Purchasing Privilege?

How Status Cues Affect Police Suspicion in Routine Traffic Stops

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Abstract:

A police officer's decision to search a driver's car during a routine traffic stop is based on many variables and indicates that the officer views the driver with suspicion. In this paper, we ask whether driving a luxury-brand car reduces police suspicion during a traffic stop. We find significant reductions in rates of search for minority drivers of luxury cars, though these benefits fade away as the car grows older. We further explore the interactions between personal identity and vehicle type and find powerful effects associated with whether the vehicle indicates occupational status. Our study is based on more than 10 million traffic stops conducted by the Texas Highway Patrol. These findings add status cues to the long list of factors that appear to influence how police treat drivers during routine traffic stops.

Keywords:

Policing, racial disparities, traffic stops, driving-while-black, class, status

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Introduction

Status signaling through conspicuous or visible consumption is one of the core elements of sociological theory, and one of the oldest and most consistent strands of research in the social sciences. Scholars since Veblen (1899), Parsons (1951), and Groffman (1959) have emphasized it as a means of signaling one's place in society. Nestor Davidson (2009) writes: "And perhaps the most ubiquitous and important messages that property communicates have to do with relative status, with the material world defining and reinforcing a variety of economic, social, and cultural hierarchies" (757). Because of the various benefits that may derive from it, individuals expend considerable money and effort to signal their position as higher, rather than lower, in social status. This desire has been seen as particularly acute among members of minority communities, especially African-Americans. The desire to "fit in" or appear to be middle class has a strong appeal among marginalized groups. Many authors have mentioned cars specifically as clear signals of middle-class membership, particularly prized by members of minority communities seeking to project higher social status (see for example and for a review of this literature Lacy 2007).

Audrey McFarlane (2009) writes:

> Public identities are how minority individuals protect against racism from Whites. Blacks use class-related strategies to protect themselves from racial discrimination. Class-related strategies require careful performance, largely by using material goods and by outward manifestations of mastery of white norms of speech and conducting oneself with high confidence that evidence high expectation for cordial treatment by others. Thus, one purchases goods, services, and clothing to project an appearance of affluence and to remove the stigma of poverty. Other class-based strategies include driving an appropriately upper-middle-class status automobile, displaying a university ID, or deploying other "cultural capital" such as manner of speech, diction, and self-presentation. Class performance includes adopting white (as opposed to black) cultural styles. Strategic assimilation involves a race- and class-based strategy to protect and preserve one's middle-class identity by limiting one's personal association with poor blacks. (p. 184).

Charles et al. (2009) rely on Veblen's concept of conspicuous consumption to study the share of income spent on "observable consumption"—goods that can readily be seen by anonymous others. Looking across racial groups, they find that US blacks and Latinx individuals spend a higher share of their income on such goods, confirming anecdotal accounts suggesting that this might be the case. "Automobiles, clothing, and jewelry are examples of these forms of "visible" consumption" (426). Lamont and Moinar (2001) note how marketing professionals understand conspicuous consumption in the black community as a means to "defy racism and share collective identities most valued in American society (.e.g, middle-class membership)" (31).

The automobile holds a special place in studies of conspicuous consumption, given the highly visible nature of a car, and the fact that the basic functions of a car can be obtained by a low-value car but so many people prefer to drive much more expensive models. Several authors have discussed the association of black drivers with certain types of cars, particularly larger and more status-laden domestic luxury brands (see, e.g., Segrue n.d.; Smith 2001; Galster 2012; Sorin 2020). Epp and colleagues document powerful differences in the rates of being stopped for black drivers depending on the brand of car they drive or its value. A black male driver under the age of 40 has a 19 percent annual chance of experiencing an investigatory traffic stop if his car is at the 25th percentile in value; these odds rise to 29 percent if the car is of lower value, at the 75th percentile (Epp et al. 2014, 69). Having a more expensive car, then, can purchase some degree of freedom from police intervention. In the context of this study, focusing on interactions with the police, the benefits of signaling higher social status are clear: It can dissociate an individual from the stereotypical criminal profile.

In this paper we show that driving a luxury car can have significant benefits for minority drivers, helping to distance them from stereotypical assessments that they fit a “criminal profile.” We also document significant but racialized differences in such police assessments based on the occupational status of the driver and the type of vehicle driven. Our study adds to the literature about racial profiling on the nation’s highways but adds significant nuance to our understandings of how one’s vehicle sends status signals to the police.

Engel and Johnson (2006) describe some of the training materials developed by the US Department of Justice, Drug Enforcement Agency (DEA) during “Operation Pipeline,” the DEA’s effort to interdict drugs on the highway. The cues targeted in this training related to the vehicle itself, the driver and other occupants of the vehicle, and the “stories” told by the occupants during a conversation with the officer. In the early years of the program, the race and ethnicity of the driver were explicit elements of the “profile,” but after outcry from civil rights activists, this element was no longer made explicit. (A positive finding in this article for race, gender, and age, consistent with a long literature on the topic, suggests that it remains an important part of police behavior, however, even if no longer explicitly taught in the police academy.) The training lists “vehicle type” as a potential trigger for increased suspicion. Larger cars are both more comfortable for longer trips and provide more space to hide illegal substances, according to the training. Thus, luxury and other large cars are an element of the “drug courier profile” according to Engel and Johnson (2006) based on their review of DEA training materials. The authors note that officers are trained to consider the “totality of the circumstances” surrounding the traffic stop, and that certain combinations of factors would raise police suspicion whereas some of the component elements by themselves might not.

Previous literature also suggests that a key driver of police suspicion relates to individuals or drivers who seem "out of place". For example, Withrow (2004) noted: "Police officers are differentially attentive toward individuals or behaviors that appear inconsistent with predetermined conceptualizations of what is usual, customary, or expected within a particular context…. Once an individual or behavior is defined by the police officer as inconsistent with what has been previously determined to be usual, customary, or expected within a particular context, the police officer may seek a pretext to justify an official encounter" (Withrow 2004, 358–349). Thus, suspicion comes first, and the traffic stop follows.

Smith and colleagues (2004) further discuss police looking for "persons who 'don't fit the car' .... African Americans, in particular, might be more likely than whites to be stopped, especially if they were somehow 'out of place' (neighborhood, type of car)" (361). Drug interdiction training programs back up this anecdotal assertion; many emphasize heightened suspicion when "the occupants' age and socioeconomic status are 'inconsistent' with the value and style of the vehicle" (Engel and Johnson, 2006, 609). In contrast to these studies, Baumgartner and colleagues (2018, 137) found that being "out of place" was detrimental only for black drivers, not for whites.

Our expectations differ somewhat and correspond in some ways to the literature above. In the DEA training manuals reviewed by Engel and Johnson (2006), officers are taught to look for drivers who "don't fit the car." A luxury car driven by a young man appearing to have no job, who does not have the keys to the trunk of the vehicle he is driving, and who cannot explain who owns the car would certainly be a trigger for police suspicion along the lines of the "out of place" theory (see Engel and Johnson 2006, 610). But most luxury cars are driven by people who do have keys to the trunk and who can explain who owns the car, generally themselves or a family member. In that much more common circumstance, the car is a signal of higher social status, not part of the drug courier profile. We therefore expect the social class heuristic to reduce racial disparities because it can disassociate racial minorities from the criminal stereotype in most cases. It is important to note this does not rule out the "out of place" theory; there are certainly instances where drivers will be searched for the reasons mentioned above. But we believe this will be the exception rather than the rule.

Theory and Hypotheses

The traffic stop is the most common form of interaction between citizens and law enforcement; tens of millions of traffic stops occur each year (Harrell 2020). Typically, these generate a warning or a citation but a small share lead to a search of the driver or the car. Such a search clearly indicates that the officer has developed suspicion of possible criminal activity, changing the nature of the traffic stop from one of enforcement of the traffic laws to keep the roads safe to an investigation of something else, generally evidence of drug or criminal activity. Searches occur in only a small share of all traffic stops but they are highly consequential for the driver. Even a "fruitless" search leading to no further adverse outcome clearly indicates to the driver that the traffic stop had morphed into a criminal investigation. And of course, a "successful" search can lead to arrest and detention. So, while most traffic stops are routine, some can have great consequence.

Officers decide to stop or search vehicles based on limited information. Previous studies have made clear that in assessing the likelihood that the driver merits search, officers take into account all the information that is apparent to them, particularly visible cues. Time of day, day of week, location, the reason the car was stopped, and a quick computer search of the license plate and driver's license all matter, as one would expect. Many scholars have looked at the "criminal profile" in a variety of settings (see for example Webb 2007 [1999]; Smith 1986; Harris 1999a, 1999b; Meehan and Ponder 2002; Withrow 2004; MacLin and Herrera 2006; Tomaskovic-Devey et al. 2004; Farnum and Stevenson 2013; Skorinko and Pellman 2013; Epp et al. 2014; Fagan and Geller 2015; Baumgartner et al. 2018; Shoub et al. 2020).

We build on this expectation by focusing on the other signals a vehicle type can send. If officers are associating various status and identity variables with the "criminal profile" then it should be true that driving a luxury-brand car may reduce it. This, of course, must be interacted with the question of whether the "driver fits the car" as discussed above. An unemployed young man driving a brand-new Mercedes without the registration papers may arouse police suspicion. On the other hand, on average, a luxury car, for most drivers, would likely reduced the odds that the officer would associate the driver with criminal activity. Similarly, a newer car would suggest higher social status.

Just as a luxury brand car may reduce the odds of search, so too may driving a work-related vehicle. Like morning commuters during the rush hour, professional drivers should benefit from an officer's assumption that their work or status dissociates them from involvement in criminal activity. This will most strongly affect drivers of tractor-trailers and buses where there is a clear occupational signal. Tradespeople may drive a utility van or pickup truck, and we expect these drivers to benefit from some reduction in suspicion as well; those with commercial driver's licenses and/or commercial plates can be seen by the officer as professionals and treated as such. Drivers of passenger cars, SUVs, motorcycles, and those with utility vans or pickup trucks who do not have commercial status would not benefit from this occupational status benefit. The police may make other distinctions, however, based on distance from the criminal profile: Pickup trucks and mom-vans are further from the profile while motorcycles may be closer to it.

Although DEA training lists “vehicle type” as a potential trigger for increased suspicion, this heuristic has not been analyzed in any large-scale studies. We assess this for the first time here. Larger cars and luxury vehicles are an element of the “drug courier profile” according to Engel and Johnson (2006) based on their review of DEA training materials. This would also include SUV’s and potentially passenger vans. Our view differs from this expectation. Passenger vans and SUVs are more likely to be driven, on average, by parents with young children than by drug couriers. In the same manner, tractor-trailers certainly have plenty of room to transport contraband, but most professional truck drivers are not drug couriers. Perhaps the disagreement between our expectation and the DEA training materials reviewed by Engel and Johnson (2006) is whether the driver of the car corresponds to a criminal stereotype; their idea of the “totality of the situation.” A suburban soccer mom in an SUV or a passenger van would seem an unlikely object of police suspicion, but a young minority male driver of such a car on an interstate highway might be read differently.

We expect that in general, drivers should benefit from exhibiting a higher social class or occupational status. We refer to these as “status” indicators in the discussion below. Some vehicles indicate “occupational” status and may reduce the odds of suspicion because an officer may not associate professional long-haul truck drivers with drug cartels, given officer training. Motorcycles may be associated in the police community with an “outlaw” image, given the association of organized motorcycle clubs with various illegal activities. Some car brands indicate “social” status since they are more expensive; we expect that officers respond differently to drivers of luxury-brand cars, and for these differences to interact with race, gender, and the age of the vehicle. By driving a luxury brand, otherwise similarly situated drivers may hope to see a reduction in the odds of search. In sum, we explore the degree to which drivers can "purchase privilege."

Of course, many other identity- and situation-based variables have consistently been shown to affect the odds of search, and we control for them here as well (see Tonry 1995; Knowles et al. 2001; Peffley and Hurwitz 2010; Plant and Peruche 2005; Tillyer et al., 2012; Tillyer and Engel 2013; Epp et al. 2014; Baumgartner et al. 2018; Seo 2019). Similarly, place, time of day, day of week, and other "situational" variables affect police behavior and we therefore control for them.

These expectations lead to the following testable hypotheses.

H1. Driving a luxury brand car reduces the odds of search.

H2. Driving a newer car reduces the odds of search.

H3. Odds of search differ depending on the type of vehicle. Search rates will be highest for those driving motorcycles and be lower for those driving utility vans, passenger cars and SUV's, and pickup trucks.

H4. Professional drivers (e.g., those with occupational licenses or driving tractor-trailers or buses) will have lower likelihood of search compared to others.

We further expect that these differences will interact with race and gender. In particular, we expect a greater benefit to status cues for black and Latinx male drivers because without these cues, they may be closer to the stereotypical criminal profile than other drivers. Therefore:

H5. Black and Latinx men will gain more benefit in the form of reduced likelihood of search than white men or than women from occupational status, vehicle type, and luxury brand vehicles.

H6. Black and Latinx men will gain more benefit in likelihood of search than white men or than women from driving a newer car.

Data and Descriptive Background on Key Variables

We test the above hypotheses using micro-level traffic stop data from the Texas Highway Patrol from 2013 to 2017. Data on Texas Highway Patrol traffic stops has been publicly available since 2011, although at the time of our analysis only 2013 to 2017 was available online (see https://www.dps.texas.gov/section/about-dps/texas-department-public-safety-high-value-data-sets). Texas SB 701 mandates the public disclosure of data for public review in order to "increase state agency accountability and responsiveness" (https://capitol.texas.gov/tlodocs/82R/billtext/html/SB00701F.HTM). To our knowledge, Texas is the only state that provides data on the vehicle make, model, age, and type.

Our analysis focuses exclusively on black, Latinx, and white drivers. Demographically, these races make up the vast majority of the Texas population (see https://www.census.gov/quickfacts/TX) and traffic stops conducted over the course of our study. Further, the Texas Department of Public Safety has changed race and ethnicity codes relating to groups other than black, Latinx, and white drivers, contributing to inconsistent reporting of data across the years for other races.

Stops, Searches, and Search Rates

While traffic stops typically end in either a citation or a warning, somewhat more than two percent of traffic stops on Texas highways result in a search of either the driver or the car. We exclude "searches incident to arrest" in the analysis below. Such searches are an automatic result of the decision to arrest an individual based on information not apparent at the time of the search. Table 1 shows the number of stops and searches by race-gender category.

[Table 1 about here]

The Table shows that of almost ten million traffic stops, almost 210,000 led to a search, just over 2 percent. It also lays out the different rates at which these outcomes occurred by race and gender of the driver; these range from 1.21 (white females) to 4.20 (black males).

Vehicle Types

Texas Highway Patrol data contains 32 different vehicle type categories, which we combine into seven groups for analysis (see Appendix Table A11). These different vehicle types are associated with different driver demographics. Table 2 shows these relations.

[Table 2 about here]

Table 2 shows, for example, that white males are 39 percent of drivers across our entire dataset, but 73 percent of those pulled over while driving a motorcycle and 57 percent of those driving a pickup truck. Black males are 7.46 percent of those pulled over overall, but are relatively over-represented among those driving tractor-trailers and utility vans. Female drivers generally are over-represented in the SUV and passenger car categories. Latinx males are particularly likely to be found in tractor-trailers, buses, and utility vans. Race and gender therefore correlate with vehicle type, so we are careful to control for this in the analysis below. Note as well that all of the numbers in our study relate to traffic stops, not the driving population. The large over-representation of males compared to females may stem from different rates of driving or different rates of attracting police attention. We focus on which drivers, having been pulled over, are searched, not on which drivers are pulled over.

Luxury Cars

We categorize all vehicle makes into two categories: luxury and non-luxury. No universal standard exists for this classification, so we turn to a recent article ranking the “Best Luxury

Vehicle Brands" to identify "luxury" brands (see Appendix Table A12, Trotter 2020). This procedure classifies the following brands as luxury: Acura, Audi, BMW, Buick, Cadillac, Land Rover, Lexus, Lincoln, Infiniti, Jaguar, Mercedes-Benz, Porsche, Volvo. We restrict our analysis in this section only to the SUV and Passenger Car categories from Table 2. (Note that SUV includes passenger vans, but not "utility vans"). We exclude pickup-trucks and motorcycles because almost all fall into the category of non-luxury brands. We further restrict our dataset to vehicle makes with over 1,000 stops. In total, this leaves us with 40 different vehicle makes, and includes the vast majority of all the traffic stops in the dataset.[1]

Table 3 displays the race and gender break-down of stops by luxury vehicle category. Because the analysis includes only passenger cars and SUVs, the total N is reduced to just under 6 million, of which approximately 14 percent involve luxury brand vehicles. The largest number of luxury car drivers pulled over are white males, followed by white females. However, black males show the highest share of all stops involving luxury cars: almost 20 percent.

[Table 3 about here]

[1] Due to the large number of brands and stops in our analysis, switching one vehicle make to luxury from non-luxury or vice versa would not substantially alter our conclusions There are many possible ways to define "luxury" vehicles, and probably none is perfect. If data allowed, we would perhaps use vehicle value data as a proxy for status. However, both data quality issues in the Texas Traffic Stops data set and the availability of price data for discontinued models makes this difficult. As a robustness check, we have looked at search rates for all vehicle makes and models appearing at least 500 times in the database. Among those with the lowest search rates, 7 of 10 are luxury cars (the others are Subaru Outback and two Toyota models). Among cars with the highest search rates, 6 of 10 are luxury brands as well, but these are Cadillacs, Lincoln, and Buicks with high average age, and high percentage of minority drivers. The combination of driver identity, vehicle age, and luxury brand captures a significant share of the dynamic we seek to address. It does appear that Buick, Lincoln, and Cadillacs (e.g., US domestic luxury brands) signal something different from Japanese and European luxury brands. The highest search rate is for the Ford Crown Victoria; these cars were searched 12 percent of the time, had an average age of 14 years, and 64 percent minority drivers. The lowest search rate was for the Lexis GX6; it had a search rate of zero, mean age of 3, and 11 percent minority drivers. Full results are available from the authors.

We have no data on the racial and gender breakdown of luxury v. non-luxury brand car drivers, or how much they drive, so we cannot assess whether black drivers are differentially targeted for traffic stops because they drive a luxury vehicle. Several studies suggest that this may well be the case (Meehan and Ponder 2002; Worthnow 2004; Epp et al. 2014; Sorin 2020). The fact that 20 percent of those pulled over while driving a luxury car are black males is consistent with the idea that police officers may have heightened suspicion of such drivers. Our analysis will focus on the odds of search, given the initial traffic stop. Once the officer stops the driver, has a conversation, and assesses the situation, does the minority driver benefit or suffer from that luxury vehicle?

Analysis

We first look at luxury cars then turn to occupational status. We estimate logistic regression models predicting whether or not a driver will be subjected to search. The same controls are included in all analyses: race and gender of the driver, high disparity officers, log vehicle age, day of the week, and hour of the day. The controls used are the same ones used in previous analysis that focused on racial disparities in traffic stop outcomes (Baumgartner, Epp, and Shoub 2018). A high disparity officer is an individual police officer who has: 1) more than 50 traffic stops of white drivers and more than 50 traffic stops of drivers of a given minority group (e.g., black or Latinx); 2) searches at a rate higher than the mean search rate for the agency; and 3) searches minorities at twice or more the rate of white drivers.

Luxury Cars

Table 4 presents our analysis of the “luxury car” benefit. The first model presents a baseline before we include complex interactions. It includes the racial and gender identity variables, vehicle age (logged), and our indicator for luxury brand vehicles. The second model includes these as well as interactions among race/gender, luxury status, and age of vehicle. While the coefficients and odds-ratios in Model 1 can be directly interpreted, we point the reader to Figure 1 in order to understand the impact of the complex interactions shown in Model 2. (Tables A8-A10 provide the numbers associated with Figures 3 and 4.)

[Table 4 about here]

[Figure 1 about here]

For each racial group, there is a significant benefit for driving a newer luxury vehicle; Model 1 shows that this benefit is approximately a 12 percent reduction in the odds of search. However, as Model 2 and Figure 1 show, this benefit differs by group. In both parts of the Figure, dotted lines show the predicted search rates for drivers of non-luxury vehicles, and solid lines refer to luxury-vehicle drivers. Lines of the same shade of gray or black reflect black, white, and Latinx drivers, respectively. Males are in Part A of the Figure, and females in Part B. Several things are immediately apparent: First, females have lower rates of search. Second, the dotted lines (non-luxury vehicles) are consistently and substantially higher than the solid lines (luxury vehicles). Third, the lines always trend upwards over time, indicating that older cars arouse more suspicion than newer ones. Fourth, the "luxury benefit" is not consistent across demographic groups. Fifth, the effect of vehicle age appears to be greater for luxury cars than for non-luxury cars (that is, the solid lines move more steeply up over time compared to the dotted lines). We explore these last two effects further in Figure 2. Because the dynamics are more powerful among male drivers than among females, we focus only on male drivers in the following analysis.

Figure 2 plots the "luxury benefit" for each male racial group over varying vehicle ages. The luxury benefit measures the difference in the predicted probability of search between luxury and non-luxury vehicles of the same age. Mathematically, this can be represented as:

Luxury Benefit=Prob.(search | non-luxury vehicle) – Prob.(search | luxury vehicle). (equation 1)

For example, a value of .01 means a driver of a luxury vehicle would experience lower odds of search by .01 compared to a driver of a non-luxury vehicle, holding age of the vehicle and all other factors constant. This would be a one percent reduction in the odds of search, a substantial benefit.

[Figure 2 about here]

Figure 2 shows that drivers of all races can purchase privilege. When the car is new, values for all three series are above 0. For black drivers, the "luxury benefit" is near 0.013, or a reduction of 1.3 percentage points in the likelihood of search; this is substantively a large value given that the overall rate of search in the database is 2.1 percent (see Table 1). Latinx males purchase a benefit of .005, and white males of .003. Of course, white male drivers start out with much lower odds of search no matter what type of car they drive. The luxury benefit appears strongest for minority male drivers, particularly black drivers, as long as the car is new.

Figure 2 also demonstrates that for racial minorities, the luxury benefit diminishes significantly as vehicles age. The slopes for black and Latinx male drivers in Figure 2 go sharply down until the point where there is no luxury benefit at all. After about 7 years for Latinx drivers and 10 years for black drivers, the odds of search for drivers of luxury cars are the same as for drivers of non-luxury brands. For white male drivers, this effect stays relatively constant as the car grows older. The results in Figure 2 are consistent for female drivers as well, although at a smaller magnitude. Minority drivers can purchase privilege, but only for a time. We therefore confirm our expectations from H1 (luxury cars confer a benefit), H2 (newer cars confer a benefit), H5 (the luxury-car benefit is greater for minority drivers), and H6 (this benefit declines more quickly as the car gets older for minority drivers as compared to white men).

Occupational Status

Bus drivers and those driving tractor-trailer rigs are typically professional drivers. Those with utility vans often are, and some other vehicle types may be professional drivers as well. The dataset allows us to know whether the driver presented a commercial driver's license and if the vehicle had commercial license plates. We code as "occupational drivers" all bus and tractor-trailer drivers as well as any others who show a commercial driver's license or commercial plates. Note that some of this information is known to the officer before the stop, and some is apparent only after the stop is initiated. All of this information is available to the officer before deciding to conduct a search, however.

Table 5 shows the results from a logistic regression predicting whether or not a driver will be subjected to search based on demographics and vehicle type. The controls used are the same ones used above.

[Table 5 about here]

Model 1 includes only the identity-based variables, excluding vehicle type. The excluded demographic group, or baseline, is white female. Therefore, the odds-ratio of 1.491 for black females can be interpreted that those drivers are 49.1 percent more likely to be subjected to search compared to white females. Note the high values for high disparity officer as well as for the interaction of minority driver x high disparity officer. That means that even white drivers are subjected to higher search rates when pulled over by these officers, which is partly by construction as our definition of the variable includes not only that they have a higher rate of searching minority drivers, but also that they have a higher rate of search overall than the average across the entire agency. Because white female drivers have the lowest search rate of any demographic (see Table 1), all of the odds-ratios for the different demographic groups are positive. This model is presented to establish a baseline for comparison with the other models.

Model 2 incorporates controls for vehicle type, and Model 3 incorporates "occupational vehicle" which is defined as described above (all drivers of busses and tractor trailers as well as drivers of other vehicle types who have an occupational driver's license or commercial tags on the vehicle). Inclusion of this variable allows us to interpret the coefficients for the vehicle type variables in Model 3 as "non-commercial" vehicles. For example, the odds-ratio for Utility Van increases from 1.47 to 1.71 between Models 2 and 3, indicating that Utility Vans whose drivers do not have occupational licenses and whose vehicles do not have occupational license plates are subjected to higher rates of search than utility vans driven by professionals. Model 3 includes no estimates for busses and tractor-trailers as they are all included in the Occupational Vehicle category. Model 3 is of greatest interest.

It is clear that drivers of occupational vehicles benefit from a presumption of a low likelihood of involvement in criminal activity, as they have a very low rate of search (.004; see Appendix Table A3 for predicted probabilities of search). Similarly, drivers of pickup trucks (.015) and SUVs (.016) see lower rates of search than drivers of other vehicle types (.021 for motorcycles, .023 for utility vans, .025 for passenger cars). This could be because SUV drivers may be older or more likely to have children, for example. Pickup-trucks may be associated with rural areas rather than cities; in any case, they have lower rates of search. Utility vans have a slightly lower rate of search than passenger cars in Model 2 in Table 5, but slightly higher once we remove the occupational drivers from this set. Motorcycles have a rate of search approximately 87 percent higher than SUV's and passenger vans, the baseline category. These findings largely confirm the expectations laid out in H3 and H4 regarding vehicle type and occupational status: these effects are substantial, and differential by race.

The signals of occupational status and vehicle type, and the advantages that stem from them in terms of officer inferences of suspicious behavior, may of course differ for drivers from different identity groups. As shown in Table 2, we have enough observations to test a model that interacts vehicle type and race. There are too few female drivers in some of the categories, so we cannot interact race x gender x vehicle type. But search rates are substantially higher for male drivers, as Table 6 makes clear. Table 6 presents a model equivalent to Model 3 in Table 5 but includes variables interacting race with vehicle type. Figure 3 presents the predicted probabilities of search, showing results for the combination of race and vehicle type.

[Table 6 about here]

Looking first at the direct effects presented in Table 6, black and Latinx drivers have much higher odds of search (88 and 54 percent higher, respectively) compared to white drivers (the baseline), and male drivers have approximately double the odds compared to female drivers (the baseline). High-disparity officers have a large effect here as in Tables 4 and 5. Moving into the vehicle types, each is interacted with indicator variables for black and Latinx drivers, with white drivers as the baseline. As the combined effects of these interactions are hard to envision, we present them in Figure 3.

[Figure 3 about here]

Figure 3 makes clear that different vehicle types are associated with different rates of search, as discussed above in the interpretation of Table 5, Model 3. Occupational vehicles have much lower rates of search; SUVs, utility vans (not driven by professionals), and passenger cars consistently have higher rates. But the Figure also shows significant racial differences within these vehicle type categories, confirming H5. For motorcycles, white and Latinx drivers have much higher rates of search than black drivers, for example. For occupational drivers, racial effects are relatively muted, and search rates are low no matter the race of the driver. Similar findings result when looking at drivers of pickup-trucks; racial differences are relatively low. With the exception of motorcycles, whites always have the lowest rates of search, though the degree of difference by race varies by vehicle type. When we look only at drivers of passenger cars, the black-white difference in search rates is quite substantial: .022 for whites but .038 percent for blacks, a difference of 73 percent (see Appendix Table A4).

The analyses presented in Tables 5 and 6 provide robust evidence in support of several of our hypotheses. Racial and gender identities matter, as do the signals associated with different types of vehicles. Professional drivers, no matter the race, enjoy significantly lower rates of search than non-occupational drivers. Further, race and vehicle-type interact strongly, as white drivers generally benefit from much lower odds of search, but this advantage differs across vehicle types. It is even inverted in the case of motorcycles where the stereotype of criminal activity associated with motorcycles gangs may work to the disadvantage of white rather than black or Latinx drivers. (For some possible reasons for this, as well as good questions about why these groups are often still referred to as "clubs" rather than "gangs", see Fernandez, Kovaleski, and Blinder, 2015, who describe a motorcycle gang-related shoot-out in Waco that led to charges against 170 bikers.)

Conclusion

We have analyzed the factors associated with an officer deciding to search a car or a driver. Such situations clearly signal to the driver that the officer views them with suspicion. The routine occurrence of these instances of suspicion, generally misplaced, can have terrible consequences for the individuals subjected to them, reducing their trust in the state, sense of citizenship, and personal safety (see Lerman and Weaver 2014; Tyler et al. 2015; Meares et al. 2016). A recent national survey showed that black and Latinx individuals are four or five times as likely to worry about police brutality as whites, and that these rates are even higher among males (see Graham et al. 2020). While our article is not about police brutality, it does relate to trust and suspicion.

Other studies have amply demonstrated various visible cues that officers use when deciding whether a given driver merits search: Age, race, gender, location, time of day, day of week, why the car was pulled over, whether the car has out-of-state plates or is a rental vehicle, and so on. Many of these factors relate to police profiles of "drug couriers" developed many decades ago. Implicit in these strategies has been the knowledge that many innocent drivers would undergo intrusive and perhaps humiliating procedures for the sake of public safety. These procedures have consistently been upheld by the courts. It is time to question whether the public safety benefit of these policies outweighs the substantial social cost.

Suspicion, we have shown, is strongly related not only to the race and gender stereotypes than many others have documented. It also relates to occupational and social class signals put out by the type of vehicle a driver operates. Professional drivers and drivers of certain luxury brand vehicles benefit from lower rates of officer suspicion than other drivers. These factors, however, are highly dependent on race and gender; they offer differential degrees of benefit. In every case except for drivers of motorcycles, minority drivers suffer from increased odds of search compared to white drivers, though this baseline also differs by gender, vehicle type, vehicle age, and whether the driver is engaged in his or her occupation while driving.

As communities around the nation struggle to assess their relations with the police, one easy way to improve relations without impinging on public safety is to use the traffic laws for what they were ostensibly intended: to sanction those who drive badly so that we can keep the roads safe and reduce traffic accidents, injuries, and fatalities. Using the traffic code as a legal justification for investigations seeking drugs and other forms of contraband is a wasteful practice and one that alienates those communities who know that they are being unfairly profiled.

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The authors report there are no competing interests to declare.

Data availability statement

All data and command files associated with the analysis presented here will be made available upon acceptance for publication.

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Table 1. Stops, Searches, and Search Rates by Race-Gender Categories

Race	Gender	Stops	Searches	Search Rate
Black	Male	742,879	31,234	4.20
Latinx	Male	2,325,886	62,934	2.71
White	Male	3,875,289	71,427	1.84
Black	Female	349,548	7,840	2.24
Latinx	Female	752,400	12,613	1.68
White	Female	1,916,323	23,121	1.21
Total		9,962,325	209,169	2.10

Note: Search rates are per 100 stops.

Table 2. Race and Gender of Drivers of Various Vehicle Types.

	Male			Female				
	Black	Latinx	White	Black	Latinx	White	Total	N
Passenger Car	9.70	17.84	29.86	6.73	10.67	25.19	100.00	3,740,175
Pickup Truck	3.93	25.32	57.25	0.47	3.71	9.32	100.00	2,675,862
SUV	4.99	16.15	31.23	3.73	11.35	32.55	100.00	2,175,531
Motorcycle	9.22	14.55	73.06	0.40	0.30	2.47	100.00	40,447
Utility Van	12.41	29.70	50.36	1.12	1.45	4.96	100.00	14,087
Bus	9.68	52.73	23.79	3.89	2.98	6.94	100.00	8,878
Tractor-Trailer	12.23	47.03	38.90	0.27	0.49	1.08	100.00	1,307,345
Total Pct	7.46	23.35	38.90	3.51	7.55	19.24	100.00	
Total N	742,879	2,325,886	3,875,289	349,548	752,400	1,916,323		9,962,325

Note: The first column of data table shows, for example, that 742,879 black males were pulled over, representing 7.46 of all drivers. They represented different shares of drivers of different types of vehicles, however: 9.7 percent of drivers of passenger cars down to 12.23 percent of those driving tractor-trailers. Reading across the rows shows the total number of such vehicles (N) as well as the percentage coming from each of the race and gender groups. See Appendix Table A1 for the N's associated with the individual cells in the table.

Table 3. Race and Gender Characteristics of those Pulled Over, by Luxury Vehicle Category

Race and Gender	Non-Luxury	Luxury	Total	Percent Luxury
Black Female	281,764	49,208	330,972	14.9
Black Male	375,807	93,327	469,134	19.9
Latinx Female	577,623	65,681	643,304	10.2
Latinx Male	901,068	113,619	1,014,687	11.2
White Female	1,423,020	220,670	1,643,690	13.4
White Male	1,523,429	262,299	1,785,728	14.7
Total	5,082,711	804,804	5,887,515	13.7

Note: Includes passenger cars and SUVs only. SUV includes passenger vans.

Table 4. Predicting Searches by Race, Gender, Luxury Car, and Age of Car.

	Model 1		Model 2	
	Coef. (SE)	Odds Ratio	Coef. (SE)	Odds Ratio
Black Female	0.432*** (0.014)	1.540	1.289*** (0.039)	3.628
Black Male	1.305*** (0.010)	3.687	2.195*** (0.029)	8.979
Latinx Female	0.226*** (0.013)	1.254	0.538*** (0.038)	1.713
Latinx Male	1.043*** (0.010)	2.837	1.440*** (0.029)	4.222
White Male	0.655*** (0.009)	1.925	0.787*** (0.028)	2.197
Vehicle Age	0.423*** (0.004)	1.527	0.570*** (0.011)	1.769
High Disp. Officer	0.594*** (0.009)	1.812	0.598*** (0.009)	1.818
High Disp. Officer*Minority	0.236*** (0.011)	1.266	0.225*** (0.011)	1.253
Passenger Car	0.496*** (0.006)	1.642	0.474*** (0.006)	1.606
Luxury	-0.134*** (0.008)	0.875	-1.523*** (0.094)	0.218
Black Female*Luxury			-0.347* (0.180)	0.706
Black Male*Luxury			0.205* (0.117)	1.228
Latinx Female*Luxury			0.639*** (0.153)	1.894
Latinx Male*Luxury			0.803*** (0.113)	2.233
White Male*Luxury			0.092 (0.111)	1.096
Black Female*Vehicle Age			-0.433*** (0.019)	0.648
Black Male*Vehicle Age			-0.441*** (0.013)	0.644
Latinx Female*Vehicle Age			-0.166*** (0.018)	0.847
Latinx Male*Vehicle Age			-0.209*** (0.013)	0.811
White Male*Vehicle Age			-0.067*** (0.013)	0.935
Luxury*Vehicle Age			0.565*** (0.039)	1.760
Black Female*Luxury*Vehicle Age			0.181** (0.074)	1.198
Black Male*Luxury*Vehicle Age			-0.049 (0.048)	0.952
Latinx Female*Luxury*Vehicle Age			-0.163** (0.064)	0.849
Latinx Male*Luxury*Vehicle Age			-0.228*** (0.046)	0.796
White Male*Luxury*Vehicle Age			-0.065 (0.046)	0.937
Constant	-5.366*** (0.018)	0.005	-5.638*** (0.027)	0.004
Day of Week FE?	Yes		Yes	
Hour of Day FE?	Yes		Yes	
Observations	5,878,474		5,878,474	
Likelihood	-658,925		-657,015	
Akaike Inf. Crit.	1,317,931		1,314,144	

Note: *p<.1,**p<.05,***p<0.01; Omitted categories are: Driver Race-Gender, “White Female”; Vehicle Type, “SUV”. Logit coefficients are shown in the first column for each model with standard errors in parentheses. Odds ratios are presented in the second column for each model. Vehicle age is logged. Table A10 replicates while omitting the “high disparity officer” variable.

Table 5. Vehicle Type and Probability of Search.

	Model 1		Model 2		Model 3	
	Coef. (SE)	Odds Ratio	Coef. (SE)	Odds Ratio	Coef. (SE)	Odds Ratio
Black Female	0.399***(0.014)	1.491	0.345*** (0.014)	1.412	0.347*** (0.014)	1.414
Black Male	1.017*** (0.009)	2.766	1.161*** (0.009)	3.193	1.196*** (0.009)	3.306
Latinx Female	0.146*** (0.012)	1.158	0.176*** (0.012)	1.192	0.170*** (0.012)	1.185
Latinx Male	0.610*** (0.008)	1.841	0.923*** (0.008)	2.516	0.940*** (0.008)	2.559
White Male	0.385*** (0.008)	1.470	0.577*** (0.008)	1.781	0.606*** (0.008)	1.832
Log Vehicle Age	0.399*** (0.003)	1.490	0.449*** (0.003)	1.566	0.438*** (0.003)	1.550
High Disparity Officer	0.658*** (0.007)	1.931	0.575*** (0.007)	1.778	0.583*** (0.007)	1.792
Minority *High Disparity Officer	0.338*** (0.010)	1.402	0.244*** (0.010)	1.277	0.257*** (0.010)	1.293
Bus			-1.218*** (0.134)	0.296		
Tractor-Trailer			-1.935*** (0.017)	0.174		
Occupational Vehicle					-1.428*** (0.012)	0.240
Motorcycle			0.293*** (0.030)	1.340	0.296*** (0.031)	1.345
Passenger Car			0.492*** (0.006)	1.635	0.484*** (0.006)	1.623
Pickup Truck			-0.076*** (0.007)	0.927	-0.050*** (0.007)	0.951
Utility Van			0.223*** (0.054)	1.250	0.386*** (0.059)	1.472
Constant	-4.815***(0.015)	0.008	-5.252*** (0.015)	0.005	-5.223*** (0.015)	0.005
Day Fixed Effects?	Yes		Yes		Yes	
Time Fixed Effects?	Yes		Yes		Yes	
Observations	9,962,325		9,962,325		9,962,325	
Log Likelihood	-961,147		-937,087		-937,009	
Akaike Inf. Crit.	1,922,370		1,874,262		1,874,105	

Note: *p<.1,**p<.05,***p<0.01; Omitted categories are: "White Female" and "SUV". Table A2 replicates using the full set of vehicle type codes, not the collapsed ones used here. Table A8 replicates while omitting the "high disparity officer" variable.

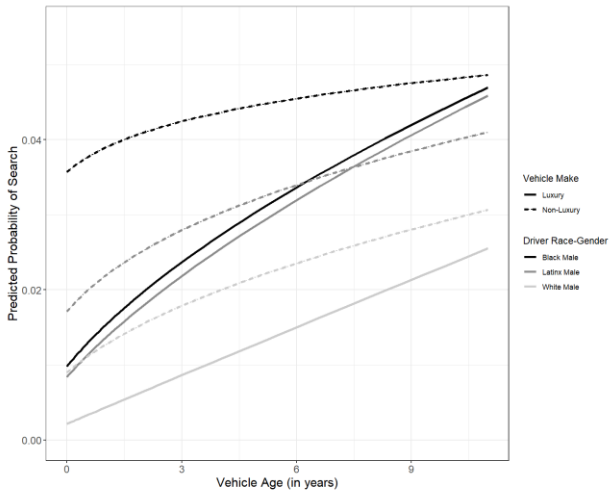
Table 6. Predicting Searches with Race and Vehicle Type Interacted.

	Coef. (SE)	Odds Ratio
Black	0.629*** (0.016)	1.876
Latinx	0.432*** (0.012)	1.540
Male	0.701*** (0.006)	2.015
High Disparity Officer	0.588*** (0.007)	1.801
Minority Driver*High Disparity Officer	0.247*** (0.010)	1.280
Log Vehicle Age	0.439*** (0.003)	1.552
Occupational Vehicle	-1.193*** (0.018)	0.303
Motorcycle	0.529*** (0.035)	1.697
Passenger Car	0.533*** (0.009)	1.704
Pickup Truck	0.037*** (0.010)	1.037
Utility Van	0.530*** (0.083)	1.699
Black*Occupational Vehicle	-0.234*** (0.034)	0.791
Latinx*Occupational Vehicle	-0.448*** (0.025)	0.639
Black*Motorcycle	-1.317*** (0.129)	0.268
Latinx*Motorcycle	-0.459*** (0.082)	0.632
Black*Passenger Car	-0.061*** (0.018)	0.940
Latinx*Passenger Car	-0.118*** (0.014)	0.889
Black*Pickup Truck	-0.314*** (0.025)	0.730
Latinx*Pickup Truck	-0.173*** (0.015)	0.841
Black*Utility Van	-0.337* (0.177)	0.714
Latinx*Utility Van	-0.257** (0.129)	0.773
Constant	-5.361*** (0.016)	0.005
Day Fixed Effects?	Yes	
Time Fixed Effects?	Yes	
Observations	9,962,325	
Log Likelihood	-936,870	
Akaike Inf. Crit.	1,873,843.000	

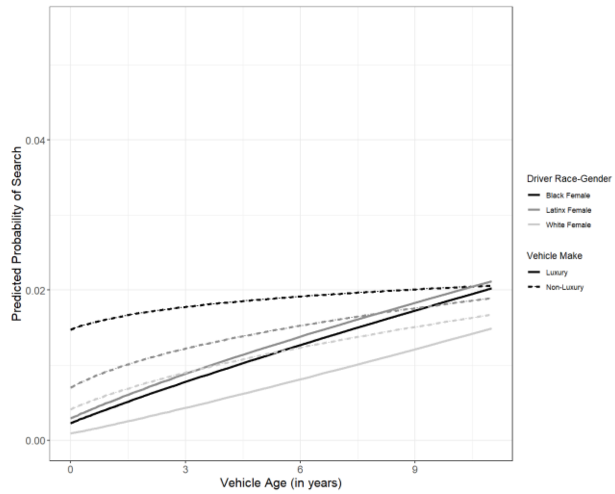
Note: *p<.1,**p<.05,***p<0.01; Omitted categories for models are: Driver Race, "White"; Vehicle Type, "SUV". Logit coefficients are shown in the first column with standard errors in parentheses. Odds ratios are presented in the second column. Table A9 replicates while omitting the "high disparity officer" variable.

Figure 1: Predicted Probability of Search by Driver Race-Gender, Luxury Vehicle Status, and Vehicle Age.

Part A. Male Drivers.

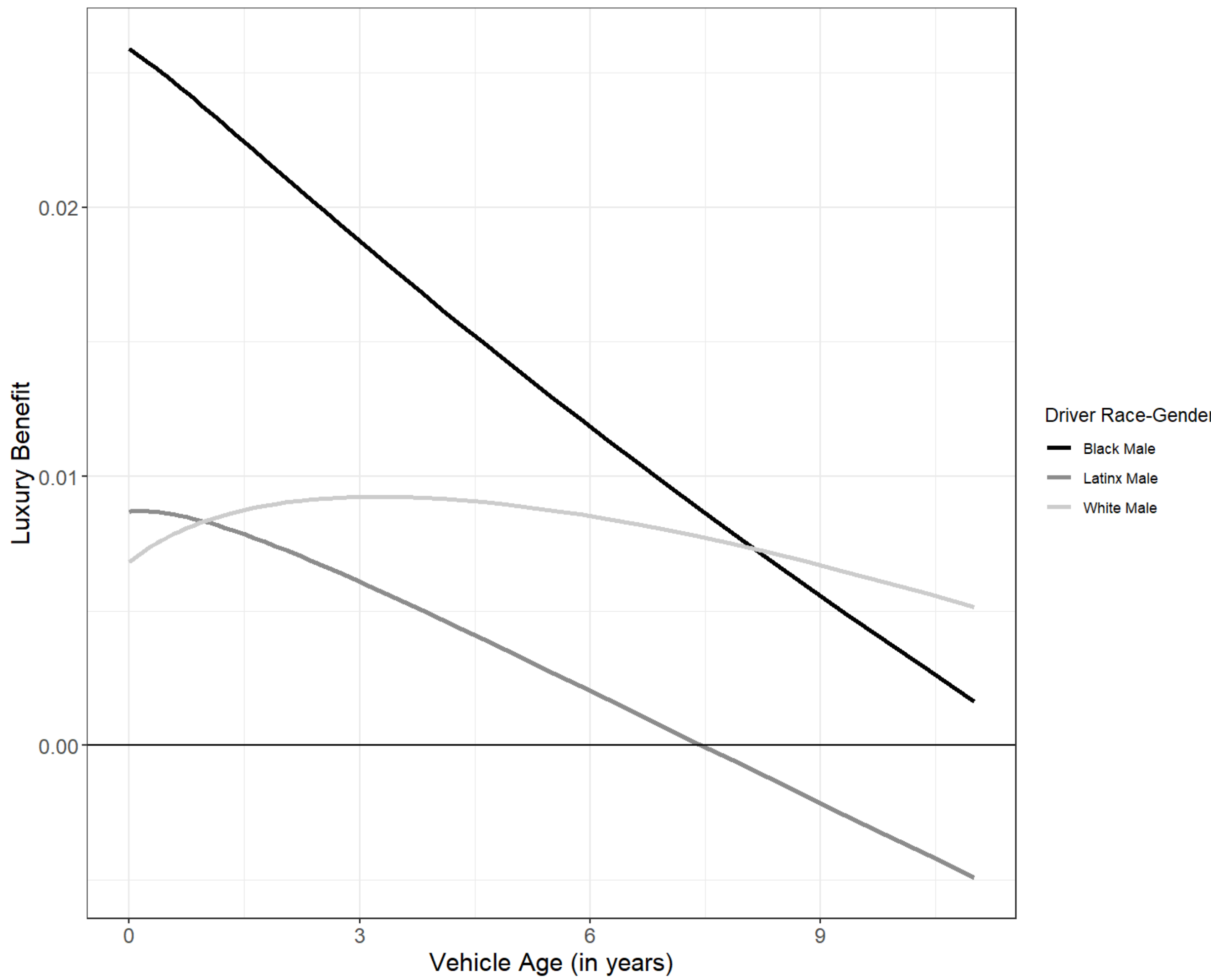


Part B. Female Drivers



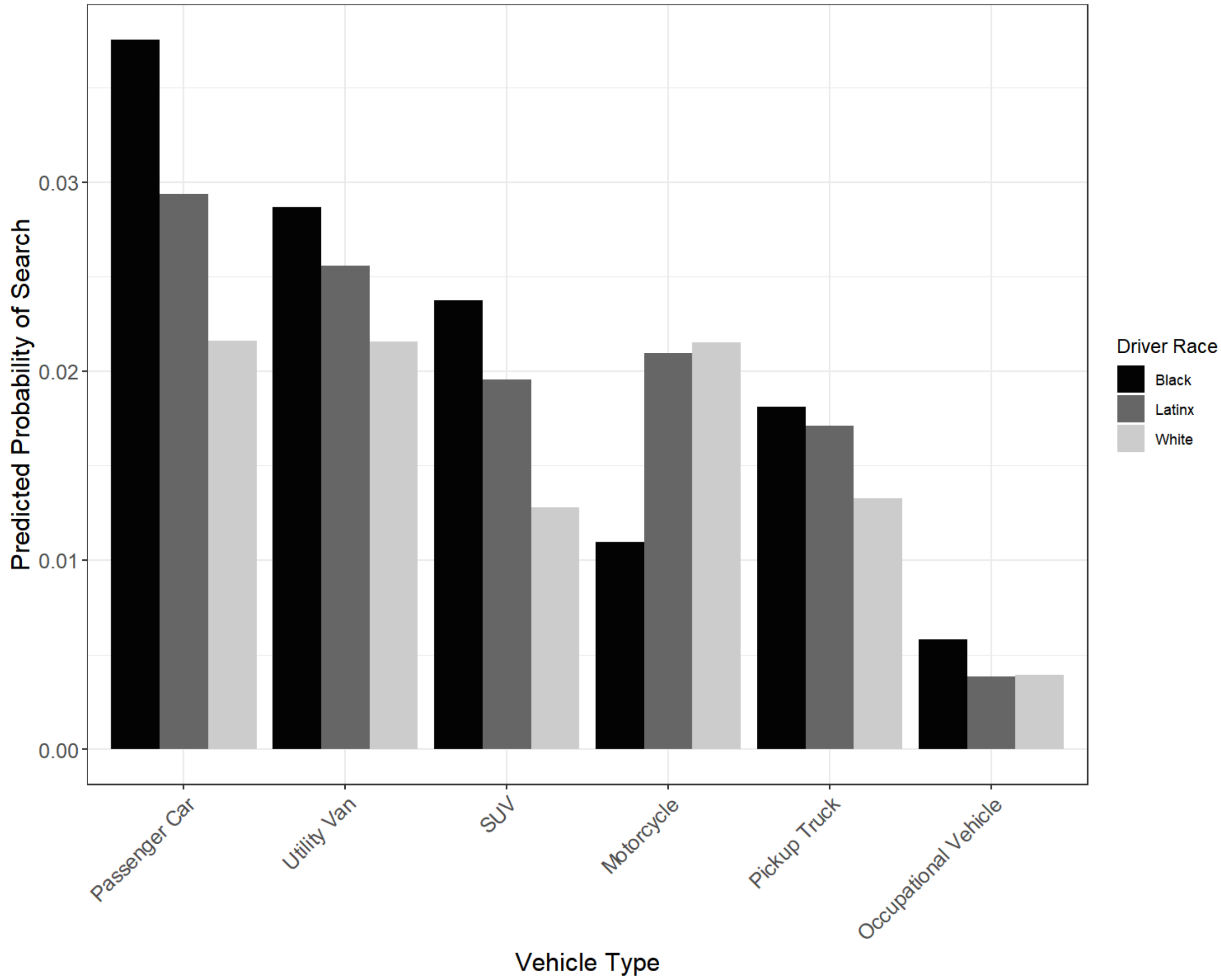
Note: Predicted probabilities derive from Model 2 of Table 4. Estimates are calculated holding all other control variables at their observed value. See Tables A5 and A6 for values.

Figure 2: The Luxury Benefit by Vehicle Age and Driver Race for Males.



Note: Luxury benefit is calculated for each racial group by subtracting the predicted probability of search for luxury vehicles from the predicted probability of search for non-luxury vehicles. See Table A7 for the data as well as equivalent data for female drivers.

Figure 3: Predicted Probability of Search by Race and Vehicle Type.



Note: Predicted probability for vehicle type category derived from Table 6. Estimates are calculated holding all other control variables at their observed value. See Table A4 for values.

Figure Captions

Figure 1: Predicted Probability of Search by Driver Race-Gender, Luxury Vehicle Status, and Vehicle Age.
Part A. Male Drivers.   Part B. Female Drivers

Figure 2: The Luxury Benefit by Vehicle Age and Driver Race for Males.

Figure 3: Predicted Probability of Search by Race and Vehicle Type.