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Observations on the Measurement of North Carolina Traffic Stop Disparities

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Qualifications

I am Mike Dolan Fliss, PhD, MPS, MSW, a research scientist at the University of North Carolina (UNC) Injury Prevention Research Center (IPRC). UNC IPRC is one of nine Injury Control Research Centers (ICRCs) across the United States with core funding provided by the Center for Disease Control (CDC). Around half of my grant-funded projects are with the North Carolina (NC) Department of Health and Human Services (DHHS), where I have worked in some capacity for nearly a decade.

I completed my Epidemiology PhD in 2009 from the UNC Gillings School of Global Public Health, the #1 public school of public health in the United States. Before my PhD I worked in public health for nearly a decade, including working at the Orange County Health Department in public health informatics. I completed my master's in social work (MSW), also from UNC, in 2009, where I focused on "macro practice" – community interventions and their evaluation.

I am a published author of both peer-reviewed manuscripts on topics including racial disparities in traffic stops, how to measure racial disparities,[1] disparities in the alcohol outlet environment,[2] and understanding motor vehicle crashes.[3] My work is frequently trusted to represent state government (although I do not write on behalf of UNC or DHHS here). I am a core team epidemiologist and the lead developer of multiple public NC data dashboards for tracking public health indicators, including tracking racial disparities, the state's Opioid Overdose and Substance Use Action Plan (OSUAP),[4] alcohol and public health in NC,[5] and motor vehicle crashes and public health in NC.[6] My projects often bridge research and public health practice, often with a focus on disparities.

My peer-reviewed PhD dissertation was "Racial Disparities in Law Enforcement Traffic Stops: Measurement, Interpretation, & Intervention Possibilities."[7] The first manuscript based on that work, "Re-prioritizing traffic stops to reduce motor vehicle crash outcomes and racial disparities,"[8] was awarded the journal *Injury Epidemiology*'s Jess Kraus Award[9] for the best paper published in that journal in 2020 and selected for a separate author interview.[10] I have studied and worked with community groups and law enforcement agencies to help understand traffic stop disparities in North Carolina since 2014.

I am involved in traffic stop research for many reasons. First, as an epidemiologist, the largest association of public health workers in the United States, the American Public Health Association, clarified that public health has a duty to address the harms of the carceral system.[11] Moreover, notable authors in social epidemiology have identified racism as a fundamental cause of health disparities,[12] including not only personal and interpersonal racism, but institutional policies and structural systems.[13] These structural disparities in the driving environment and social determinants of health, as example, are also strongly associated in multilevel models with the disparate (by race) distribution of severe injury crashes.[14] Moreover, police violence and over-policing in communities of color has real, harmful effects and can create both negative personal health consequences around toxic, racialized stress[16] and neighborhood consequences, like reduced 911 calls for serious events.[17] In the most extreme outcome, traffic stops are also one of the more common settings for "death by legal intervention" (being shot by a police officer). As an example, Philando Castille was stopped nearly 50 times in the fifteen years before his death.[15] Lastly, as a trained social worker, our National Association of Social Workers

(NASW) body's membership requires adherence to a national code of ethics[18] that explicitly includes social justice as a required ethical principle.

Traffic Stop Research: Residential-based traffic stop disparities underestimate disparities accounting for driving differences

Group-specific traffic stop rates (*e.g.*, rates by race-ethnicity) are typically based on jurisdiction resident populations. These rates, like many justice-system indicators, demonstrate race-ethnicity disparities. Residential-based rates implicitly assume race-ethnicity groups have equal vehicle access, equal driving volume, and that all driving occurs in resident's jurisdictions.[19] In contrast, national government surveys suggest Black non-Hispanic and Hispanic households often have less access and may drive less than White non-Hispanic households.[20] Legal frameworks call this a ”benchmark,” but to a public health professional we simply think of this as establishing an appropriate denominator for a group-specific rate. Note that it is not convention in public health to adjust denominators for differences in risk factors that may confound an association with a rate. As an example, when I measure and report on suicide rates by gender using the NC Violent Death Reporting System, we use the residential populations by year for a "person-time" denominator.[21] These rates, accounting for the "time at risk" of an event, demonstrate that men die by suicide at a much greater rate than women do (and by different means, etc.).[22] When appropriate, the association of this person-time rate and an outcome can be further adjusted for differences in confounders (as determined by a causal diagram) in causal models, and by including those confounders in the model. However, the raw "rate" is real, whatever its cause, and it should not be adjusted to account for structural, institutional, or behavioral dynamics that may lead to those disparities. We would separately consider the disparity in exposure, the outcomes, and their associations.[1]

Below is a simple residential comparison for example. Note that the ten traffic stop types captured in SBI-122 have different disparity patterns: discretionary investigation and economic-based stop types (regulatory and equipment violations that impact low-income drivers most) typically have higher disparities.

	NC Traffic Stops		NC Population	
Race-Ethnicity	#	%	#	%
White non-Hispanic	14,187,645	57%	6,605,027	62.60%
Black non-Hispanic	8,066,090	32%	2,342,358	22.20%
Total	24,980,777	100%	10,551,162	100%

Table. Traffic stop (2002-2020) and resident (2021) disparities in NC.

Aim 1 of my peer-reviewed dissertation accounted for these driving factors in North Carolina to understand the direction and degree of change in traffic stop disparities when accounting for these driving factors. Data from over 20 million traffic stops in North Carolina were combined with US Census data and race-ethnicity driving factors from the 2017 National Household Travel Survey to calculate traffic stop rate-ratios (TSRRs) under multiple model assumptions. Spatial simulation models distributed Vehicle Miles Traveled (VMT) across the state and rebuilt rates for 177 law enforcement agencies. Adjusting for three driving factors simultaneously (access to vehicles, driving volume, and driving between jurisdictions), disparity indices increased 15% on average for North Carolina LEAs, from 2.02 (1.86, 2.18) to 2.33 (2.07, 2.59) for Black non-Hispanic drivers and were largely unchanged for Hispanic drivers. All models suggested both groups experience disparate traffic stop rates compared to White non-Hispanic drivers. In short: in North Carolina, even though residential-based rates demonstrate stark disparities in traffic stops by race-ethnicity, **accounting for appropriate driving**

denominators demonstrates that those residential-based disparities still underestimate true disparities accounting for driving differences.

I replicate first a summary of the survey data on driving differences in North Carolina, below:

	Measures of Survey Representation		
Race-Ethnicity	**Number surveyed**	**Number represented**	**Number drivers represented**
Asian	307	251,577	184,748
American Indian	156	78,171	57,496
Black	2,444	2,015,261	1,294,804
Hispanic	600	828,660	532,834
Other	522	324,620	199,508
White non-Hispanic	13,556	5,950,650	4,894,298
Total	17,585	9,448,939	7,163,689

Table. NC survey demographics from the 2017 National Household Travel Survey.

And second, measures of access and driving volume in NC derived from the national study:

	Measures of Access		
Race-Ethnicity	**Household has personal vehicle access (%)**	**Household vehicle use at least a few times a month (%)**	**Any driving during year* (%)**
Asian	99.8	99.0	73.4
American Indian	90.3	95.4	73.6
Black	85.3	88.2	64.2
Hispanic	97.0	97.2	64.3
Other	96.1	97.6	61.5
White non-Hispanic	98.4	98.0	82.2
Total	95.8	96.2	76.8

	Measures of Driver VMT		
Race-Ethnicity	**Annual VMT per driver* (miles)**	**Annual VMT per person (miles)**	**Average miles per trip (miles)**
Asian	8,677	6,372	10.0
American Indian	12,219	8,987	10.8
Black	9,775	6,280	9.7

Hispanic	12,434	7,995	12.4
Other	8,762	5,385	8.6
White non-Hispanic	10,819	8,898	10.4
Total	10,649	8,196	10.4

Table. NC differences in access and amount of travel (2017 NHTS).

Lastly, I report results of the model that derives driving denominators. Black non-Hispanic and Hispanic traffic stop rate-ratios are ratios compared to the White non-Hispanic rate – all rates based on stops per 1,000 vehicle miles traveled (except M1 which is per 1,000 people). Rates above 1 demonstrate a racial disparity. These model results were for 177 large law enforcement agencies in North Carolina.

		Total	Black n-H	Hispanic
		IR (CI)	TSRR (CI)	TSRR (CI)
Residential-based models				
M1	Residential only model	1.88 (1.59, 2.16)	2.02 (1.86, 2.18)	1.43 (1.32, 1.54)
M2	M1 scaled to total VMT	1.88 (1.59, 2.16)	2.02 (1.86, 2.18)	1.43 (1.32, 1.54)
Driving models: single adjustment				
M3	Access only	1.89 (1.60, 2.18)	2.58 (2.38, 2.78)	1.83 (1.70, 1.97)
M4	Volume only	1.89 (1.60, 2.17)	2.24 (2.06, 2.41)	1.24 (1.15, 1.34)
M5	Multi-agency only	8.85 (7.12, 10.59)	1.65 (1.46, 1.83)	1.24 (1.11, 1.36)
Two-factor adjustment models				
M6	Access & volume	1.90 (1.61, 2.19)	2.86 (2.64, 3.08)	1.59 (1.48, 1.71)
M7	Access & multi-agency	8.90 (7.15, 10.64)	2.10 (1.87, 2.34)	1.58 (1.43, 1.74)
M8	Volume & multi-agency	8.90 (7.15, 10.64)	1.82 (1.62, 2.03)	1.08 (.97, 1.18)
Three-factor adjustment model				
M9	Access, volume, & multi-agency	8.95 (7.19, 10.70)	2.33 (2.07, 2.59)	1.38 (1.24, 1.51)

Table. Model results using real NC traffic stop data and improved driving-based benchmark models, using 0, 1, 2, or all 3 driving adjustment factors

Model Complexity

My driving model is admittedly complicated. Weighted daily trip data from the National Household Travel Survey was used to calculate an average distribution of VMT at given unidirectional distances, converted to percent of VMT within each radius ring around their residence every single mile up to 400 miles. These raw, exact percentages of VMT within each radius ring were then converted to simple exponential decay linear models, well fit by using the log of the radius multiplied by an interaction term that was a 1 if the radius were under 25 miles, and a zero otherwise. This allowed an inflexion point at 25 miles, and good graphical and statistical fit of these functions. Such a function could then be used for a simple operation for the subsequent spatial model to return, for a VMT catch point at a given distance from a residential point, the percent of VMT to distribute into points at that ring distance.

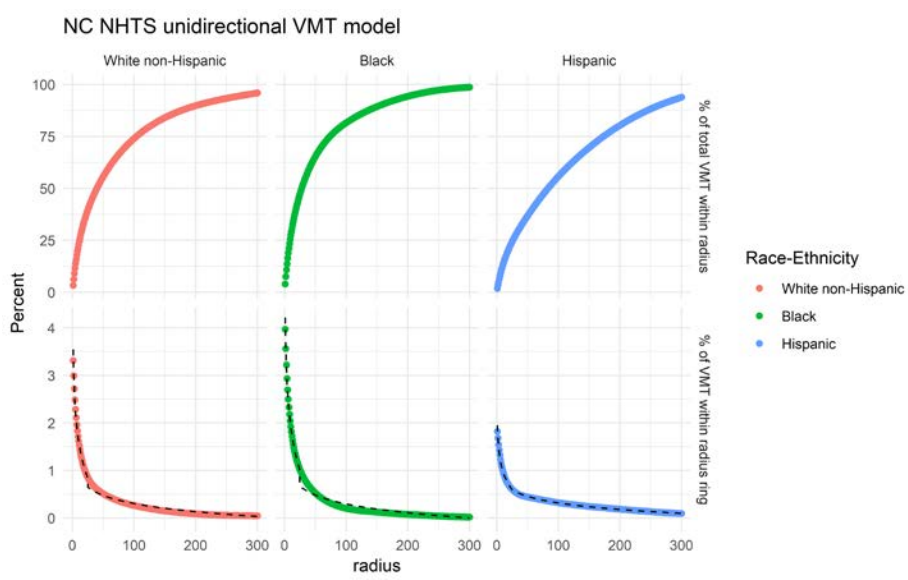

Figure (Supplemental) Percent of ring and total VMT at given unidirectional radius using the NHTS NC driving survey data.

Model complexity is no excuse - traffic stop racial disparity benchmarks seem uniquely privileged by a self-protective perfectionism that leads to a lack of accountability.

I have worked with dozens of administrative datasets in NC, including data on births; death certificates; overdoses; violent crime and death; motor vehicle crashes; emergency department visits; in-patient hospital discharges; risky behavior of adults and youth; census data; health insurance data; tobacco and alcohol outlet locations; historical redlining; income inequality; school population, test, and free and reduced lunch records; homeless shelter data; administrative office of the courts (AOC) records, infectious disease data; water well records; concentrated animal feed operations; hurricane and weather data; and more.

In no other setting, other than comparing traffic stops (and crash) outcomes by race ethnicity to assess disparities, have I come across a public health related event where a sector has refused to create reasonable estimations of appropriate disparity measures. As our traffic stop dataset is over 20 years old, this refusal has spanned at least decades in North Carolina.

My driving model was admittedly complex, even though more complex driving models than mine are possible. However, many simpler methods are also available, and have been available for many years. It is my professional opinion that the law enforcement and traffic safety communities have effectively conspired to shirk their duty to produce reasonable driving-based benchmarks. Instead, law enforcement has enumerated problems without any serious attempt to propose solutions.

Below is a partial list of many possible methods that have been available to them. The US Census Bureau provides daytime commuting estimates that could be prorated using residential denominators. Survey data (such as I used) could be used to estimate vehicle access or driving volume. NC DMV car registration or license data could be used to prorate residential populations into driver or VMT benchmarks. First, the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) file describes the residence and employer location of working individuals. LEHD LODES is also produced by the census, representing a complementary data product to the Census ACS.[23] The Bureau of Transportation Statistics (BTS) Local Area Transportation Characteristics for Households (LATCH) data may be useful and the closest tool to providing estimates needed for a nationally consistent method of calculating traffic stop rates and their disparities. LATCH combines vehicle access and travel information from NHTS with census tract data at the tract level that incorporates urban/suburban/rural distinctions and US regional differences. That national model provides estimated weekday household person miles traveled, person trips, vehicle miles traveled, and vehicle trips for each census tract. Two of those datasources are visualized, below (analysis by author).

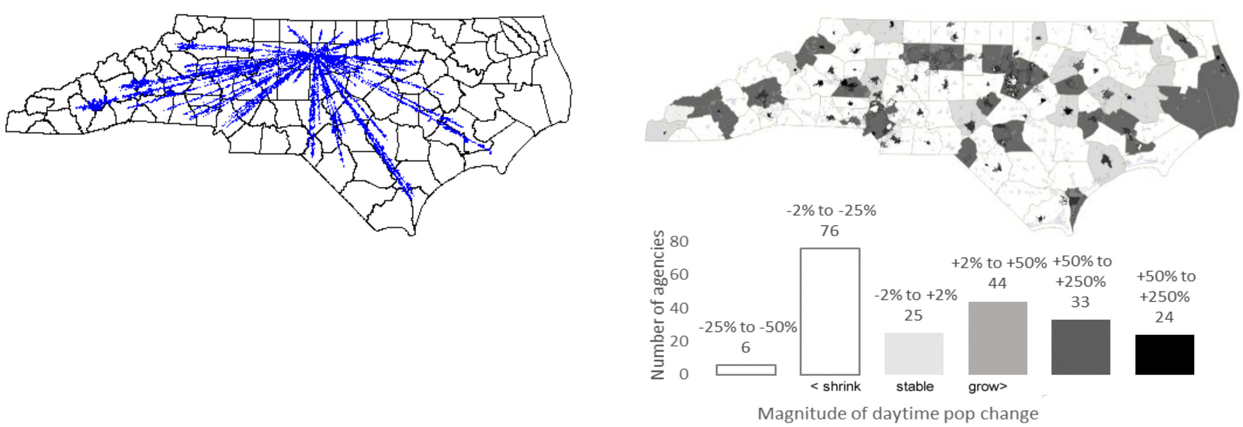

Figure 6. LODES and ACS commuting maps for supplemental variables. For LODES [Left], 250 work commute origin-destination paths to a census block are visualized. For ACS Census [Right], demonstrates daytime population increase during daytime.

There are many other methods in the traffic stop and safety literature, including some less complicated than my method, but still complex, such as using odds ratios based on the not-at-fault crashes.[24] Some highly limited measures of traffic stop disparities still find major disparities,[25,26] even when based on a tunnel-vision framework of racism (one that requires an officer to see a driver's racial phenotype during daylight, ignoring the reality and data that demonstrate institutionally policing neighborhoods with relatively higher Black, Indigenous, and other People of Color populations differently during night and day). These methods are beyond the capacity of a typical driver to defend themselves, but they should not be beyond a group of willing, committed researchers and law enforcement administrators.

The absence of a benchmark at this stage in data collection is not normal, nor something I have ever seen in any other setting where accountability and disparity tracking matter. In contrast, I give two examples of dozens I could share. First, one of the many indicators I track on the state's Opioid & Substance Use Action Plan data dashboard is the number of infants with a substance exposure related Plan of Safe Care (POSC). We receive that number on a monthly basis before we receive the final birth certificate dataset necessary for building denominator appropriate rates (*i.e.*, number of POSC infants divided by number of live births). However, our branch at the state health department uses a previous year's number as a placeholder. We could further adjust that denominator using a population growth model or even a simple population multiplication factor for all counties.

In the driving space, it is essential for Department of Transportation (DOT) and Division of Motor Vehicles activities that we have some method to understand crash rates – both to support between-locality comparisons and track trends. The North Carolina DOT estimates average annual miles traveled for all counties and most major cities to allow crash rates to be compared between jurisdictions.[27] Having worked closely with NC DOT data in the past, I'm aware that these estimates may be based on surprisingly few driving count samples. When working on the NC Crash & Public Health data dashboard,[6] I discovered that sometimes, for estimating current and near-future year VMT, they may up or down-weight all counties by the same factor to account for increased driving similar to a previous year or reduced driving (such as due to COVID-19). Yes, clearly, not all driving changes year to year is the same in counties. But the point is this: reasonable estimation is often essential to convert a metric (count of traffic stops, or crashes, etc.) into a rate-based indicator. Research and practice-based teams would often agree to a convention, and that becomes a common standard. I find it hard to believe that if NC LEAs truly wanted a solution to this apparent measurement problem, they couldn't have approached NC DOT two decades ago (or last year) and asked for a best guess benchmark based on a reasonable estimate to at least improve on the residential-based method. I spent three years to build a more reasonable rate-based measure of traffic stop programs to address the "benchmark" issue; I could do much simpler over a weekend if I had to. I find it incriminating that law enforcement and partners in the transportation safety space have had twenty years to come to some consensus around reasonable estimates of vehicle miles traveled by race by jurisdiction and have failed to make what strike me as even a modest attempt to do so.

This rate-based indicator is essential for three tasks of population surveillance common to public health and safety: trend tracking, peer-to-peer comparison, and comparison against a baseline. For a VMT-based traffic stop rate, that comparison is against a 1.0 benchmark for a ratio measure, *i.e.*, the ratio of (a) the rate Black non-Hispanic stops per 1,000 VMT to (b) the rate ratio of White non-Hispanic; for a difference measure (the subtraction of those two rates) the benchmark is 0.0. Small ratios or differences can get into issues of statistical significance;

however, we have much more often found these residential (or driving adjusted) disparities to be stark disparities, far outstripping issues of many decimal points.

Law Enforcement Agencies have wide discretion in traffic stop programs, and disparities are largely of their own making.

After measuring traffic stop disparities in all NC counties and many large municipal agencies, I used a modern causal inference techniques called synthetic control to assess changes in those disparities, crashes, and crime outcomes in Fayetteville, North Carolina. At the time, Fayetteville's police chief (Harold Medlock), responding to community organizing, redirected his traffic stop program to focus on movement and safety violations. On average, over the intervention period as compared to synthetic controls (high quality comparison built from a weighted combination of other NC cities to best match Fayetteville characteristics), Fayetteville increased both the number of safety stops (+121%) and the relative proportion of safety stops (+47%). Traffic crash and injury outcomes were reduced, including traffic fatalities −28%, injurious crashes − 23%, and total crashes − 13%. Disparity measures were reduced, including Black percent of traffic stops − 7% and Black vs. White traffic stop rate ratio − 21%. In contrast to the Ferguson Effect hypothesis (the idea that crime will increase if police reduce their presence and social control techniques like "tough on crime" "broken window policing"), the de-prioritization of investigatory and economic stops was not associated with increases in crime.

Though a deep study, it was of only one agency. However, when looking at Fayetteville's dramatic changes and the wide spread of traffic stop program patterns across NC, it's clear that, "bad apple" officers and explicit interpersonal racism aside, law enforcement administrators like police chiefs and sheriffs have wide discretion in the prioritizing and design of their traffic stop programs. Agencies elect to focusing on investigatory and economic stops, prioritizing certain neighborhoods, intersections, and times of day, and prioritizing low-level property and drug-crime enforcement over moving violation and traffic safety drive agency-to-agency and agency-over-time differences in disparities.

Racism / traffic stop disparities are structural, not just interpersonal

Lastly, I want to remind the reader that racism, and racial disparities in traffic stops, are more than something done from one officer to one driver based on implicit or explicit prejudice leading to disparate treatment in that moment. Certainly implicit racism exists; data suggest that officers use different levels of respectful language based on race,[28] for example. But institutional decisions, highly discretionary, allow agencies to police low-income and Black drivers and bodies differently at their will. The percent of movement and safety violation related traffic stops may be less than half of an agency's tens of thousands of traffic stops, or nearly 90% of traffic stops, if it so chooses. It may subjectively pull over drivers for "investigation" or for regulatory and equipment violations (disproportionately impacting low-income drivers, and unsurprisingly given the compounding effect of racism and wealth distribution, disproportionately impacting drivers of color). This also means that touted solutions (such as Automated Enforcement Systems like traffic light cameras), though "objective" machines less impacted by implicit bias on their face, can and have still had very different impacts by race-ethnicity on populations when their placement patterns and fee and fine structure isn't done in an equity-focused way – as was discovered in Chicago when camera-based ticket outcomes were starkly racially disparate.[29]

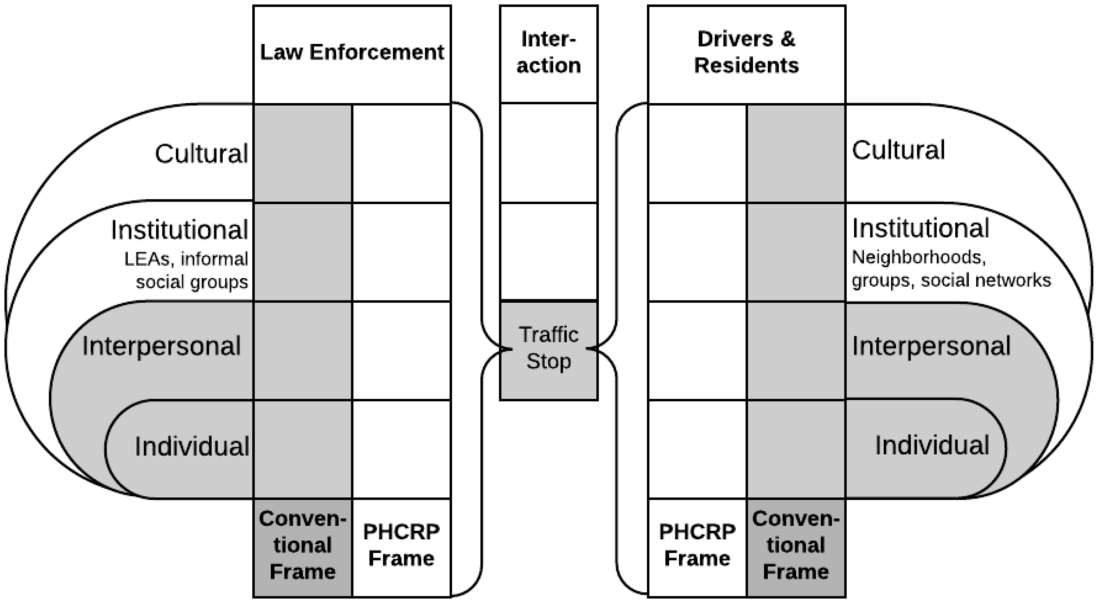

Figure 2. Multi-level critical framework for evaluation of traffic stops programs and disparities.

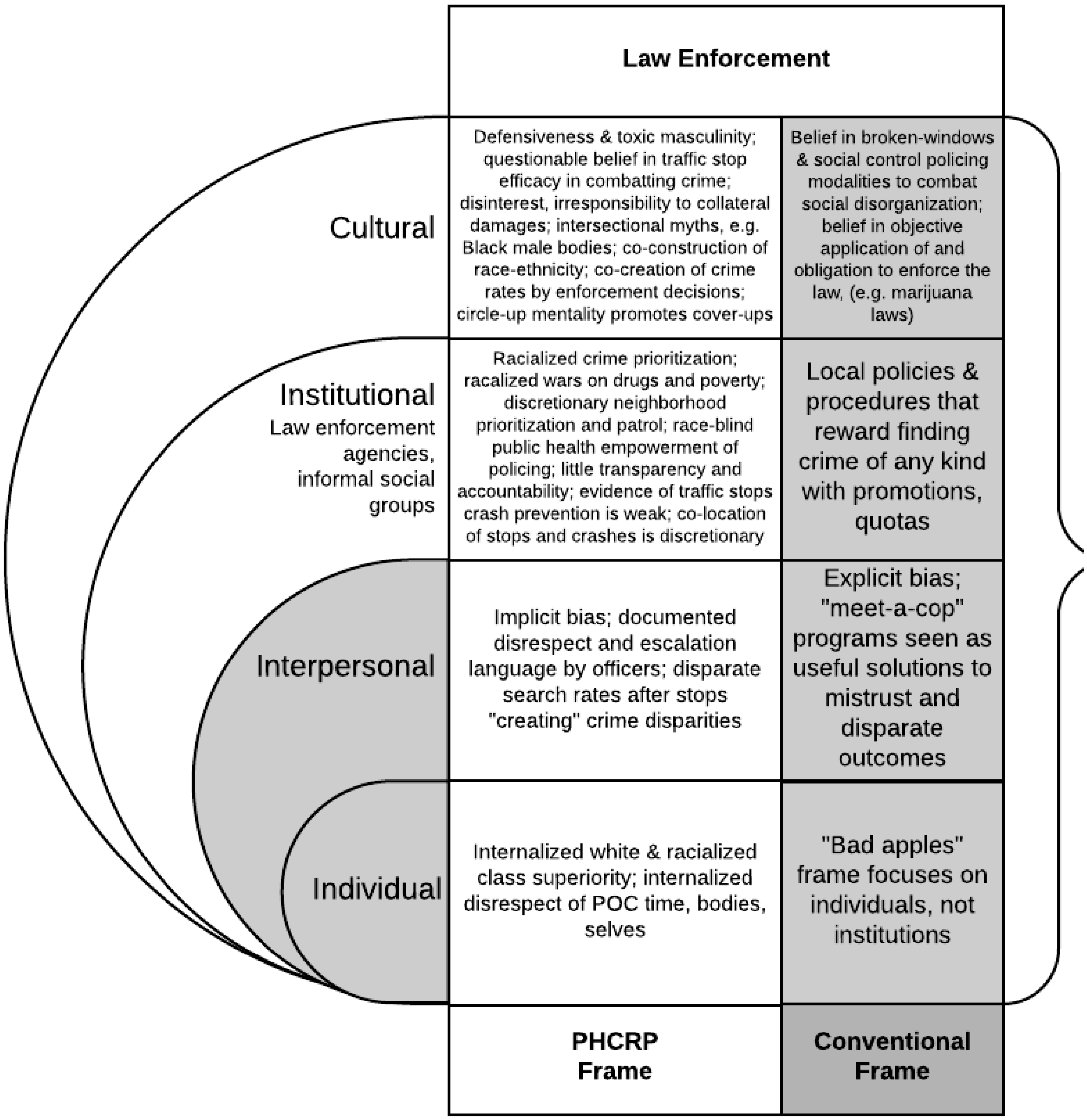

Figure ***Error! No text of specified style in document.****.1 Nested PHCRP framework, left side*

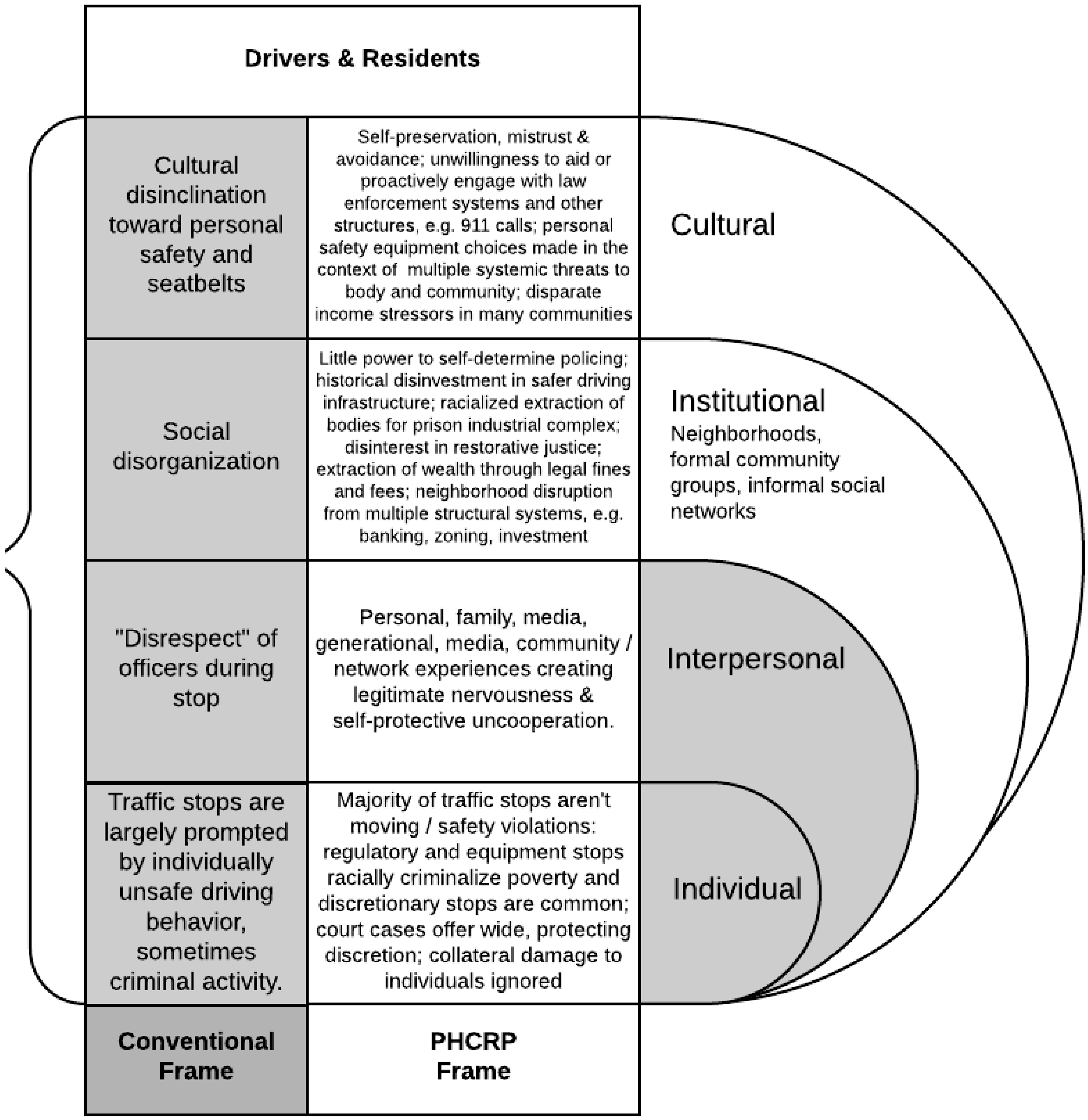

*Figure **Error! No text of specified style in document.**.2 Nested PHCRP framework, right side*

As a research scientist, I find it striking and strange that comparably so little has been done in this space, and that the law enforcement and legal community is still (after decades) unclear what disparities look like here. **Residential-based disparities, already high, likely underestimate disparities adjusting for driving differences in North Carolina.** Many reasonable methods to benchmark traffic stops have existed for years. Knowing the literature and practice well, I am unaware of any comparably reasonable effort by law enforcement to work with highway safety. If they were serious about such an effort for self- and community accountability, they would move beyond proposing problems (effectively defending their lack of accountability in perpetuity) to proposing best effort solutions that support them tracking and reducing the obvious racial disparities in NC traffic enforcement programs.

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