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Intersectional stereotyping in policing: an analysis of traffic stop outcomes

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ABSTRACT

Identity-based stereotyping often operates on perceptions about the intersection of multiple identities. Intersectional stereotyping predicts that certain combinations of attributes lend themselves more readily to perceived suspicion than others. In this paper, I test the way that suspicion-evoking stereotypes affect police-citizen interactions. Through the use of traffic stop data from Illinois spanning ten years and amounting to more than 20 million observations, I am able to produce accurate estimates for the relative degree of targeting that individual drivers face based on their racial, gender, age, and class-based perceived identities. Overall, I find both theoretical and methodological support for the necessity of intersectional analyses of identity-based profiling.

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Intersectionality; identity; racial profiling; policing; stereotyping

The 2013 acquittal of George Zimmerman in the shooting of Trayvon Martin sparked the development of the #BlackLivesMatter (BLM) movement, which brought focus to charges of racial profiling and brutality against people of color in the United States. One year later, public interest in racial profiling was amplified by the police shooting of Michael Brown in Ferguson, Missouri, which sent Google searches for "police brutality" up by 300%.[1] In 2014, the #SayHerName campaign was launched to direct attention specifically to the way that black women and girls have been victimized by the police. Such accusations of police brutality have captured media attention ever since and subsequent incidents of alleged targeting have been highly publicized.

Leaders of these movements argue that the police target people of color in their enforcement of the law. This charge has been backed up by empirical research, confirming that there is significant bias against racial minorities and, in particular, young African American men, in policing (Bates 2010; Baumgartner et al. 2017a, 2017b; Fagan and Davies 2000; Fagan et al. 2010; Meehan and Ponder 2002; Tomaskovic-Devey, Mason, and Zingraff 2004). One study demonstrates that in North Carolina, young, black men are about twice as likely to be searched following a traffic stop compared to similarly situated whites (Baumgartner et al. 2017b).

Despite #BlackLivesMatter and #SayHerName's explicit focus on the intersection of multiple identities, research on racial profiling largely focuses on outcomes for individuals in the most highly targeted group (i.e., young men of color). However, we know that there

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are persistent stereotypes associated with a host of other identity-based groups as well (Fiske et al. 2002) that likely produce relative degrees of targeting and leniency by police. As police are encouraged to investigate "suspicious" actors to proactively seek out and eradicate crime (Epp, Maynard-Moody, and Haider-Markel 2014), widely held stereotypes about race, gender, age, and class, likely inform this process. Intersectional identity-based stereotypes lead to heavy targeting of certain identity groups and to more lenient treatment of other identity groups.

In this paper, I propose that we conceive of racial profiling as explicitly grounded in an intersectional understanding of identity and stereotyping. I analyze identity-based profiling in the context of police traffic stops, with a dataset from Illinois that spans ten years, resulting in over 20 million observations. My analysis demonstrates that a driver's race, gender, age, and class all play an interactive role in whether a police officer decides to search a car following an initial traffic stop and in whether or not that driver receives a warning. Tested against an additive model, I find that an intersectional model is better equipped to explain the disparate outcomes that drivers face, both theoretically and methodologically. Analyzing multiple, intersecting identities allows for a clearer understanding of profiling and the way that group-based stereotypes operate, individually and institutionally, to produce both targeting and leniency in policing.

Intersectional stereotypes

Stereotypes are generalizations about a group of people that are both individual and collective; they are the "pictures in the head" that individuals have about others, but they are also conceptions about groups of people that are widely shared among a culture (Stangor and Shaller 1996). The most readily available and visible categories are used most frequently, like race (Devine 1989; Devine and Elliot 1995), age, and gender (Brewer and Lui 1989). Stereotyping does not operate on one identity at a time, but rather across multiple identities simultaneously (Fiske 1993). Each individual has an identity that is a result of the manner in which their multiple identities interact. Rather than an additive relationship, these factors are seen as mutually constructing an identity (Collins 1990; Crenshaw 1989, 1991; Hancock 2004; Harris-Perry 2011).

Crenshaw (1989, 1991) first coined the term intersectionality to describe the way that black women were unable to make use of *either* race-based antidiscrimination claims *or* gender-based antidiscrimination claims, though the concept itself extends back much further (see, e.g., Combahee River Collective [1983] 1983; Hancock 2016). Because discrimination against black women does not operate solely on the basis of their race or solely on the basis of their gender, their experience differs from those for whom the policies were designed to protect. It was impossible for the black women in Crenshaw's case studies to untangle whether their race or gender disadvantaged them and, as a result, they tended to be unsuccessful in their antidiscrimination claims (Crenshaw 1989).

Recent work has emphasized the importance of context in understanding how subgroups are stereotyped. McConnaughy (2018) demonstrates the way that identity-based stereotypes affect the perceived legitimacy of non-violent protestors. Black men, often stereotyped as violent and aggressive, are the least likely race-gender subgroup to be viewed as legitimate, while white women, conversely stereotyped as moral and peaceful, are considered most legitimate. The context here, a question of the level of legitimacy that a group possesses, determines how powerful and relevant certain stereotypes will become in the decision-making process (McConnaughy 2018). In this instance, black males experience the most negative outcomes; while in Crenshaw's work, it was black women who were disadvantaged at the intersection. It is not that there is always one most highly targeted group in every situation, but instead that the context shapes which intersectional stereotypes will be most influential in determining outcomes.

Stereotypes of suspicion

In the context of policing, stereotypes that evoke suspicion are most relevant, as the police are charged with seeking out and eradicating crime. Especially since the growth of proactive policing in the 1980s, officers have been encouraged to approach and question "suspicious" people in order to prevent crime – to be *proactive* rather than reactive (Epp, Maynard-Moody, and Haider-Markel 2014; Fagan and Geller 2015; Harcourt 2003). However, it is impossible to investigate every single person on the street. Instead, this has led to both relying on and codifying into practice stereotypes about suspicion (Epp, Maynard-Moody, and Haider-Markel 2014; Fagan and Geller 2015).

Epp, Maynard-Moody, and Haider-Markel (2014) describe the "institutional practices" that result in disparate policing. These practices are "common ways of doing things that, while not required by any specific official policy, are supported and legitimated by rules, training, and law, and that spread widely to become commonly accepted activity" (11). The authors argue that institutional practices that dictate what constitutes reasonable suspicion are informed by culturally held racial stereotypes about black criminality and are the source of much of the racial disparities in police-citizen interactions (Epp, Maynard-Moody, and Haider-Markel 2014). These commonly held beliefs amount to "scripts of suspicion" that informally define who is suspicious – in ways that are race and neighborhood dependent (Fagan and Geller 2015). Then, such suspicion becomes a self-fulfilling prophecy (Harris 2003). When law enforcement focus their efforts on certain populations and define crime in ways that target certain populations, they inevitably end up finding more crime there (Harcourt 2003, 2009; Harris 2003).

According to one police training manual cited in Epp, Maynard-Moody, and Haider-Markel (2014), police officers are taught to use investigatory traffic stops as a way to "'sniff out' possible criminal behavior" (36). Often, the police are looking for drug offenders. The traditional profile of a drug courier, developed and taught during the War on Drugs, is that of a young, poor, black male. While officers are now taught that racial profiling is not legal, a section of a recent police training manual reads: "Traditional profile characteristics still *do* correlate closely with a sizeable portion of drug couriers" (Epp, Maynard-Moody, and Haider-Markel 2014, 40). African Americans are often stereotyped as linked with crime, criminality, and violence (Epp, Maynard-Moody, and Haider-Markel 2014; Gilliam and Iyengar 2000; Loury 2008; Muhammad 2010; Welch 2007) and youths who "look tough" are often assumed to have committed crimes (Fagan and Geller 2015, 57). Because officers are taught to act on notions of suspicion to seek out drug offenders that are informed by culturally held stereotypes, young black men experience undue scrutiny by the police.

Women of color are also caught up in the push to seek out drug offenders. While men, especially men of color, are still most likely to be incarcerated, the rate of which women are being incarcerated is growing at a faster pace than men. This surge in growth is largely due to nonviolent drug offenses and has disproportionately impacted poor women of color. 70% of women in prison are black, Latina, Native American, or Asian, and most are working class. Black women are four times as likely to be incarcerated as white women, and twice as likely as Latinas (Lawston 2008). While black men may fill the traditional drug courier profile, black and Latina women are likely similarly profiled for committing drug offenses, and thus treated with more suspicion than their white counterparts.

In addition to seeking out drug offenders, officers are increasingly asked to prioritize immigration enforcement. In her analysis of the Nashville Police Department, Armenta (2017) finds that, "Through [the officers'] implementation of the MNPD's policing priorities, officers subject Latino residents to lengthier inspections, sanctions, and sometimes arrest" (92). The integration of immigration enforcement into the day-to-day criminal justice operations results in heightened scrutiny of Latinx drivers. Again, often minor traffic violations are used as a way in to investigate the driver more closely. This leads to harsher treatment of Latinx drivers by the police, as they are often stereotyped as immigrants, who warrant suspicion on the part of the officer (Armenta 2017).

Finally, location informs suspicion that officers develop. Poorer neighborhoods with larger black and Latinx populations are targeted, as biased ideas about increased criminality in these areas guide police practice. In their analysis of New York City's stop and frisk policy, Fagan and Geller (2015) find that "most stops were concentrated in a relatively small number of neighborhoods with high crime rates, concentrations of non-White residents, and severe socioeconomic disadvantage" (62). The pressure to make as many stops as possible leads officers to concentrate their efforts in certain contexts – especially those in which a potential arrest seems easiest. While there is no difference in drug dealing rates between black and white communities, deals tend to occur outdoors in black communities and indoors in white communities (Epp, Maynard-Moody, and Haider-Markel 2014). This, combined with the way that crime is defined and sought out (Harcourt 2009; Harris 2003), anti-black stereotypes (Epp, Maynard-Moody, and Haider-Markel 2014), and a penal system developed to criminalize blacks (Loury 2008) leads to heavy targeting of poor, non-white areas. Indeed, poverty and racial makeup of a location predict police presence more than crime rates (Fagan and Davies 2000; Fagan et al. 2010).

Stereotypes based on race, class, age, and gender shape suspicion that police may develop about particular citizens. Often, the focus is on the most highly targeted groups (young, poor, black and Latino men). However, there are a host of culturally-held stereotypes about identities beyond race, and about racial groups beyond blacks and Latinx. Stereotypes about these identities interact to generate differential levels of perceived suspicion.

Counter to blacks or Latinx, whites are often stereotyped positively and associated with wealth or hard work (Winter 2006), as whiteness was developed from a privileged position and continues to occupy and reap the benefits of that position – including better treatment by police (Alcoff 2015). Gender conditions this stereotype, as white women tend to be viewed as victims who deserve empathy rather than punishment (Dirks, Heldman, and Zack 2015). Because Asian Americans tend to have higher levels of education and income than other racial minorities (in the aggregate), they are often stereotyped as the "model minority" (Kim 2003; Chou and Feagin 2015). They are held up as the example to other minority groups, like blacks and Latinx, as justification for the individualistic notion that hard work will lead to success in America (Kim 2003; Lee and Fiske 2006; Taylor and Stern 1997; Wong et al. 1998). While this stereotype is damaging and casts Asians as permanent outsiders (Kim 2003), it does not evoke suspicion in ways that stereotypes about black and Latinx people do.

While often overlooked, Native Americans have been negatively stereotyped in ways that evoke suspicion – as they have been stereotyped as welfare dependent and economically depressed, while simultaneously undeserving of the wealth they have accumulated through casinos and the gaming industry (D'Errico 2000). In the context of policing, Native Americans are the racial group is most likely to be killed by police (Revesz 2016), These class-based stereotypes of poverty and police targeting evoke suspicion, as they are closely linked to criminality.

Race, gender, age, and class are tied together as they work jointly to produce stereotypes that evoke relative levels of perceived suspicion. Depending on the intersectional combination of identities, these stereotypes may be magnified or mitigated and influence the perception of suspicion about an individual. Perhaps the most recognized stereotype of the "criminal predator" is that of the poor, young, black or Latino male (Baumgartner et al. 2017b; Welch 2007, 276). This stereotype is so inextricably tied with suspicion that it is likely that as an individual's identity approaches this criminal trope, they come under increasing suspicion. This intersectional identity group is often the focus of empirical work on policing, since members are so highly targeted. But all of the stereotypes outlined above demonstrate that there are likely degrees of targeting and leniency produced by stereotypes beyond that of the often-recognized "criminal predator."

A reconception of identity-based profiling

There is a well-documented bias against people of color in policing, especially young men (Bates 2010; Baumgartner et al. 2017b; Epp, Maynard-Moody, and Haider-Markel 2014; Fagan and Davies 2000; Fagan et al. 2010; Meehan and Ponder 2002; Warren et al. 2006). Baumgartner et al. (2017b) demonstrate through the use of over 18 million traffic stops in North Carolina that young black and Latino men are consistently targeted for searches and arrests. They find that this disparity persists even after controlling for the "bad apple" hypothesis, the notion that disparities result from the actions of a few, racist police officers. Instead, the racial disparities that they find are prevalent throughout the entire police force (Baumgartner et al. 2017b). Such outcomes may instead rely on policing practices that codify widely shared stereotypes about young, black and Latino men as suspicious and thus lead to targeting by the police.

While there has been substantial work demonstrating the high level of police targeting that young, poor, black and Latino males face, the consequences of this targeting for other identity groups is often overlooked. Sampaio (2014) analyzes immigration enforcement through a raced and gendered lens. She finds that while men are more likely to be the target of immigration enforcement, their experience with immigration enforcement differs dramatically than that of women, who are often exposed to harassment and sexual violence when they are detained (Sampaio 2014). Sampaio's findings illustrate the importance of a broad, intersectional lens: a singular focus on the most highly targeted group (in this case, men) obscures and conceals the treatment that women receive in immigration enforcement.

Steffensmeier, Painter-Davis, and Ulmer (2017) similarly take an intersectional perspective in their analysis of criminal sentencing. They find that race, gender, and age are all critical components in understanding sentencing and that the effects of age vary by race and gender. Black and Latino men experience harsher sentences regardless of age, while age has a curvilinear effect for females – younger and older females receive the most lenient treatment. Age has a different effect on sentencing, depending on race and gender (Steffensmeier, Painter-Davis, and Ulmer 2017).

Such evidence points to the need to broaden our understanding of racial profiling in a way that incorporates intersectional identity and stereotyping beyond an analysis of the most highly targeted group. It also demonstrates the importance of quantitative analysis that is informed and motivated by theory. Here, following intersectionality theory leads to conclusions that might have otherwise been overlooked with an additive approach (Collins 1990).

The context of traffic stops

While traffic stops may be brief interactions with law enforcement and, overall, occur fairly rarely, such interactions still have substantial, political effects on the individual driver and on their community. Direct contact with law enforcement leads to political demobilization (Burch 2011; Lerman and Weaver 2014a; Weaver and Lerman 2010; though see Lawless and Fox 2001) – especially when this contact involves searches or the use of force (Lerman and Weaver 2014b). Effects of contact with law enforcement can ripple throughout a community, though there is mixed evidence about whether it mobilizes or suppresses political participation (Burch 2013, 2014; Owens and Walker 2018; Walker 2014; Walker and García-Castañon 2017).

Traffic stops are the most common way that people interact with the police. Individuals from a variety of racial, gender, age, and class groups are stopped – allowing for a test of intersectional identity-based profiling that is fairly inclusive. The stop is usually a quick and surface interaction, which provides a good context with which to test the use of stereotypes, whether those held by the individual officer or those reinforced through policing norms and training, as stereotypes act as heuristics that can be used when full information is not available (Fagan and Geller 2015; Fiske 1993).

Police officers are trained to search a driver or vehicle based on suspicion (Epp, Maynard-Moody, and Haider-Markel 2014; Fagan and Geller 2015). Officers take in the entire context in which the stop occurs, such as the time of day, the reason the driver was stopped, as well as the identity of the driver (Fagan and Geller 2015). When a car or driver is perceived as suspicious, the officer is more likely to search that vehicle or its occupants.

Substantively, race, gender, age, and class all evoke stereotypes that may result in relative levels of perceived suspicion by the officer. My measure of suspicion is the officer's decision to search the vehicle or driver following an initial traffic stop. This measure captures suspicion, as it directly measures whether the officer wants more information about the person with whom they are interacting. As a secondary outcome variable, I operationalize the officer's leniency with their decision to give the driver a warning. While less directly linked to suspicion, this outcome measures the degree to which an officer feels the driver warrants some leniency – a perception that is at least partially determined by the officer's training and culturally held stereotypes. While there may be slightly less discretion in terms of whether the officer can give a warning, compared to their decision to search a car, there is nevertheless a degree of discretion at work.

The data contain the race, gender, and age of the driver stopped. In addition, I use the age of the vehicle stopped as a proxy for class. While not a perfect measure, it is likely the case that on average, individuals who drive newer cars are perceived as having higher socioeconomic status than those who drive older cars. A better measure would include not only the age of the vehicle, but also the make and model, which combine to create a broader perception about class. Illinois does collect data on the make of the vehicle (though not model), but it is recorded as a write-in variable – resulting in more than 63,000 unique values and thus making it unusable for analysis. Another downfall to using vehicle age to approximate class is that it assumes linearity both in movement from year to year and in its translation to a linear measure for class. Overall though, it is the best approximation for perceived class that the data provides.

I follow previous research and expect black and Latino males to be most highly targeted for searches. Native Americans, while often overlooked, are the racial group that is most likely to be killed by the police (Revesz 2016), so I expect that their probability of harsh treatment to follow. Whites should come next, followed by Asians, who are the least likely to be targeted. Of course, these race-based expectations will be conditioned by other identities. Young (compared to old), male (compared to female), and drivers with old vehicles (compared to those with new vehicles) should experience higher levels of targeting, based on stereotypes that both produce and suppress suspicion. In terms of leniency, the same expectations should hold but in the reverse. Those drivers who are perceived as least suspicious should be most likely to receive a warning from the police.

In sum, the crux of my expectations lies in two realms. First, there should be a spectrum of targeting (rather than a bimodal distribution of those who are targeted versus those who are not). Instead, intersectional identities should produce varying levels of targeting as a consequence of the way that stereotyping results in a range of suspicion. Second, I expect that suspicion compounds. Drivers who possess more and more suspicious identities should also experience higher and higher degrees of targeting. As individuals' racial, gender, age, and class characteristics approach those of the "criminal profile," they are likely subject to harsher treatment by police.

Data and methods

The data[2] I analyze is comprised of every individual traffic stop from every agency in Illinois over the years 2004–2014, collected by the state Department of Transportation. This large amount of data offers some benefits. It allows for accurate estimates of traffic stop outcomes for minority racial groups that are often omitted due to their low sample size, like Asians and Native Americans. Further, it is a dataset that is high in naturalism. It involves police officers making probabilistic decisions in the field, and thus, it is a potentially useful venue for testing the way that stereotyping functions in a real-world context. The data records whether or not the officer searched the car, which makes for a relatively good indicator of the level of perceived suspicion. It also records the outcome of the stop, which allows me to operationalize leniency afforded to the driver by whether or not s/he receives a warning.

I use the presence or absence of a search as my main dependent variable and whether or not the driver receives a warning as a secondary dependent variable.[3] Of course, merely analyzing the outcome of a traffic stop does not account for other factors that could be working to produce biased outcomes, such as the true level of warranted suspicion. It may be appropriate that certain groups evoke more suspicion, as they tend to be more likely to be breaking the law. I test for this explanation with analysis of whether the search results in the discovery of contraband, presented in Online Appendix H. This analysis demonstrates that the heightened targeting of certain drivers based on identity is not justified as they are no more likely to be carrying contraband than those who are not being targeted. Still, it could be that groups' latent risk distributions of carrying contraband differ. While I do not account for this explanation in this paper, work by Simoiu, Corbett-Davies, and Goel (2017) has demonstrated that even when these risk distributions can be estimated, the discrimination detected in benchmarking and outcome tests remains. As such, there is reason to have some confidence that while not perfect, a test of differential probabilities of search does indeed estimate the direction of the bias appropriately.

Further, recent work has demonstrated that if the police discriminate when choosing who to investigate, analyses that use administrative records are statistically biased. So, if the police are racially motivated when they decide who to pull over for a traffic stop in the first place, any subsequent analyses using data on traffic stops likely underestimate the racial bias present (Knox, Lowe, and Mummolo 2019). Any racial discrimination that is revealed from this analysis then, likely underestimates the true level of bias present in policing.

Searches are rare, they only comprise about 4.1% of the data. While the search of a car or driver is not a frequent occurrence, it is nevertheless an impactful one that takes a toll both on the individual driver and more broadly on the relationship between individuals and law enforcement (Burch 2011, 2013, 2014; Lerman and Weaver 2014a, 2014b; Weaver and Lerman 2010). Warnings, on the other hand, are much more common: about 38.8% of traffic stops in this dataset result in a warning. These are not mutually exclusive, you could both be searched and receive a warning.

The main independent variables of interest are the race, gender, and age of the driver and the age of the vehicle. For my first analysis, I use a categorical variable that identifies the intersectional identity of the driver in terms of race, gender, age, and class (measured by vehicle age). I split the driver's age variable at its median (32 years old) and recode it into two groups: old drivers and young drivers. I then split the vehicle age variable at its median (8 years old)[4] and recode it into two groups: old car and new car. This leads to 40 separate identity categories. The breakdown of this intersectional identity measure is presented in Table 1. In subsequent analyses, I estimate models that preserve age and vehicle age as continuous variables, and interact these terms with race and gender for an intersectional and continuous estimate.

The dataset includes a variety of contextual factors for which I control, including the hour, day of the week, and year of the stop. If individuals driving at late hours or on the weekend are more likely to be searched, I will capture that effect in this control. I also control for the purpose of the stop (collected by Illinois as a registration, equipment, or moving violation) to capture the effect of the type of offense on the outcome the driver receives (Epp, Maynard-Moody, and Haider-Markel 2014). As a robustness check, I

Table 1. Number of stops, searches, and warnings for all intersectional identity groups.

Demographic	Stop *N*	Search *N*	Search rate	Warning *N*	Warning rate
Old, white, male, old vehicle	3,184,994	41,800	0.013	1,437,961	0.451
Young, white, male, old vehicle	2,867,287	151,221	0.053	1,250,202	0.436
Old, white, male, old vehicle	2,459,323	81,846	0.033	11,79,131	0.479
Young, white, male, new vehicle	2,327,746	71,298	0.031	878,879	0.378
Old, white, female, new vehicle	2,033,518	16,515	0.008	941,281	0.463
Young, white, female, new vehicle	1,617,979	25,378	0.016	677,794	0.419
Young, white, female, old vehicle	1,401,416	46,183	0.033	658,285	0.470
Old, white, female, old vehicle	1,151,330	26,841	0.023	576,987	0.501
Young, black, male, old vehicle	934,082	120,066	0.129	357,779	0.383
Young, Latino, male, old vehicle	824,808	125,213	0.152	251,400	0.305
Old, black, male, old vehicle	717,101	62,844	0.088	302,251	0.421
Old, Latino, male, old vehicle	590,056	51,608	0.088	218,871	0.371
Old, black, male, new vehicle	555,122	22,109	0.040	223,805	0.403
Young, black, male, new vehicle	511,261	44,153	0.086	177,501	0.347
Young, black, female, old vehicle	474,380	28,411	0.060	179,167	0.378
Young, Latino, male, new vehicle	422,812	36,264	0.086	130,630	0.309
Old, black, female, new vehicle	398,193	6,008	0.015	152,789	0.384
Young, black, female, new vehicle	367,628	11,507	0.031	123,875	0.337
Old, black, female, old vehicle	340,847	13,776	0.040	145,701	0.427
Old, Latino, male, new vehicle	311,804	11,905	0.038	117,645	0.377
Young, Latina, female, old vehicle	235,345	15,683	0.067	83,680	0.356
Young, Latina, female, new vehicle	191,015	6,224	0.033	64,302	0.337
Old, Asian, male, new vehicle	169,901	1,575	0.009	62,750	0.369
Old, Latina, female, old vehicle	168,849	8,270	0.049	65,353	0.387
Old, Latina, female, new vehicle	142,416	2,649	0.019	53,545	0.376
Young, Asian, male, new vehicle	136,570	2,853	0.021	47,354	0.347
Old, Asian, male, old vehicle	111,094	1,864	0.017	46,259	0.416
Old, Asian, female, new vehicle	95,589	404	0.004	35,758	0.374
Young, Asian, male, old vehicle	93,988	3,351	0.036	37,484	0.399
Young, Asian, female, new vehicle	65,843	604	0.009	24,253	0.368
Old, Asian, female, old vehicle	48,252	348	0.007	20,039	0.415
Young, Asian, female, old vehicle	34,429	574	0.017	14,451	0.420
Old, Native American, male, new vehicle	9,968	182	0.018	3,643	0.365
Young, Native American, male, new vehicle	8,308	308	0.037	2,556	0.308
Young, Native American, male, old vehicle	8,243	651	0.079	2,942	0.357
Old, Native American, male, old vehicle	8,133	339	0.042	3,236	0.398
Old, Native American, female, new vehicle	4,590	53	0.012	1,694	0.369
Young, Native American, female, new vehicle	4,113	73	0.018	1,364	0.332
Young, Native American, female, old vehicle	3,111	121	0.039	1,161	0.373
Old, Native American, female, old vehicle	3,063	87	0.028	1,255	0.410
Total stops, searches, and warnings	25,034,507	1,041,159		10,555,013	
Mean search rate and warning rate			0.041		0.388

Note: demographic groups ordered from high to low in terms of the total number of stops.

estimate models predicting searches with fixed effects for police agencies in order to control for disparate agency-level policing behavior. Online Appendix C reports and compares these models with the categorical additive and intersectional models presented in the body of the paper. The results are nearly identical. These controls and additional tests isolate the effect that identity plays in the outcome of traffic stops.

For my main dependent variable (whether or not the driver is searched), I estimate three models: an additive categorical model, an intersectional categorical model, and an intersectional continuous model. The first two models will be used to compare the utility of an intersectional approach against an additive approach. Specifying the identity of the driver as a categorical variable makes for an easier comparison of the different estimates produced from each model. Further, it allows for a subsequent analysis of the treatment of the driver based on the number of "suspicious" identities held. Then, the third model makes it possible to estimate treatment of the driver across a range of vehicle and driver ages. This is helpful because it does not require any decisions be made about which ages classify as "old" or "young" (for driver age) or "old" or "new" (for vehicle age). Instead, it estimates the level of targeting a driver receives at each age.

The additive categorical model treats identity as additive, rather than interactive, and includes separate indicators for the driver's race, gender, age, and the age of the vehicle. This constrains each variable to a single effect, regardless of the value of the other identity-based variables. For example, in this model, the effect of the driver being black is constrained to having one, single effect on the dependent variable (whether the driver is searched), regardless of whether the driver is male or female, old or young, or driving a new or old car.

The second model I estimate is the intersectional categorical model. This model uses an intersectional identity categorical variable with every combination of identity (age, race, gender, and vehicle age), which allows the effects of one identity to vary based on the particular combination of other identities. Here, the effect of race on the dependent variable can vary based on the driver's gender, age, and vehicle age. For example, the effect of being black on the probability of being searched can be different for males than it is for females. This model allows for identity to vary in an interactive way and as such, does not expect that a single identity will have a uniform effect, but rather that the effect of one identity will vary based on the presence of other identities. I will be able to compare this model with the first model to determine whether an intersectional measure of identity is methodologically necessary.

Next, I estimate an intersectional continuous model, in which vehicle age and driver age are preserved as continuous variables. These are then interacted with a categorical measure of race and gender. Preserving the variation in these continuous variables allows for a clearer understanding of the effect of vehicle age and driver age on the probability of search, and the way that these effects vary by race and gender. It also means that I do not need to make any decisions about what is considered an old or new vehicle or an old or young driver.

Because my comparison of the additive and intersectional models reveals that the intersectional model is more methodologically appropriate, I then specify the two intersectional models (one categorical and one continuous) to predict whether or not a driver receives a warning following an initial traffic stop (my secondary dependent variable). Taken together, these models demonstrate that intersectional modeling is important, both methodologically and theoretically, to properly estimating and understanding the experience that individuals have with the police, based on their group membership.

Analysis and findings

The first, additive model treats race, gender, age, and vehicle age as discrete categories and allows each to have a single effect. The second, intersectional model includes a categorical variable with every combination of identity, allowing the effects of an identity to vary based on the particular combination of identities. The results of these logistic regressions are presented in Online Appendix B. The fit statistics produced from each model indicate that the intersectional model fits the data better (i.e., it has a higher log likelihood, lower AIC, and lower BIC). However, this is at least partly due to the fact that the intersectional model estimates so many more parameters than the additive model. That is, the intersectional model estimates different effects for forty different intersectional identity groups (rather than for seven) – so by design, it will be more accurate in its estimates.

To better test the performance of these models, I split the data into training and testing sets. 80% of the data is used to estimate the additive and intersectional models: the training set. The models' fit statistics are then calculated using the remaining 20% of the data that was never used to estimate the models: the testing set. These statistics determine which model fits the data better, divorced from their role in generating the models. Then, I compare the actual values of the dependent variable (whether or not a driver was searched) to the predicted values. The better performing model gets these predictions right more often. Table 2 reports the results from all of these tests and Appendix E discusses the specifics of these tests in greater detail.

The intersectional model consistently performs better than the additive model, across all indicators. Because the intersectional model estimates so many more parameters (compare the 49 degrees of freedom in the additive model to the 81 in the intersectional model), there may have been concern that the model was simply overfitting this particular dataset. If that were the case, it would not perform better on data that was not used to generate the model. Even though the intersectional model only does slightly better than the additive model (i.e., it correctly predicts the dependent variable 0.17% more often), it performs no worse despite estimating nearly double the number of parameters. The intersectional model allows us to study the mechanism implied by intersectionality: the notion that the effect of one identity will depend on the value of other identities held by the individual driver – and even still, does no worse than the additive model despite the additional demands it places on the data.

In order to truly determine the utility of the intersectional model, I calculate and compare predicted probabilities for each identity group using both models (these are reported in Online Appendix D). All of the estimates are statistically significant from zero. Even a cursory examination of this table demonstrates that there is a spectrum of targeting. The distribution does not appear to be bimodal – with some groups targeted and others not targeted. Instead, there seem to be relative degrees of targeting that exist, based on an intersectional conceptualization of identity.

Upon further inspection, a pattern emerges in these estimates. Estimates for the probability of search for black and Latino male drivers from the intersectional model tend to exceed those in the additive model. Accordingly, estimates of the probability of search for black and Latina female drivers from the intersectional model tend to be lower than those of the additive model. Figure 1 plots the predicted probabilities of search for all black and

Table 2. Fit statistics for additive and intersectional models using the testing set of data.

	Additive model	Intersectional model	Better fit?
Degrees of freedom	49	81	
Log Likelihood	−778,415	−777,185	Intersectional
AIC	1,556,929	1,554,532	Intersectional
BIC	1,557,655	1,555,732	Intersectional
AUC	0.7572 (75.72%)	0.7589 (75.89%)	Intersectional

Note: Models with higher log likelihoods, lower AICs, and lower BICs have a better fit. The AIC and BIC penalize models for the number of parameters estimated. AUC refers to the area under the curve. This is the proportion of observations for which the predicted values gained from the regression successfully match the true value of the dependent variable. Here, a higher value means the model gets the outcome right more often.

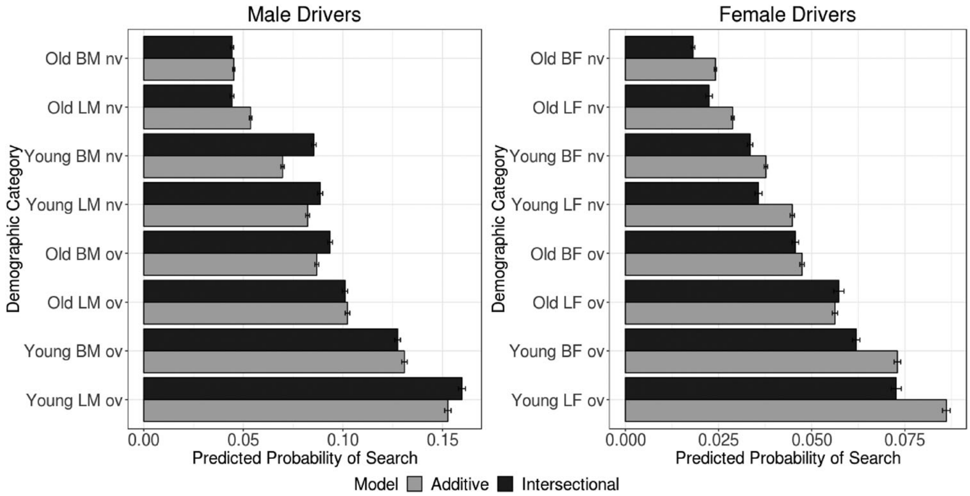

Figure 1. Comparing predicted probabilities from additive and intersectional models for black and Latinx drivers.

Latinx identity groups. The y-axis indicates the identity of the driver with respect to age, race, gender, and vehicle age (in that order). Racially, W = white, B = black, L = Latinx, A = Asian, and N = Native American; and in terms of gender, M = male and F = female. New vehicles are abbreviated with "nv" and old vehicles, with "ov." So, the observation for "Young BF ov" refers to a young, black, female driver with an old vehicle.

Figure 1 demonstrates that the additive model systematically overestimates the probability of search for black and Latina female drivers, but underestimates the probability of search for black and Latino male drivers. For young black and Latina females with old vehicles, the additive model overestimates the probability of search by 0.011 and 0.013, respectively. When the average probability of search is only 0.044, these differences are sizable. The same is true for every black and Latina female identity group – no matter the age of the driver or vehicle. For males, the probability of search for young black and Latino drivers with new vehicles are overestimated by 0.015 and 0.007, respectively. For almost every black and Latino male identity group, with the exception of two, the additive model underestimates the probability of search.

This illustrates the pitfall with treating race as an additive variable that has a single effect on all drivers, regardless of other identities that those drivers may hold. Here, the effect of race for black and Latinx drivers is higher for males than for females. As such, its value needs to be permitted to vary based on gender. This demonstrates that an intersectional conception of profiling may not only be theoretically relevant, but methodologically necessary as well, as allowing the effect of race to vary based on other identities, such as gender, is paramount to obtaining the most accurate estimates.

Targeting across class and age

Continuing with an intersectional approach, I then estimate the intersectional continuous logistic regression; results are presented in Online Appendix B. Instead of splitting age and vehicle age at their medians, they are preserved as continuous variables. The predicted probabilities of search by race and gender, over vehicle age is presented in Figure 2. Covariates were held at their modes, and driver age was held at its mean. Vehicle age is plotted here from 0 to 30 years old for ease of interpretation, though the variable itself extends beyond 30 years. As vehicle age moves from low to high, the predicted probability of search increases, for all gender and racial groups. This suggests that older vehicles may signal class-based stereotypes that result in higher levels of suspicion.

Male drivers experience significantly higher predicted probabilities of search than their female counterparts – some reaching beyond a 0.2 probability of search (for Latino males in 30-year-old vehicles). Female drivers, on the other hand, experience a high of 0.152 probability of search. But, this single-axis interpretation is not sufficient. While males, as a group, have higher probabilities of search than females, Latina and black females' probabilities of search exceed that of white and Asian males. With 30-year-old vehicles, Latina women have a 0.152 probability of search and black women have a 0.111 probability. Contrast this with that of white men (0.083) and Asian men (0.055).

For both genders, the order of racial groups in terms of the probabilities of search is the same: Latinx drivers experience the highest probability of search, followed by blacks, Native Americans, whites, and Asians. Racially, this is in line with expectations. Latinx and black drivers, who experience stereotyping that makes them prone to suspicion, experience the highest probabilities of search following a traffic stop. For males, black and Latino drivers with 30-year-old vehicles have a 0.171 and 0.216 probability of search, respectively. That means, for this particular subgroup, a search is likely to occur approximately every one in five stops. Stereotypes of criminality make these drivers prone to undue scrutiny, when all other contextual factors are taken into consideration.

While black and Latinx drivers are most prone to searches, on the other end of the spectrum, Asians' probabilities of search fall below that of white drivers. While Asians are a negatively stereotyped group, the associated stereotypes do not particularly elicit

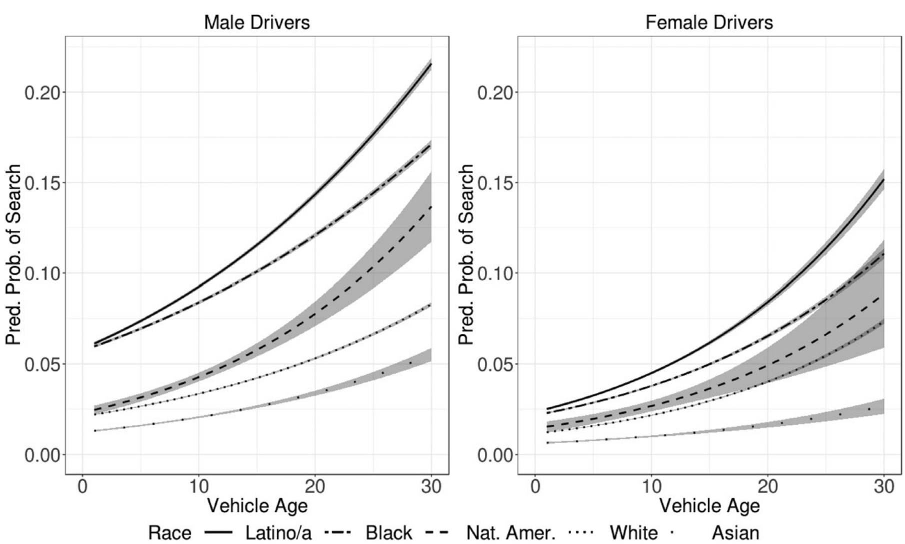

Figure 2. Predicted probabilities of experiencing a search, by racial group, over vehicle age.

suspicion. This illustrates two points. First, context matters for the way that stereotyping will produce outcomes. Asians are negatively stereotyped in the US, but their particular stereotypes do not happen to elicit suspicion, which is likely the dominant consideration in whether to search a car. Second, stereotypes do not solely operate to produce targeting, but also to produce a lack of targeting. A singular focus on the most highly targeted misses this inverse function of stereotypes.

With the newest vehicles, female drivers' predicted probabilities of search are all fairly clustered, with probabilities ranging from 0.006 to 0.025. Male drivers do cluster closer when they have newer vehicles than when they have older vehicles, but black and Latino male drivers are in their own group above the others from the beginning. While white, Native American, and Asian male drivers all begin in the 0.013–0.025 range, similar to the female drivers, the probabilities of search for black and Latino males never get this low, no matter the vehicle age. Instead, they begin above 0.06; a probability that Native American male drivers do not reach until vehicle age is 16 years old. White male drivers do not exceed this probability until their vehicle age is 23 years old. Asian males' probability never exceeds 0.06 for any range of vehicle age in this plot (it caps at 0.055 for 30-year-old vehicles). At no point are black and Latino male drivers' probability of search comparable to any other group.

For both male and female drivers, the average differences in probabilities of search between racial groups with newer vehicles are much smaller than those that emerge with older vehicles. For males, the average difference in probability of search between minority drivers and white drivers is 0.038 points when vehicle age is 1 year old. When it is 30 years old, this difference increases by about 43%, to 0.088 points. For females, there is a similar but less dramatic increase. When vehicle age is 1 year old, the average difference in probabilities of search is 0.011. This increases by about 28% percent to 0.037 at a vehicle age of 30 years old. This points to the expectation that disadvantage mounts. First, the increase in the spread of the probabilities of search is much more dramatic among men (the more suspicious gender identity) than women. Second, the difference in probabilities of search is greater for drivers with old vehicles (the more suspicious identity) than those with new vehicles. As suspicion-evoking identities grow (in this case, as vehicle age gets larger), the differences in search grow. Vehicle age matters more – in the sense that it functions to produce greater probabilities of search – for those subgroups that already experience higher levels of searches because they also possess racial or gender identities that are suspicion-evoking.

For age, an opposite but theoretically consistent pattern emerges. Figure 3 plots the predicted probabilities of search for male and female drivers, by racial group, across a range of ages. The y-axis represents the probability of search and the x-axis plots this probability over ages 15 through 70.

Of course, male drivers are searched more than female drivers. Racially, Latinx drivers are searched the most, followed by black, Native American, white, and finally by Asian drivers. Though, note that the predicted probability line for black and Latino male drivers switch places around age 50. Similar to vehicle age, the differences between racial and gender subgroups are largest when age is at its "most" suspicious – meaning, when drivers are young. At older ages, these differences start to shrink. For males, the mean difference in the probability of search between minority and white drivers when age is 70 years old is 0.022. When age is 16 years old, the average difference

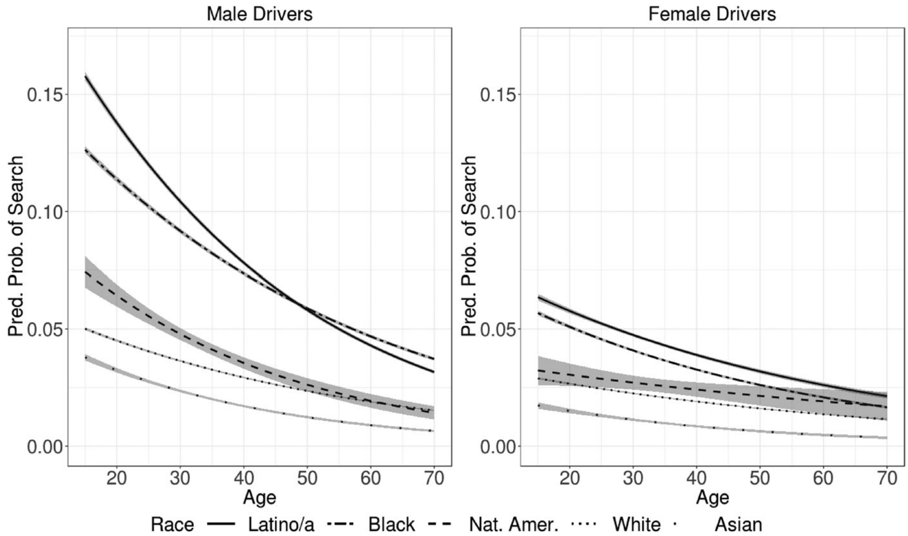

Figure 3. Predicted probabilities of experiencing a search, by racial group, over driver age.

in probabilities increases by 29%, to 0.075. For female drivers, when age is 70 years old, the mean difference in probabilities of search by racial group is 0.005, which grows by 19% to 0.027 when the driver's age is 16 years old. The differences in the probabilities of search is largest for young drivers, compared to older drivers, and for male drivers, compared to female drivers. The more and more suspicious identities that a person holds, the level of targeting grows. The effect of being younger or being in an old vehicle is largest for those drivers who already experience targeting based on their suspicion-evoking racial and gender identities.

Leniency in traffic stops

Whether a driver receives a warning following a traffic stop measures leniency afforded by the officer. The logistic regressions predicting a warning are presented in Online Appendix F. Predicted probabilities of receiving a warning are plotted over a range of vehicle ages in Figure 4.

First note that women receive more warnings than men, by about 0.02 on average, though this ranges from a difference of 0.043 for whites to 0.002 for blacks, when the vehicle is new. Racially, whites receive by far the most warnings, which is counter to my expectation that Asian drivers would be most apt to receive warnings. Asians are the second most likely group to receive a warning, which may be due to negative stereotyping of Asians, divorced from notions of suspicion, that result in harsher treatment during a traffic stop. After Asians, Native Americans and blacks are likely to receive a warning, followed by Latinx drivers, who experience the least amount of warnings, by far. A Latino male in a 30-year-old vehicle has a 0.173 probability of receiving a warning while a white male is almost double that (a 0.312 probability). For females, the difference is similarly stark: white females in a 30-year-old vehicle have a 0.335 probability of receiving a warning while Latina females only have a 0.203 probability. Disparities

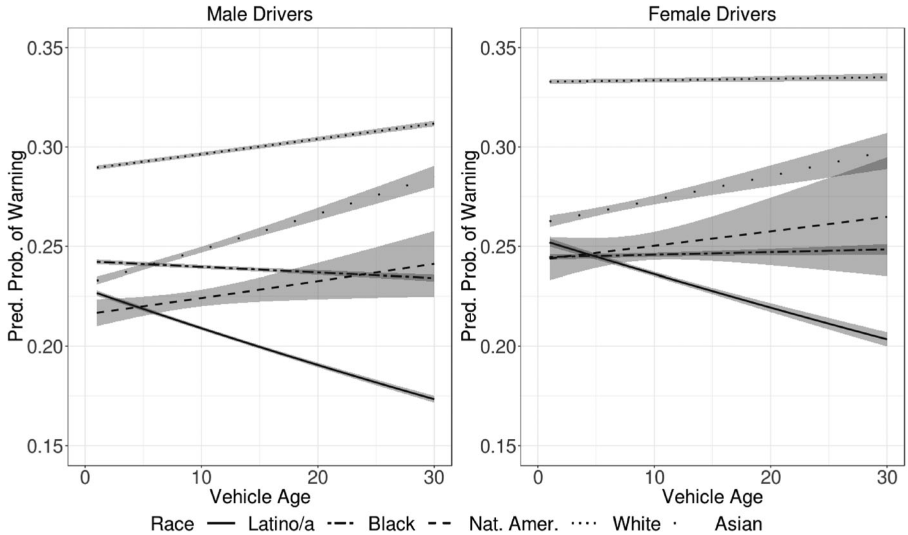

Figure 4. Predicted probabilities of receiving a warning, by racial group, over vehicle age.

between racial minority groups are smaller at newer vehicle age values, but they grow as vehicle age increases (that is, as vehicle age starts to signal a more "suspicious" identity); for men, the difference between the most likely and least likely group to receive a warning grows from 0.063 to 0.138 and for women, from 0.088 to 0.132.

For whites, Asians, and Native Americans, the probability of receiving a warning increases with vehicle age – though the trend is most pronounced among Asians. This is unexpected, as theory would dictate that older vehicles would signal lower class status and result in less leniency. The expected trend does hold for black and Latinx, though most prominently among Latinx drivers, who appear to be punished most heavily for having an older vehicle. This finding illustrates the importance of intersectional analyses. An additive model would not have allowed vehicle age to have different effects depending on race and gender.

Figure 5 plots predicted probabilities from the same model, computed over a range of driver ages. Here, women consistently receive more warnings than men, when compared within racial groups by about 0.3, on average. Again, this depends on the racial group. White females' probability of receiving a warning is about 0.040 higher than their male counterparts, while for blacks, the difference is only 0.004. Whites receive the most warnings, again followed by Asians. Similar to the plots for vehicle age, the disparities between racial groups are more prominent at younger ages (the more "suspicious" group) than at older ages. After about age 50, all racial minorities have a similar probability of receiving a warning, following a traffic stop, though whites are still much more likely to experience this leniency – by a probability of about 0.062 for male drivers and 0.088 for female.

The disparities between all groups within warnings are less pronounced than those among searches, potentially because the decision to search a car is much more closely tied to perceptions of suspicion than the decision to issue a warning. Nevertheless, there are clear, theoretically consistent disparities that emerge in whether or not the officer gives the driver a warning. Female drivers receive more leniency than their

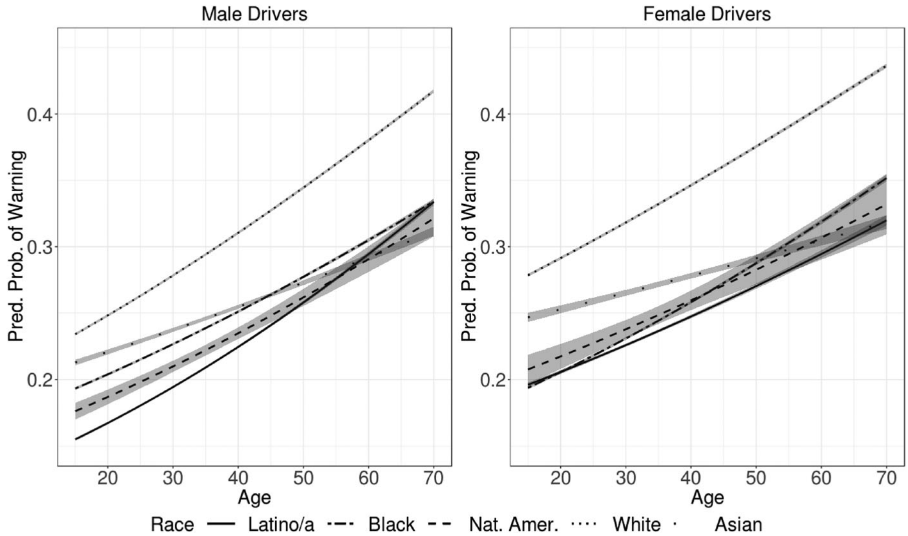

Figure 5. Predicted probabilities of receiving a warning, by racial group, over driver age.

within-race male counterparts. Whites receive the most leniency, by far. Then, Asians receive leniency followed by blacks and Native Americans. Latinx drivers consistently receive the least leniency. Leniency increases with driver age, but its effect with vehicle age depends on the racial and gender group analyzed. Most notably, whites are significantly advantaged in this arena, across gender, vehicle age, and class.

Categorical compounding of suspicion

To illustrate this targeting one final way, I return to the intersectional categorical models. Recall that these models include indicators for each of the 40 different identity categories (for which vehicle age and driver age were split at their medians into new/old vehicles and young/old drivers). I assign a suspicion-level to each of the 40 identity categories. This level ranges from 0 to 4 and represents the number of suspicion-evoking identities that the group holds. Recall the suspicious identities are male (versus female), young (versus old), and old vehicles (versus new vehicles). Racially, I consider black, Latinx, and Native American drivers to hold suspicion-evoking identities and white and Asian drivers to hold non-suspicious identities. This dichotomy, of course, is a gross generalization and there is much room for debate about these categories. The mean probability of search and warning, by the number of suspicion-evoking identities that a driver holds, is plotted in Figure 6. Broad trends in both outcomes are immediately apparent: as the number of suspicious identities that a driver holds increases, their probability of being searched increases and their probability of receiving a warning decreases.

The mean probability of receiving a warning when a driver holds no suspicion-evoking identities is 0.323. This drop to 0.289 when the driver holds one of these identities, and then to 0.258 (for two), 0.225 (for three), and 0.196 (for four). The mean probability of warning drops by about 0.03 points with each addition of another suspicion-evoking identity, though the difference slightly grows as the number of suspicious identities increases

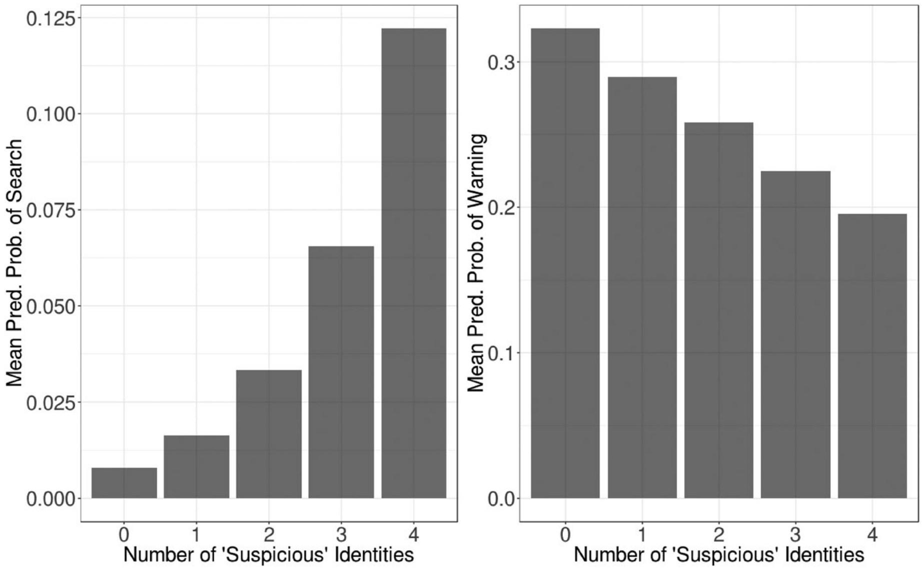

Figure 6. Predicted probabilities of traffic stop outcomes (search or warning), by the number of "suspicious" identities held by the driver.

(e.g., the difference is 0.029 when moving from zero to one suspicious identity, but 0.034 when moving from three to four). The more suspicion-evoking identities held by the driver, the less likely they are to experience lenient treatment by the officer.

Drivers with no suspicion-evoking identities experience a mean predicted probability of search of 0.008. For drivers with one suspicion-evoking identity, the mean probability is 0.016. For those with two, it is 0.033; with three, it is 0.066; and with four, 0.122. Note that the differences produced in the mean search rate gets larger and larger as the number of suspicion-evoking identities increase. Moving from 0 suspicion-evoking identities to one produces a difference of 0.008. From one to two, the difference jumps up about 49%, to 0.017. The difference in mean probability of moving from two suspicion-evoking identities to three is 0.032: a 53% increase. Finally, the largest increase in the mean probability of search is produced by moving from three suspicion-evoking identities to four. The difference jumps up to 0.057, which is a 57% increase. The differences in gaining one more suspicion-evoking identity are most prominent for those groups that already have highly suspicious identities. The jump in the probability of search for drivers with one suspicious identity to two is lower than that of the jump from three to four. Again, this points to the notion that disadvantage mounts as suspicion compounds for an individual driver.

Overall, we can conclude that certain intersectional identity groups do experience higher probabilities of search – and lower probabilities of receiving a warning – following a traffic stop than others, even once all confounding variables that the data provides are taken into account. These disparate probabilities cannot be accounted for with the reason the driver was stopped, the time of day, or any other variables for which the regression controlled. Instead, even after these confounding variables were accounted for, identity remains a significant explanatory and predictive variable for a search or a warning following a traffic stop. Beyond the often-analyzed identities of race and gender, I find that class (measured by vehicle age) and driver's age are important predictors for police targeting. This targeting is better conceived as a spectrum, in which stereotyping operates to produce a presumed level of guilt *and* of innocence for drivers.

Further, the effect of moving from a less suspicion-evoking identity to a more suspicion-evoking identity generally has larger effects for those groups that already possess other suspicion-evoking identities. Intersectionally, these identities compound the effect of one another and are larger as the driver moves more closely to the targeted profile of a young, black or Latino, poor, male driver. The effect that targeting this trope has extends beyond the individuals that possess this specific intersectional identity. Instead, other individuals are effected to a relative extent, depending on how closely their intersectional identity approaches the targeted criminal trope.

Conclusion

Broadening the concept of racial profiling to include multiple, intersectional identities allows for a more precise understanding of the way that stereotyping and police targeting operate. Stereotypes can result in both increased and depressed levels of targeting. Rather than conceiving of profiling as a dichotomy between who is targeted and who is not, we should think of targeting as a spectrum. The degree to which a certain identity group approaches the criminal trope of a young, black or Latino, poor man determines the degree to which they will be targeted.

Even though searches are relatively rare in traffic stops, the consequences that they have can ripple throughout a community. After controlling for a myriad of factors, it is clear that certain racial, gender, age, and class groups are much more heavily targeted than others. Racially, black and Latinx drivers are targeted most heavily, with Native American, white, and Asian drivers following behind. Males are targeted more than females, young drivers are targeted more than old drivers, and those with old vehicles are targeted more than those with new vehicles. An analysis of whether or not the driver receives a warning demonstrates that stereotypes do not only result in harsh treatment or targeting, but in leniency as well. Those drivers who are more likely to be searched are also less likely to receive a warning – and those who are not likely to be searched, are likely to receive warnings.

What does this mean for police-citizen relations for these communities? This analysis focused on individual drivers, but the effect of police contact extends to an individual's network (Owens and Walker 2018; Walker 2014; Walker and García-Castañon 2017) and neighborhood (Burch 2013, 2014; Lawless and Fox 2001; Lerman and Weaver 2014b). When someone experiences harsh treatment by the police, they likely talk about their experience with friends and family. When certain groups are more heavily targeted than others, such experiences start to build and animosity likely grows. Being searched less than one in 200 times that an individual is stopped (like old, Asian females with new vehicles) results in a much different lived experience than being searched 15 in 100 times (like young, Latino males with old vehicles). These experiences are tangible disparities that result in different realities for individuals in the United States.

Further, these experiences have concrete political consequences. Lerman and Weaver (2014b) find that police contact that involves searches or the use of force leads to decreased neighborhood-level outreach to local government. Burch (2011, 2014) finds consistently that contact with law enforcement demobilizes voter turnout at the individual and neighborhood level. Further, she finds that this demobilizing effect extends to other forms of political participation as well, such as signing petitions, protesting, volunteering, and participating in community groups (Burch 2013). At the same time, there is some evidence that proximal contact with an individual who has experienced contact with the criminal justice system may produce political mobilization (Walker 2014).

This study demonstrates that intersectional models of identity can help obtain more precise estimates of targeting and a deeper understanding of identity itself – at least with respect to traffic stop outcomes in Illinois. Further work should seek to expand the scope of this study, both geographically and contextually. The police operate in many contexts beyond traffic stops that may produce different outcomes. Further, there are likely important geographical differences in perceived suspicion that identities evoke, and expanding the scope of the study beyond one state would help outline these differences. Finally, this study makes headway by studying the intersection of four visible identities: race, gender, age, and class. However, there are many more unmeasured identities that likely combine to have an effect on how an individual is treated. For example, Burch (2015) finds that lighter-skinned blacks receive prison sentences that are not statistically significantly different from those received by whites, even though medium and dark-skinned blacks receive sentences that are about 4.8 percent higher than whites. Stereotypes associated with darker skin tone likely lead to increased police targeting and are another element of intersectional identity that could be explored further. Apart from race, gender identity (beyond the binary male/female) and sexual orientation have been absent from this paper, as the data do not include such information, but may contribute to the way that an individual is stereotyped, and potentially to the outcome from contact with law enforcement that they ultimately experience.

Intersectionality emphasizes the need to study the interaction of multiple identities, and this paper demonstrates that this claim is both theoretically and methodologically warranted. Intersectional models, without any constraints on the way that a single identity's effect can vary, produce better estimates than additive models. Theoretically, intersectional understandings of identity allow for a more specific understanding of the way that stereotyping operates – beyond a singular focus on the most highly targeted group. All in all, conceiving of profiling as intersectional is paramount to accurate analyses when studying identity-based disparities in the United States.

Notes

1. See Online Appendix A for more details.
2. Only eight states collect and report individual-level traffic stop data at the moment. Within those, Illinois is the only state that includes both a variable for vehicle age and for driver's age, in addition to the driver's racial and gender identity.
3. I also analyze whether or not the driver receives a ticket – the other outcome recorded in the data. The ticket analysis largely mirrors the search analysis, as it is also a harsh outcome, though there are less disparities – see Online Appendix G for a lengthier discussion.
4. Robustness checks compare this model to those estimated with different driver age cut points (21 years old and 25 years old) and different vehicle age cut points (at 3 and 5 years old) and results are nearly identical. See Online Appendix C. Further secondary analyses in the paper preserve driver age and vehicle age as continuous.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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