underlying group conflict that fueled punitiveness, opening political space for reform.

To summarize, ours is an elaboration about the generalizability of group threat and conflict theories, which posit that perceptions of racial or ethnic threat emerge in contexts of intergroup competition over resources and status. Blalock's racial threat theory traditionally emphasized targeted reactions of White Americans to the growing presence of African Americans. Our results suggest incarceration outcomes appear to be influenced not by the size of a specific minority group, but more importantly *by the relative balance between competing groups*. The racial bifurcation index captures a *structural* demographic dimension of group conflict that is missed by traditional *compositional* measures: *relative* group size, balance, and parity are key drivers of conflict beyond absolute group size or *im*balance.

In addition, the harms of this bipolar conflict are diffuse. A dominant group that stiffens laws or sentences to suppress an emerging threat is also likely to harm its own vulnerable members, who—because of their marginalization—are unable to shield themselves from punitive targeting. This would be the case, for instance, when a member of the majority group is sentenced harshly for using a drug associated with a threatening minority group. While biases may shape the formulation of such laws, their enforcement is not always as selective.

If the problem is structural conflict, and not merely racial animus, then policy solutions must also be structural and possibly general. Anti-discrimination laws, improved data collection, and implicit bias training may still be necessary, but they are insufficient. Instead, reforms should challenge a zero-sum, two-group logic, or a semse of fractionalism and tribalism that favors in-group members, instead prioritizing fairness, neutrality and tolerance (McGhee, 2022; Horowitz, 2000).

If racial bifurcation contributes to factionalism and polarized politics, then electoral system reforms may be necessary. Ranked-choice/preferential voting disincentivizes extremist rhetoric, because candidates must have broader appeal in order to secure second- and third-choice votes. These types of systems necessitate cross-group coalition building, promoting *political* identities that are not entirely absorbed by *ethnic* identities, and that are not as sensitive to the extremes of the political spectrum (Reilly 2018; cf. McDaniel 2018).

Strategies that incentivize inter-group cooperation may also be productive. In a simple majority-rules system, a 51% majority group has no institutional reason to cooperate with the 49% minority. This can lead to a "tyranny of the majority," reinforcing division and conflict (Lijphart, 1999; de Tocqueville, 2000). To ameliorate bipolar conflict, it is important to design political bodies that *mandate* cross-group coalitions. For instance, formal consociationalism is used in both polarized regions like Northern Ireland and diverse, multiethnic regions like Belgium and Switzerland, and involves coalition governments, minority veto power, and proportional representation (Howe, 2019). However, local and less formalized bodies such as economic development boards, police oversight committees, redistricting committees, and parole boards could also mandate multi-group coalitions. This not only ensures more representative decision making; it also alleviates conflict and eases anxieties of political domination by avoiding a winner-takes-all governance structure.

Intergroup conflict becomes most acute when racial or ethnic identity aligns perfectly with other socially relevant identities, such as class, religion, and geography. For instance, when one group is uniformly urban, working-class, and of one race, while another group is uniformly suburban, professional-class, and of another race, there is little to no common ground. In this environment, every political debate, whether about taxes, infrastructure, or education, becomes a simple proxy for the single, underlying racial conflict. The antidote, as Horowitz (2000) argues, is the intentional fostering of cross-cutting cleavages. This strategy aims to foster alternative, non-ethnic identities that are more fluid and voluntary (e.g., economic class, profession, or regional affiliation) increasing their political salience relative to fixed ethnic categories. The goal is to create a society where an individual's identity is not primarily linked to a rigid racial/ethnic classification, preventing political mobilization from occurring along a single polarized axis.

For example, in a political environment with strong cross-cutting cleavages, voters may unite based on a shared class identity (e.g., poor White, Black, and Latino residents aligning on economic policy) or a regional identity (e.g., urban residents of all races aligning on infrastructure funding), rather than defaulting to a purely racial faction. When identities as a "teacher," "union member," or "city-dweller" become politically relevant, they compete with and strain the primary racial-political identity. This process effectively breaks the bipolar, zero-sum logic linked to increased incarceration. By creating multiple, overlapping dimensions of political identity, cross-cutting cleavages lower the existential stakes of the primary racial conflict. This diffusion of identity can ameliorate factionalism and status-based fears that, as this study indicates, are the engine for diffuse, drained pool politics. While this is the most difficult prescription to implement via direct policy, it suggests that efforts to strengthen non-ethnic civil society—such as labor unions, professional associations, and issue-based advocacy groups—can be a key long-term strategy for reducing intergroup conflict and, ultimately, the impulse for more punitiveness.

Our study has several limitations. First, though we used fixed effects and accounted for control variables, our estimated associations are not necessarily causal and could be driven by other dynamic factors that may be associated with both racial bifurcation and incarceration trends. Second, our estimates are specific to counties within the U.S. and thus do not investigate the potential of group theories for explaining the criminal sanctioning in other societies globally, which have distinct racial and ethnic compositions, and which approach group relationships differently (but see Marier & Cochran 2023). The extent our findings are generalizable, rather than specific to the U.S. context, remains an open question for investigation. Finally, though we examined the effects of percentage Black and Racial Bifurcation, we did not explore all possible alternative measures (e.g., Latino Threat, racial diversity). The most adequate operationalization of group conflict theories is ultimately a theoretical question, to the extent utilized measures can adequately represent racial dynamics as outlined in the literature. To the extent this paper elaborates on the longstanding racial threat hypothesis that racial demographics predict punishment, it supports many questions for future research. Is Black/White polarization more salient than other types of polarization? Does racial polarization predict factionalism and political polarization, as we assume? Is the mechanism strictly political—operating through democratic process—or does it act through the decision making of judges, jurors, prosecutors, police officers, and citizens who make complaints?

Despite these limitations, our study argued for and effectively demonstrates the potential of Racial Bifurcation as a measure of racial treat dynamics, and as a major predictor of jail and prison outcomes for all racial groups across the U.S. The generality and strength of that relationship indicates that the structure of racial demographics are a key predictor of incarceration rates across the country, a finding which both supports and extends group conflict theories that were first proposed many decades ago. Efforts to reduce incarceration must confront the social and political conditions reinforcing punishment. Regions marked by high levels of polarization may require distinct policy approaches that reduce intergroup tensions and avoid zero-sum logics of law and policy. Within that pursuit, policymakers, researchers, and practitioners should consider adopting the Racial Bifurcation index, which more effectively captures the relational and competitive balance between groups.

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APPENDIX

A SUPPLEMENTAL MODELS

The models in Tables A1, A2, and A3 are identical to the PPML HDFE models presented in the main manuscript, except that they use one-dimensional, county fixed effects (omitting fixed effects for each year). There are no substantive differences, except that *Racial Bifurcation* predicts significantly higher Black Prison Populations and Black Jail Populations when modeled simultaneously with *Percentage Black* in the supplemental models (Models 15 and 17). These effects are somewhat modest (IRR = 1.0067, $p < .05$ for each).

The models in Tables A4, A5, and A6 are identical to those presented in the main manuscript, except that they include one-year lags. We do not report these models in the main manuscript because such models introduce the 'Nickell Bias Problem,' (Nickell, 1981) for which there is currently no established statistical correction for fixed effects Poisson models (although some exist for other types of dynamic panel models). Nonetheless, there are no substantive differences with the main models regarding the magnitude, significance, or direction of the relationships.

The models in Tables A7, A8, and A9 are identical to those in the manuscript, except that they use the maximum possible sample for each model based on listwise deletion, and are not all restricted to the same 1,739 counties. There are no substantive differences with the main models regarding the magnitude, significance, or direction of the relationships.

The models in Tables A10, A11, and A12 use log-transformed incarceration and admissions *rates* (not counts) and employ ordinary least squares regression using county and year fixed effects. A constant was added to each incarceration count in order to avoid the loss of counties with zero prisoner populations or admissions (i.e., $ln(\frac{y+1}{100{,}000 pop.})$). Minor differences with the main models emerge:

1. Models 2 and 16: *Percentage Black* demonstrates a stronger, statistically significant relationship with Black Prison Admissions in OLS models, although the direction of this relationship remains contrary to threat theory propositions.
2. Model 8: Whereas *Racial Bifurcation* demonstrated a non-significant relationship with Black Prison Populations in the main manuscript, it demonstrates a significant, negative relationship in the OLS model.
3. Model 9: Whereas *Racial Bifurcation* demonstrated a significant negative relationship with Black Prison Admissions in the main manuscript, it demonstrates a non-significant relationship in the OLS model.
4. Model 18: When modeling both threat measures simultaneously, *Percentage Black* no longer demonstrates a significant relationship with the Total Prison Population.

Overall, the various supplemental models provide a comprehensive robustness and sensitivity check for the main models. The supplemental results overwhelmingly reinforce the predictive power of *Racial Bifurcation*, the relatively poor predictive power of *Percentage Black*, and the consistent evidence for diffuse, rather than targeted, effects. The results therefore do not appear to be an artifact of modeling strategy.

TABLE A1 One Dimensional (County) Fixed Effects Models: Compositional Threat Measure (Percentage Black)

	Targeted Effects			Diffuse Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Black Prison Pop	Black Prison Adm	Black Jail Pop	Total Prison Pop	Total Prison Adm	Total Jail Pop	Total Jail Adm
Percentage Black	0.9755**	1.0347	0.9427***	1.0579***	1.1304***	1.0156	1.0073
	(.0088)	(.0188)	(.0103)	(.0092)	(.0242)	(.0094)	(.0085)
Percentage Black^2	1.0002*	0.9996*	1.0007***	0.9995***	0.9988***	1.0001	0.9999
	(.0001)	(.0002)	(.0002)	(.0001)	(.0002)	(.0002)	(.0001)
Population Density	0.8743*	0.8176*	0.8573**	0.7643***	0.7012**	0.7682***	0.7450***
	(.0470)	(.0659)	(.0467)	(.0606)	(.0777)	(.0383)	(.0572)
Percentage Male	0.9687**	0.9460**	1.0652***	1.0187	1.0323*	1.0840***	1.0264
	(.0114)	(.0180)	(.0181)	(.0102)	(.0145)	(.0262)	(.0148)
Poverty Rate	0.9894***	0.9752***	0.9984	0.9992	0.9853***	1.0094***	0.9994
	(.0022)	(.0037)	(.0027)	(.0022)	(.0044)	(.0020)	(.0021)
Median Income	0.9911***	0.9781***	0.9893***	1.0005	0.9895***	0.9960***	0.9882***
	(.0010)	(.0033)	(.0009)	(.0014)	(.0029)	(.0008)	(.0009)
Gini Index	0.9950	0.9792***	0.9836***	0.9896**	0.9763***	0.9953	0.9927*
	(.0035)	(.0057)	(.0043)	(.0032)	(.0049)	(.0036)	(.0037)
Property Crime Rate	1.0002	1.0009	1.0012	1.0002	1.0001	1.0007*	1.0013
	(.0006)	(.0018)	(.0007)	(.0003)	(.0010)	(.0003)	(.0007)
Violent Crime Rate	0.9957*	0.9949	1.0006	1.0038*	1.0100	1.0028	1.0065
	(.0022)	(.0088)	(.0035)	(.0019)	(.0074)	(.0027)	(.0035)
Counties	1,739	1,739	1,739	1,739	1,739	1,739	1,739
Observations	27777	24750	40132	38951	39559	44012	44015
AIC	399590.7	449290.9	709411.3	1125535.2	1402366.6	1417552.3	24775424.5
BIC	399664.8	449363.9	709488.7	1125612.3	1402443.9	1417630.5	24775502.7

Incident Rate Ratios. Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE A2 One Dimensional (County) Fixed Effects Models: Structural Threat Measure (Racial Bifurcation)

	Targeted Effects			Diffuse Effects			
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Black Prison Pop	Black Prison Adm	Black Jail Pop	Total Prison Pop	Total Prison Adm	Total Jail Pop	Total Jail Adm
Racial Bifurcation	0.9995	1.0128***	0.9945**	1.0197***	1.0333***	1.0125***	1.0117***
	(.0020)	(.0037)	(.0018)	(.0016)	(.0037)	(.0014)	(.0014)
Population Density	0.8723*	0.8251*	0.8621*	0.8187***	0.7855**	0.8134***	0.7770***
	(.0495)	(.0691)	(.0632)	(.0469)	(.0727)	(.0424)	(.0533)
Percentage Male	0.9695*	0.9481**	1.0637***	1.0112	1.0242	1.0723**	1.0171
	(.0120)	(.0191)	(.0192)	(.0096)	(.0154)	(.0250)	(.0133)
Poverty Rate	0.9881***	0.9722***	0.9979	0.9949*	0.9785***	1.0055*	0.9930**
	(.0023)	(.0040)	(.0031)	(.0022)	(.0045)	(.0022)	(.0022)
Median Income	0.9906***	0.9755***	0.9890***	0.9959**	0.9820***	0.9936***	0.9851***
	(.0011)	(.0036)	(.0011)	(.0014)	(.0034)	(.0008)	(.0010)
Gini Index	0.9928*	0.9785***	0.9800***	0.9894**	0.9762***	0.9934	0.9877**
	(.0036)	(.0063)	(.0046)	(.0034)	(.0050)	(.0036)	(.0037)
Property Crime Rate	1.0005	1.0006	1.0013	0.9998	0.9989	1.0004	1.0013
	(.0006)	(.0019)	(.0007)	(.0005)	(.0018)	(.0003)	(.0007)
Violent Crime Rate	0.9939**	0.9933	1.0001	1.0011	1.0073	1.0021	1.0041
	(.0021)	(.0090)	(.0037)	(.0022)	(.0094)	(.0026)	(.0033)
Counties	1,739	1,739	1,739	1,739	1,739	1,739	1,739
Observations	27777	24750	40132	38951	39559	44012	44015
AIC	402408.7	445206.7	722226.5	1045328.2	1319532.9	1390423.7	24174675.7
BIC	402474.6	445271.6	722295.3	1045396.8	1319601.6	1390493.3	24174745.2

Incident Rate Ratios. Robust standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE A3 One Dimensional (County) Fixed Effects Models: Both Threat Measures Modeled Simultaneously

	Targeted Effects			Diffuse Effects			
	(15) Black Prison Pop	(16) Black Prison Adm	(17) Black Jail Pop	(18) Total Prison Pop	(19) Total Prison Adm	(20) Total Jail Pop	(21) Total Jail Adm
Percentage Black	0.9536***	0.9879	0.9233***	0.9823	1.0215	0.9563***	0.9541***
	(.0132)	(.0201)	(.0153)	(.0101)	(.0209)	(.0121)	(.0097)
Percentage Black^2	1.0005**	1.0001	1.0009***	1.0004***	1.0000	1.0008***	1.0006***
	(.0002)	(.0002)	(.0002)	(.0001)	(.0002)	(.0002)	(.0001)
Racial Bifurcation	1.0067*	1.0145***	1.0067*	1.0221***	1.0312***	1.0185***	1.0171***
	(.0031)	(.0041)	(.0031)	(.0019)	(.0037)	(.0021)	(.0017)
Population Density	0.8824*	0.8272*	0.8645**	0.8235***	0.7722**	0.8100***	0.7920***
	(.0448)	(.0690)	(.0448)	(.0470)	(.0754)	(.0300)	(.0486)
Percentage Male	0.9697*	0.9475**	1.0636***	1.0172	1.0275	1.0807***	1.0200
	(.0117)	(.0185)	(.0182)	(.0097)	(.0153)	(.0244)	(.0137)
Poverty Rate	0.9883***	0.9726***	0.9970	0.9935**	0.9768***	1.0023	0.9926***
	(.0023)	(.0042)	(.0027)	(.0021)	(.0046)	(.0021)	(.0022)
Median Income	0.9898***	0.9754***	0.9884***	0.9953***	0.9821***	0.9928***	0.9847***
	(.0012)	(.0035)	(.0011)	(.0013)	(.0031)	(.0008)	(.0010)
Gini Index	0.9954	0.9795***	0.9836***	0.9890***	0.9740***	0.9925*	0.9895**
	(.0037)	(.0060)	(.0043)	(.0032)	(.0049)	(.0035)	(.0036)
Property Crime Rate	0.9999	1.0003	1.0011	0.9999	0.9995	1.0006*	1.0013
	(.0006)	(.0018)	(.0006)	(.0004)	(.0014)	(.0003)	(.0006)
Violent Crime Rate	0.9953*	0.9940	0.9999	1.0003	1.0052	1.0007	1.0040
	(.0022)	(.0090)	(.0034)	(.0020)	(.0089)	(.0025)	(.0033)
Counties	1,739	1,739	1,739	1,739	1,739	1,739	1,739
Observations	27777	24750	40132	38951	39559	44012	44015
AIC	397429.1	444977.6	707342.4	1032994.5	1312962.0	1355558.2	23943922.8
BIC	397511.4	445058.8	707428.4	1033080.2	1313047.9	1355645.1	23944009.7

Incident Rate Ratios. Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE A4 Dynamic Panel Models: Compositional Threat Measure (Percentage Black)

	Targeted Effects			Diffuse Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Black Prison Pop	Black Prison Adm	Black Jail Pop	Total Prison Pop	Total Prison Adm	Total Jail Pop	Total Jail Adm
Percentage Black	0.9724***	1.0353*	0.9402***	1.0394***	1.1102***	0.9954	1.0003
	(.0079)	(.0178)	(.0091)	(.0087)	(.0232)	(.0096)	(.0090)
Percentage Black^2	1.0002*	0.9995**	1.0007***	0.9995***	0.9988***	1.0002	1.0000
	(.0001)	(.0002)	(.0002)	(.0001)	(.0002)	(.0002)	(.0001)
Population Density	0.9424	0.9268	0.9040*	0.8409*	0.8075*	0.8220***	0.7525***
	(.0442)	(.0504)	(.0448)	(.0711)	(.0827)	(.0477)	(.0642)
Percentage Male	0.9952	1.0222	1.0806***	1.0225*	1.0730***	1.0734*	1.0571***
	(.0098)	(.0197)	(.0177)	(.0099)	(.0185)	(.0309)	(.0160)
Poverty Rate	0.9968	0.9992	0.9990	0.9947	0.9867	1.0025	0.9986
	(.0028)	(.0084)	(.0044)	(.0030)	(.0078)	(.0041)	(.0035)
Median Income	0.9882***	0.9775***	0.9887***	0.9858***	0.9716***	0.9852***	0.9904***
	(.0017)	(.0033)	(.0019)	(.0018)	(.0029)	(.0016)	(.0020)
Gini Index	0.9938*	0.9862**	0.9915*	0.9792***	0.9720***	0.9825***	0.9917*
	(.0031)	(.0051)	(.0038)	(.0029)	(.0045)	(.0035)	(.0040)
Property Crime Rate	0.9996	0.9993	1.0022**	1.0013*	1.0008	1.0010*	1.0011*
	(.0006)	(.0016)	(.0007)	(.0007)	(.0016)	(.0005)	(.0005)
Violent Crime Rate	1.0025	1.0019	0.9983	1.0135***	1.0221*	1.0134***	1.0151***
	(.0020)	(.0064)	(.0035)	(.0028)	(.0091)	(.0035)	(.0035)
Counties	1,739	1,739	1,739	1,739	1,739	1,739	1,739
Observations	26751	23699	38510	37412	37997	42294	42301
AIC	346761.7	371700.9	614168.4	903339.0	1174601.3	1185701.5	21824235.0
BIC	346835.4	371773.6	614245.4	903415.8	1174678.2	1185779.4	21824312.8

Incident Rate Ratios. Cluster robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE A5 Dynamic Panel Models: Structural Threat Measure (Racial Bifurcation)

	Targeted Effects			Diffuse Effects			
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Black Prison Pop	Black Prison Adm	Black Jail Pop	Total Prison Pop	Total Prison Adm	Total Jail Pop	Total Jail Adm
Racial Bifurcation	0.9978	1.0105***	0.9920***	1.0157***	1.0295***	1.0081***	1.0086***
	(.0018)	(.0031)	(.0017)	(.0015)	(.0033)	(.0015)	(.0016)
Population Density	0.9326	0.9259	0.9025	0.8805	0.8806	0.8536*	0.7800**
	(.0470)	(.0546)	(.0650)	(.0579)	(.0722)	(.0548)	(.0620)
Percentage Male	1.0014	1.0287	1.0803***	1.0205*	1.0680***	1.0663*	1.0510***
	(.0106)	(.0195)	(.0191)	(.0088)	(.0187)	(.0295)	(.0140)
Poverty Rate	0.9963	0.9955	1.0008	0.9885***	0.9751**	0.9983	0.9939
	(.0028)	(.0084)	(.0058)	(.0026)	(.0082)	(.0042)	(.0033)
Median Income	0.9897***	0.9759***	0.9898***	0.9820***	0.9643***	0.9828***	0.9884***
	(.0018)	(.0036)	(.0017)	(.0017)	(.0031)	(.0017)	(.0018)
Gini Index	0.9930*	0.9873*	0.9884**	0.9796***	0.9741***	0.9808***	0.9897*
	(.0031)	(.0053)	(.0042)	(.0028)	(.0043)	(.0035)	(.0041)
Property Crime Rate	0.9998	0.9990	1.0025**	1.0010	1.0001	1.0010*	1.0010*
	(.0006)	(.0017)	(.0008)	(.0006)	(.0018)	(.0004)	(.0004)
Violent Crime Rate	1.0005	1.0002	0.9980	1.0095***	1.0166	1.0112***	1.0122***
	(.0019)	(.0067)	(.0036)	(.0026)	(.0099)	(.0033)	(.0032)
Counties	1,739	1,739	1,739	1,739	1,739	1,739	1,739
Observations	26741	23692	38482	37383	37970	42265	42272
AIC	349873.5	370530.6	623695.4	851500.7	1117203.3	1170435.1	21538544.4
BIC	349939.1	370595.2	623763.9	851568.9	1117271.6	1170504.3	21538613.6

Incident Rate Ratios. Cluster robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE A6 Dynamic Panel Models: Both Threat Measures Modeled Simultaneously

	Targeted Effects			Diffuse Effects			
	(15) Black Prison Pop	(16) Black Prison Adm	(17) Black Jail Pop	(18) Total Prison Pop	(19) Total Prison Adm	(20) Total Jail Pop	(21) Total Jail Adm
Percentage Black	0.9599**	1.0056	0.9302***	0.9784*	1.0158	0.9510***	0.9595***
	(.0124)	(.0216)	(.0142)	(.0100)	(.0222)	(.0134)	(.0108)
Percentage Black^2	1.0004*	0.9999	1.0009***	1.0003*	0.9999	1.0007***	1.0005***
	(.0002)	(.0002)	(.0002)	(.0001)	(.0002)	(.0002)	(.0002)
Racial Bifurcation	1.0038	1.0091*	1.0035	1.0184***	1.0278***	1.0147***	1.0136***
	(.0028)	(.0038)	(.0031)	(.0019)	(.0036)	(.0025)	(.0021)
Population Density	0.9466	0.9313	0.9092	0.8900	0.8730	0.8602**	0.7924***
	(.0430)	(.0538)	(.0463)	(.0555)	(.0742)	(.0412)	(.0557)
Percentage Male	0.9959	1.0232	1.0800***	1.0220*	1.0687***	1.0725**	1.0538***
	(.0101)	(.0202)	(.0176)	(.0091)	(.0185)	(.0289)	(.0149)
Poverty Rate	0.9958	0.9963	0.9977	0.9880***	0.9752**	0.9959	0.9924*
	(.0026)	(.0087)	(.0039)	(.0026)	(.0082)	(.0035)	(.0031)
Median Income	0.9873***	0.9754***	0.9880***	0.9815***	0.9651***	0.9824***	0.9876***
	(.0017)	(.0033)	(.0017)	(.0017)	(.0028)	(.0017)	(.0019)
Gini Index	0.9941	0.9867**	0.9918*	0.9806***	0.9735***	0.9826***	0.9916*
	(.0032)	(.0051)	(.0038)	(.0027)	(.0043)	(.0033)	(.0040)
Property Crime Rate	0.9995	0.9991	1.0021**	1.0008	1.0002	1.0010*	1.0010*
	(.0005)	(.0016)	(.0007)	(.0006)	(.0016)	(.0004)	(.0004)
Violent Crime Rate	1.0021	1.0009	0.9978	1.0097***	1.0160	1.0103**	1.0115***
	(.0020)	(.0065)	(.0035)	(.0026)	(.0095)	(.0032)	(.0032)
Counties	1,739	1,739	1,739	1,739	1,739	1,739	1,739
Observations	26741	23692	38482	37383	37970	42265	42272
AIC	346032.2	370236.6	612881.3	848516.8	1116460.0	1151549.6	21373987.2
BIC	346114.1	370317.4	612966.9	848602.1	1116545.5	1151636.1	21374073.7

Incident Rate Ratios. Cluster robust standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE A7 Maximum Sample Models: Compositional Threat Measure (Percentage Black)

	Targeted Effects			Diffuse Effects			
	(1) Black Prison Pop	(2) Black Prison Adm	(3) Black Jail Pop	(4) Total Prison Pop	(5) Total Prison Adm	(6) Total Jail Pop	(7) Total Jail Adm
Percentage Black	0.9696***	1.0281	0.9250***	1.0460***	1.1043***	0.9969	0.9973
	(.0084)	(.0171)	(.0103)	(.0088)	(.0236)	(.0073)	(.0055)
Percentage Black^2	1.0003**	0.9996**	1.0007***	0.9995***	0.9988***	1.0000	1.0000
	(.0001)	(.0002)	(.0002)	(.0001)	(.0002)	(.0001)	(.0000)
Population Density	0.9374	0.9377	0.9133	0.8541*	0.7991*	0.7992***	0.7299***
	(.0460)	(.0556)	(.0491)	(.0684)	(.0904)	(.0500)	(.0558)
Percentage Male	0.9922	1.0162	1.0719***	1.0259***	1.0519***	1.0861***	1.0562***
	(.0105)	(.0199)	(.0177)	(.0077)	(.0156)	(.0194)	(.0140)
Poverty Rate	0.9973	0.9998	1.0096	0.9915**	0.9851*	1.0059	0.9991
	(.0029)	(.0077)	(.0054)	(.0027)	(.0073)	(.0042)	(.0035)
Median Income	0.9884***	0.9782***	0.9916***	0.9849***	0.9715***	0.9844***	0.9886***
	(.0017)	(.0031)	(.0021)	(.0013)	(.0028)	(.0017)	(.0017)
Gini Index	0.9918*	0.9862*	0.9852***	0.9802***	0.9724***	0.9794***	0.9890***
	(.0032)	(.0054)	(.0043)	(.0026)	(.0042)	(.0041)	(.0033)
Property Crime Rate	0.9993	0.9982	1.0009*	1.0006*	1.0003	1.0014	1.0013
	(.0005)	(.0017)	(.0005)	(.0003)	(.0009)	(.0009)	(.0007)
Violent Crime Rate	1.0027	1.0034	1.0099**	1.0094***	1.0244**	1.0112**	1.0181***
	(.0023)	(.0071)	(.0037)	(.0023)	(.0080)	(.0038)	(.0042)
Counties	1,920	1,803	2,723	2,773	2,699	3,023	3,019
Observations	28,801	25,119	58,001	59,688	57,358	72891	72939
AIC	371330.4	393948.1	880178.0	1231465.0	1404848.8	2045335.1	32224249.3
BIC	371404.8	394021.3	880258.7	1231545.9	1404929.4	2045417.8	32224332.1

Incident Rate Ratios. Cluster robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE A8 Maximum Sample Models: Structural Threat Measure (Racial Bifurcation)

	Targeted Effects			Diffuse Effects			
	(8) Black Prison Pop	(9) Black Prison Adm	(10) Black Jail Pop	(11) Total Prison Pop	(12) Total Prison Adm	(13) Total Jail Pop	(14) Total Jail Adm
Racial Bifurcation	0.9981	1.0107***	0.9894***	1.0159***	1.0291***	1.0086***	1.0071***
	(.0020)	(.0032)	(.0023)	(.0015)	(.0033)	(.0016)	(.0015)
Population Density	0.9269	0.9383	0.8867	0.8794	0.8764	0.8344**	0.7476***
	(.0491)	(.0604)	(.0564)	(.0593)	(.0790)	(.0501)	(.0533)
Percentage Male	0.9989	1.0245	1.0824***	1.0143	1.0509**	1.0827***	1.0560***
	(.0114)	(.0205)	(.0179)	(.0080)	(.0169)	(.0224)	(.0141)
Poverty Rate	0.9963	0.9953	1.0095	0.9866***	0.9742***	1.0026	0.9953
	(.0030)	(.0077)	(.0059)	(.0026)	(.0076)	(.0041)	(.0032)
Median Income	0.9898***	0.9769***	0.9946**	0.9814***	0.9650***	0.9819***	0.9873***
	(.0019)	(.0033)	(.0019)	(.0017)	(.0030)	(.0016)	(.0016)
Gini Index	0.9910**	0.9874*	0.9817***	0.9791***	0.9739***	0.9789***	0.9874***
	(.0033)	(.0057)	(.0046)	(.0028)	(.0042)	(.0043)	(.0033)
Property Crime Rate	0.9995	0.9980	1.0012	1.0004	0.9997	1.0014	1.0013
	(.0006)	(.0018)	(.0006)	(.0003)	(.0015)	(.0010)	(.0007)
Violent Crime Rate	1.0004	1.0009	1.0084*	1.0113***	1.0174	1.0149***	1.0162***
	(.0021)	(.0075)	(.0040)	(.0023)	(.0095)	(.0044)	(.0044)
Counties	1,907	1,793	2,718	2,712	2,685	2,962	2,957
Observations	28,640	24,976	57,676	57,225	56,293	70,619	70,631
AIC	374362.9	390669.8	896238.8	1068577.0	1325528.7	1881790.1	31270496.5
BIC	374429.0	390734.8	896310.5	1068648.7	1325600.2	1881863.4	31270569.8

Incident Rate Ratios. Cluster robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE A9 Maximum Sample Models: Both Threat Measures Modeled Simultaneously

	Targeted Effects			Diffuse Effects			
	(15) Black Prison Pop	(16) Black Prison Adm	(17) Black Jail Pop	(18) Total Prison Pop	(19) Total Prison Adm	(20) Total Jail Pop	(21) Total Jail Adm
Percentage Black	0.9536***	0.9921	0.9187***	0.9774*	1.0110	0.9468***	0.9606***
	(.0128)	(.0202)	(.0155)	(.0100)	(.0216)	(.0137)	(.0108)
Percentage Black^2	1.0004**	1.0000	1.0008**	1.0003*	0.9999	1.0006**	1.0005**
	(.0002)	(.0002)	(.0003)	(.0001)	(.0002)	(.0002)	(.0002)
Racial Bifurcation	1.0050	1.0112**	1.0022	1.0186***	1.0279***	1.0152***	1.0117***
	(.0029)	(.0038)	(.0032)	(.0019)	(.0034)	(.0024)	(.0019)
Population Density	0.9438	0.9472	0.9169	0.8898	0.8720	0.8579**	0.7691***
	(.0440)	(.0594)	(.0507)	(.0566)	(.0809)	(.0441)	(.0498)
Percentage Male	0.9930	1.0178	1.0721***	1.0160*	1.0504**	1.0870***	1.0588***
	(.0109)	(.0207)	(.0178)	(.0081)	(.0165)	(.0218)	(.0144)
Poverty Rate	0.9961	0.9961	1.0092	0.9862***	0.9743***	1.0018	0.9947
	(.0028)	(.0081)	(.0050)	(.0026)	(.0076)	(.0038)	(.0032)
Median Income	0.9873***	0.9755***	0.9913***	0.9808***	0.9655***	0.9811***	0.9864***
	(.0017)	(.0031)	(.0020)	(.0017)	(.0027)	(.0017)	(.0016)
Gini Index	0.9924*	0.9870*	0.9853***	0.9802***	0.9735***	0.9807***	0.9890***
	(.0034)	(.0055)	(.0043)	(.0027)	(.0040)	(.0042)	(.0033)
Property Crime Rate	0.9991	0.9978	1.0009*	1.0003	0.9998	1.0013	1.0013
	(.0005)	(.0017)	(.0004)	(.0003)	(.0013)	(.0008)	(.0006)
Violent Crime Rate	1.0022	1.0022	1.0094*	1.0113***	1.0172	1.0147***	1.0157***
	(.0023)	(.0072)	(.0038)	(.0024)	(.0091)	(.0042)	(.0042)
Counties	1,907	1,793	2,718	2,712	2,685	2,962	2,957
Observations	28,640	24,976	57,676	57,225	56,293	70,619	70,631
AIC	368811.0	390061.9	876838.2	1065127.0	1325174.8	1860279.3	31089045.0
BIC	368893.7	390143.1	876927.9	1065216.5	1325264.2	1860371.0	31089136.7

Incident Rate Ratios. Cluster robust standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE A10 OLS Fixed Effects Models: Compositional Threat Measure (Percentage Black)

	Targeted Effects			Diffuse Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Black Prison Pop	Black Prison Adm	Black Jail Pop	Total Prison Pop	Total Prison Adm	Total Jail Pop	Total Jail Adm
Percentage Black	0.9305***	0.9533***	0.8825***	1.0303***	1.0598***	0.9901	0.9922
	(.0075)	(.0087)	(.0090)	(.0058)	(.0083)	(.0070)	(.0070)
Percentage Black^2	1.0007***	1.0003*	1.0013***	0.9995***	0.9990***	1.0000	1.0000
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Population Density	0.7654***	0.6386***	0.7145**	0.5566***	0.4291***	0.6515***	0.6034***
	(.0461)	(.0723)	(.0740)	(.0525)	(.0674)	(.0595)	(.0677)
Percentage Male	0.9771**	0.9816*	1.0208	0.9905	0.9893	1.0451*	1.0303*
	(.0071)	(.0086)	(.0132)	(.0055)	(.0070)	(.0187)	(.0126)
Poverty Rate	0.9982	0.9910**	0.9995	0.9934***	0.9866***	0.9948*	0.9976
	(.0022)	(.0028)	(.0030)	(.0018)	(.0026)	(.0026)	(.0026)
Median Income	0.9905***	0.9851***	0.9872***	0.9910***	0.9889***	0.9836***	0.9877***
	(.0015)	(.0023)	(.0016)	(.0014)	(.0022)	(.0013)	(.0014)
Gini Index	0.9960	0.9904**	0.9966	0.9934**	0.9905**	0.9892***	0.9919**
	(.0028)	(.0033)	(.0034)	(.0023)	(.0030)	(.0024)	(.0027)
Property Crime Rate	0.9989	0.9990	1.0002	1.0000	1.0001	1.0005	1.0008
	(.0006)	(.0008)	(.0002)	(.0001)	(.0001)	(.0004)	(.0005)
Violent Crime Rate	0.9998	1.0057*	0.9988	1.0097***	1.0149***	1.0048	1.0068*
	(.0038)	(.0028)	(.0041)	(.0015)	(.0022)	(.0025)	(.0027)
Counties	1,739	1,739	1,739	1,739	1,739	1,739	1,739
Observations	27,777	24,750	40,132	38,951	39,559	44,012	44,015
R-squared	0.156	0.153	0.089	0.308	0.129	0.210	0.061
AIC	2345.5	19263.8	48151.7	-5353.3	31295.4	22884.9	45443.3
BIC	2617.1	19531.6	48469.9	-5070.5	31578.7	23206.5	45764.9

Unstandardized regression coefficients. Robust standard errors in parentheses.

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

TABLE A11 OLS Fixed Effects Models: Structural Threat Measure (Racial Bifurcation)

	Targeted Effects			Diffuse Effects			
	(8) Black Prison Pop	(9) Black Prison Adm	(10) Black Jail Pop	(11) Total Prison Pop	(12) Total Prison Adm	(13) Total Jail Pop	(14) Total Jail Adm
Racial Bifurcation	0.9912***	0.9983	0.9878***	1.0103***	1.0169***	1.0051***	1.0048***
	(.0014)	(.0019)	(.0016)	(.0010)	(.0015)	(.0013)	(.0012)
Population Density	0.6847***	0.5744***	0.6144***	0.5670***	0.4272***	0.6379***	0.5875***
	(.0546)	(.0645)	(.0878)	(.0530)	(.0645)	(.0636)	(.0717)
Percentage Male	0.9689***	0.9778*	1.0037	0.9939	0.9958	1.0421*	1.0279*
	(.0076)	(.0089)	(.0136)	(.0051)	(.0068)	(.0188)	(.0126)
Poverty Rate	0.9986	0.9893***	0.9984	0.9907***	0.9819***	0.9920**	0.9949
	(.0022)	(.0029)	(.0031)	(.0017)	(.0026)	(.0025)	(.0026)
Median Income	0.9931***	0.9866***	0.9886***	0.9885***	0.9858***	0.9819***	0.9863***
	(.0015)	(.0024)	(.0017)	(.0014)	(.0022)	(.0013)	(.0014)
Gini Index	0.9941*	0.9877***	0.9931*	0.9917***	0.9885***	0.9870***	0.9899***
	(.0029)	(.0033)	(.0035)	(.0023)	(.0030)	(.0025)	(.0027)
Property Crime Rate	0.9990	0.9994	1.0003	1.0000	1.0002	1.0006	1.0009
	(.0006)	(.0008)	(.0002)	(.0001)	(.0001)	(.0004)	(.0005)
Violent Crime Rate	1.0000	1.0043	0.9992	1.0082***	1.0124***	1.0037	1.0057*
	(.0039)	(.0028)	(.0043)	(.0015)	(.0020)	(.0025)	(.0027)
Counties	1,739	1,739	1,739	1,739	1,739	1,739	1,739
Observations	27,777	24,750	40,132	38,951	39,559	44,012	44,015
R-squared	0.138	0.142	0.067	0.320	0.139	0.212	0.061
AIC	2943.4	19596.0	49115.2	-6042.6	30877.1	22776.3	45401.2
BIC	3206.8	19855.7	49424.8	-5768.4	31151.8	23089.2	45714.2

Unstandardized regression coefficients. Robust standard errors in parentheses.

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

TABLE A12 OLS Fixed Effects Regression Models: Compositional and Structural Threat Modeled Simultaneously

	Targeted Effects			Diffuse Effects			
	(15)	(16)	(17)	(18)	(19)	(20)	(21)
	Black Prison Pop	Black Prison Adm	Black Jail Pop	Total Prison Pop	Total Prison Adm	Total Jail Pop	Total Jail Adm
Percentage Black	0.9334***	0.9320***	0.8789***	0.9916	1.0031	0.9597***	0.9645***
	(0.0095)	(0.0119)	(0.0116)	(0.0073)	(0.0103)	(0.0096)	(0.0089)
Percentage Black^2	1.0006***	1.0005***	1.0014***	1.0000	0.9997*	1.0004**	1.0003**
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Racial Bifurcation	0.9991	1.0065**	1.0012	1.0111***	1.0161***	1.0093***	1.0084***
	(0.0016)	(0.0024)	(0.0020)	(0.0014)	(0.0020)	(0.0018)	(0.0016)
Population Density	0.7630***	0.6491***	0.7179**	0.5833***	0.4536***	0.6762***	0.6241***
	(0.0460)	(0.0730)	(0.0732)	(0.0521)	(0.0690)	(0.0578)	(0.0678)
Percentage Male	0.9767**	0.9827*	1.0212	0.9952	0.9956	1.0487**	1.0336**
	(0.0072)	(0.0085)	(0.0132)	(0.0053)	(0.0068)	(0.0183)	(0.0123)
Poverty Rate	0.9984	0.9894***	0.9992	0.9909***	0.9827***	0.9925**	0.9955
	(0.0022)	(0.0028)	(0.0030)	(0.0017)	(0.0025)	(0.0024)	(0.0026)
Median Income	0.9908***	0.9835***	0.9869***	0.9879***	0.9844***	0.9815***	0.9858***
	(0.0015)	(0.0024)	(0.0016)	(0.0014)	(0.0022)	(0.0013)	(0.0014)
Gini Index	0.9961	0.9898**	0.9964	0.9919***	0.9884***	0.9880***	0.9908***
	(0.0028)	(0.0033)	(0.0034)	(0.0023)	(0.0030)	(0.0024)	(0.0027)
Property Crime Rate	0.9988	0.9991	1.0002	1.0000	1.0002	1.0005	1.0009
	(0.0006)	(0.0007)	(0.0002)	(0.0001)	(0.0001)	(0.0004)	(0.0005)
Violent Crime Rate	1.0000	1.0045	0.9986	1.0082***	1.0126***	1.0037	1.0057*
	(0.0038)	(0.0028)	(0.0041)	(0.0014)	(0.0020)	(0.0025)	(0.0026)
Counties	1,739	1,739	1,739	1,739	1,739	1,739	1,739
Observations	27,777	24,750	40,132	38,951	39,559	44,012	44,015
R-squared	0.156	0.155	0.089	0.000	0.143	0.216	0.064
AIC	2345.1	19215.1	48151.2	133768.8	30681.5	22536.7	45272.8
BIC	2625.0	19491.1	48478.0	134060.2	30973.4	22867.0	45603.1

Unstandardized regression coefficients. Robust standard errors in parentheses.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$