Purchasing Privilege?

Driver Identity, Status Cues, and Police Suspicion

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Abstract:

In a traffic stop, officers routinely make decisions about the possibility of criminal activity of drivers based on very little information; the decision to conduct a search is an indicator of this suspicion. We review more than 10 million traffic stops conducted by the Texas Highway Patrol to assess which drivers are subjected to search, confirming previous findings with regard to identity-related variables. We are able to assess two new variables here, however: Occupational status, and social status. Professional drivers of long-haul trucks and inter-city buses are rarely subjected to search. Among drivers of passenger cars and SUVs, we assess social status by comparing luxury brands with others. In both cases, we find that status-cues strongly affect the odds of search. Many citizens are routinely subjected to increased police scrutiny, and many see reduced scrutiny. These routine police decisions are clearly based on systematic and inaccurate stereotypes.

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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. A small share lead the officer to decide to search the driver or the car, and an even smaller share lead to the discovery of contraband or criminal behavior. Officers' decisions to stop or search a vehicle are made based on limited information. Some of these factors, such as the driver's identity and type of license, are made clear only after the stop has been initiated, but some, such as the type of vehicle or the time and location of the stop are apparent before the stop begins. 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).

Race, gender, age, and other identity-based variables have also been shown consistently to affect the odds of search, and we assess 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). We are able to explore one element of the traffic stop that has not previously been extensively analyzed in the published literature (but see Knowles et al. 2001): the type of vehicle. Professional drivers of tractor-trailers or buses, for example, might be expected to have low odds of search whereas motorcycle drivers have higher odds of raising the suspicion of the officer who pulled them over. For passenger cars and SUVs, we further assess the differential odds of search for drivers of luxury brands compared to other cars. And, as we know the model year of the car as well, we can assess the impact of vehicle age. 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. Some car brands indicate "social" status since they are more expensive; we expect that officer respond differently to drivers of luxury brand cars, and for these differences to interact with race, gender, and the age of the vehicle.

Taking into account as much information as the dataset allows, we confirm that officers have higher rates of search based on identity-based and other factors that have previously been demonstrated in the literature. We add consideration of the vehicle type and find powerful effects, and we can show that these are conditional on identity. Professional drivers (e.g., those with occupational licenses or those driving buses and tractor-trailers) also see low rates of search; they do not fit the criminal profile. Among drivers of SUVs and passenger cars, we also show that drivers can "purchase privilege." By driving a luxury brand, otherwise similarly situated drivers see a significant reduction in the odds of search. This benefit is permanent for White drivers of luxury cars; no matter how old the car is, they continue to benefit from a lower rate of search. For Black and Hispanic drivers, new luxury cars provide a benefit; their rates of search are lower than similarly situated drivers without luxury brand vehicles. But this benefit fades away as the vehicle ages. Black male drivers, in fact, see the largest reduction in rates of search when they have a new luxury vehicle, over a one percent reduction. This benefit fades to zero as the car reaches ten years old, however. For Latino drivers, the initial benefit is more modest and it reduces sharply over time. For White male drivers, the luxury benefit is near a half of a percent but it does not decline substantially over time.

Our paper proceeds as follows. In the following section we explain our theoretical approach and expectations. We then explain our data collection and present descriptive statistics. Next we explore the issue of vehicle type, which allows us to compare trucks, buses, and other vehicles normally driven by professional drivers in the course of their jobs to passenger cars, SUV's, and motorcycles. We then concentrate on passenger cars and SUVs, focusing on the difference between luxury brand vehicles and others. We conclude with an assessment of our findings, which consistently show support for identity-based differences in rates of search as well as for the impact of occupational and social class cues.

Four Heuristics of Suspicion

A police officer's decision to search a driver or car as a result of a traffic stop is clearly a low-information decision. Officers use their training and the information available to them to assess the odds that the driver may be harboring contraband. Engel and Johnson (2006) describe some of these training materials developed by the US Department of Justice, Drug Enforcement Agency (DEA) during "Operation Pipeline", the Agency'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, might suggest that it remains an implicit part of the training or of police culture in general, however.) 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. 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. This would also include SUV’s and potentially passenger vans. 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 definitely raise police suspicion whereas some of the component elements by themselves might not.

Based on the training officers receive, we focus on four heuristics officers may use to make the decision to search. Broadly speaking, we expect that when these heuristics can be associated with criminal stereotypes, the likelihood of a driver being subjected to search will increase. When these heuristics disassociate drivers from the criminal stereotype, we expect the likelihood of search to decrease.

The first heuristic is situational. Officers are likely to associate the criminal stereotype with certain locations, times of day and days of the week, and to use different legal justifications to pull over drivers who alert their attention for different reasons. Speeding, the most common form of a traffic stop, may have nothing to do with suspicion of criminal activity, particularly if the stop occurs in the middle of the afternoon or during rush hour; a radar gun provides a reading, and a traffic stop follows. No search typically ensues because the reason for the stop was straightforward; the driver was observed to be speeding. As officers may not associate speeders with a criminal stereotype, there is no signal to warrant an officer’s increased suspicion.

On the other hand, in many cases the driver does appear suspicious to the officer for some reason. Drivers who arouse officer suspicion may be stopped for a variety of reasons; expired tags, vehicle equipment problems, or other justifications may be more common. In these cases, if the suspicion came first and the legal justification for the traffic stop came second, a search of the car or the driver may be more likely. Of course, a search is not certain or even highly probable, as the officer will start with a conversation with the driver, and that may alleviate the officer's concern. Only if it does not will the officer seek to conduct a search.

Charles Epp and colleagues (2014) make the distinction between traffic safety stops on the one hand and "investigatory" or "pretextual" traffic stops, on the other. Pretextual stops have been shown to contribute to higher rates of search (Epp et al. 2014). Further, driving during the morning rush hour rather than late at night when the bars close can all reduce the odds of arousing officer suspicion (see Christiani 2020; Baumgartner et al. 2020). While we lack the data on stop purpose, and certainly don't know what is in the mind of the officer, we can control for time of day and day of week to account for these factors.

Our second heuristic is the driver's identity: age, race, and gender. Officers associate men, younger people, and racial minorities with the stereotypical criminal profile. Prior literature has shown consistently these identities have implications for traffic stop outcomes (for recent book-length examples see Epp et al. 2014; Baumgartner et al. 2018; Seo 2019). We have no data on age, so we cannot assess it. But we can assess the impact of race and gender. We expect that racial minorities and male drivers should be more likely to be subjected to searches.

Third is occupational status and the type of vehicle. DEA training lists "vehicle type" as a potential trigger for increased suspicion. 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 moms and dads 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 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 being a professional driver can reduce it; just like morning commuters during the rush hour or older white female drivers, 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.

Officers do not observe these heuristics in a vacuum. We further expect these occupational status heuristics to interact with identity heuristics. If racial disparities in traffic stop outcomes are the result of Black and Latinx drivers being associated with the criminal stereotype, we should expect that presenting occupational status can reduce disparities. By disassociating drivers from the criminal stereotype, the occupational status heuristic should counteract these criminal stereotypes for Black and Latinx drivers leading to a larger reduction in likelihood of search when compared with White drivers.

Finally, we propose a social class heuristic. The wealthy may differ from the poor in the eyes of the police by their lower odds of being associated with the stereotype of the criminal suspect. Social class can be assessed by several factors associated with the vehicle one drives. Wealthier individuals may be more likely to drive passenger cars or SUVs than to drive motorcycles, pickup-trucks, or utility vans; they may be more likely to drive luxury-brand cars; and they may drive newer vehicles. We expect that in general, drivers should benefit from exhibiting a higher social class.

In addition to assessing these heuristics independently, we also expect interactions among them. We focus on two competing theories for how these heuristics might interact. The first is the "out of place" theory. Previous literature suggests that one element of police suspicion relates to individuals or drivers who seem "out of place". For example, Brian 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" (Withrow 2004, 358). And, he writes: "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, 359). Thus, the suspicion comes first, and the traffic stop follows.

William 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.

We focus on a competing theory consistent with the "totality of the circumstances" concept. A luxury car driving 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.

These expectations lead to the following testable hypotheses.

<u>Identity-based hypotheses</u>:

H1. Minority drivers will have a higher likelihood of search compared to White drivers.

H2. Male drivers will have a higher likelihood of search compared to female drivers.

<u>Occupational-status hypotheses</u>:

H3. Drivers whose vehicles signal occupational status will have lower likelihood of search compared to drivers of non-occupational vehicles.

Social-class hypotheses:

H4. Among non-occupational drivers, those with vehicle types associated with poverty or criminal suspicion will see higher likelihood of search. This will affect, in order: motorcycles, utility vans, passenger cars and SUV's, and pickup trucks.

H5. Among drivers of passenger cars and SUV, those with luxury-brand vehicles will have a lower likelihood of search compared to drivers of non-luxury-brands.

H6. Among passenger car and SUV drivers, those with newer vehicles will have a lower likelihood of search compared to drivers of older vehicles.

Interaction effects:

H7. Identity variables (race and gender) will interact with the occupational and social class variables listed above to the detriment of men of color. That is, Black and Hispanic men will gain more benefit in likelihood of search than White men or than women from occupational status, vehicle type, luxury brands, and new cars.

Note that we do not test the situational heuristic here but include these as controls. We also control for whether the driver is pulled over by an officer whose overall statistics show a tendency to search minority drivers at more than twice the rate of White drivers, based on previous literature (see Baumgartner et al. 2018).

Data and Analysis

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, Search Rates, and Search Rate Ratios

While traffic stops typically end in either a citation or a warning, somewhat fewer than three percent of traffic stops on Texas highways result in a search being conducted 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, and it compares the search rates of minority drivers to those of Whites of the same gender. Search Rate Ratios are defined as the search rate for drivers of color divided by the rate for White drivers of the same gender. This is a simple indicator of racial disparity.

This shows, for example, that Black male drivers are searched at 2.28 the rate of White males and that Black females are search at 1.85 the rate of White females.

Vehicle Types

Texas Highway Patrol data contains 32 different vehicle type categories. Table 2 shows these categories as well as our collapsed codes, which consist of seven categories for analysis plus “other,” which we exclude in the analysis below because it is made up of many diverse vehicle types, often with low numbers of observations.

[Table 2 about here]

Different types of vehicles are typically associated with different types of drivers. Table 3 shows the relationship.

[Table 3 about here]

Table 3 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 can be seen to 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.

Having now presented our database, our analysis is divided into two parts. We first focus on the vehicle type, and the distinction between occupational drivers versus others. Then we focus on two of the most common types of vehicles, passenger cars and SUVs, and we assess the impact of driving a luxury brand. In both sections, we pay careful attention to driver identity as these relate to differential rates of search.

Race, Gender, and Occupational Status

As laid out in the section on hypotheses, we explore a range of variables associated with the identity of the driver in predicting which drivers are more likely to be subjected to search. These relate to their race and gender identity and from the cues that they send by the type of vehicle that they drive. The vehicle-related information we are concerned with here is whether it signals 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 or 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.

We estimate a logistic regression predicting whether or not a driver will be subjected to search at a traffic stop. We also include controls for 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 Texas traffic stop outcomes (Baumgartner, Epp, and Shoub 2018). A high disparity officer is an individual police officer who over the span of our study has 1) more than 50 White traffic stops and more than 50 traffic stops for a minority group 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. The same controls will be included in all subsequent analysis throughout our paper.

Note that our primary focus here is on the identity-based and occupational variables. The "high disparity" officer variable has been demonstrated to matter in previous research, and we include it as a control here. It is a matter of interest in itself, of course, as a large share of all officers in the Texas Highway Patrol meet our definition of searching minority drivers at more than double the rate of white drivers. Including a statistical control for this factor allows us to assess the other variables in the model without concern that they are spuriously related to this possible confounding variable. Tables A11-A13 replicate our main results showing that excluding this variable from the model does not appreciably change the results. Table 4 presents the results.

[Table 4 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 for the purpose of establishing a baseline.

Model 2 incorporates controls for vehicle type, and Model 3 incorporates “occupational vehicle” which is defined as described above (all drivers of bus and tractor trailer 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 1.711 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 the model of greatest interest. Figure 1 shows the predicted probabilities of search across vehicle types, drawing from Model 3.

[Figure 1 about here]

It is clear that occupational vehicles benefit from a presumption of a low likelihood of involvement in criminal activity, as they have a very low rate of search. Similarly, drivers of pickup trucks and SUVs see lower rates of search than drivers of other vehicle types. SUV drivers may be older, more likely to have children, for example. (Table 3 showed that they are more likely to be driven by white women as well, but that is controlled in the predicted probabilities shown in Figure 1. Table 2 clarifies that the category includes passenger vans, a category officers may associate with families with children.) Pickup-trucks may be associated with rural areas rather than cities; in any case, they have lower rates of search. (Table 3 showed also that they are very much associated with White male drivers, with Latinx males slightly over-represented, Black males and female drivers under-represented, but again, these demographic differences are controlled in the presentation in Figure 1.) Utility vans have a slightly lower rate of search than passenger cars in Model 2 in Table 4, but slightly higher once we remove the occupational drivers from this set. So Figure 1 shows a higher rate of search for those non-occupational drivers of these vehicles. Motorcycles have a rate of search approximately 87 percent higher than SUV's and passenger vans, the baseline category.

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 3, 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 4 makes clear. Table 5 presents a model equivalent to Model 3 in Table 4 but includes variables interacting race with vehicle type. Figure 2 presents the predicted probabilities of search, similar to those presented in Figure 1, showing results for the combination of race and vehicle type.

[Table 5 about here]

Looking first at the direct effects presented in Table 5, 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 Table 4. 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 2.

[Figure 2 about here]

Figure 2 makes clear that the effect of racial identity is quite different depending on the type of vehicle in question. 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. In the other categories, Whites always have the lowest rates of search. Among occupational drivers, the racial disparities between White drivers and racial minorities almost disappear in terms of predicted probability. For example, when considering occupational vehicles, Black drivers are about 0.25 percent more likely to be searched than White drivers. When we look at drivers of passenger cars, that Black-White difference is more than 1 percent, or four times greater.

The analyses presented in Tables 4 and 5 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, face 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.) We explore these dynamics further in the next section where we look closely at two of the largest vehicle types, passenger cars and SUVs, looking at the difference between those driving "luxury" brands and the rest of the drivers. Can one purchase privilege? Our analysis will show that the answer is yes, at least as long as the car is new.

Luxury Cars

We now shift to analyzing traffic stops of vehicles driven by drivers with no signal of occupational use or professional drivers. We restrict our analysis to the SUV and Passenger Car categories (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.

We categorize all 40 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 Trotter 2020). Table 6 lays out the distinction. 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.[1]

[Table 6 about here]

Table 7 displays the race and gender break-down of stops by luxury vehicle category. Because the analysis includes only passenger cars and SUV's, the total N is reduced to just under 6 million, of which approximately 14 percent involve luxury brand vehicles. The largest number

[1] 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, age of 3, and 11 percent minority drivers. Full results are available from the authors.

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 7 about here]

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; Sorin 2020). Rather, we can assess whether they are searched as a result of the stop. With regards to that likelihood, we expect drivers of luxury cars to benefit from an association with higher social status. This benefit may decline substantially as the age of the vehicle increases, however, as luxury cars depreciate in value quickly. The driver of an older luxury car may not benefit from an inference about higher social status / lower odds of involvement in criminal activity on the part of the officer.

We estimate two models in order to better understand the effect of driver race, gender, luxury car status, vehicle age, and their interactions, on likelihood of search. The first model can be seen as 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 model also controls for whether the car is a passenger car or SUV (omitted category), the high-disparity officer variable included in the models above, and day-of-week and hour-of-day controls (results not shown). 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 3 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 8 about here]

[Figure 3 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 3 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 4. Because the dynamics are more powerful among male drivers than among females, we focus only on male drivers in the following analysis.

Figure 4 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 4 about here]

Figure 4 shows that every driver has the opportunity to 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 percent in the odds 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). It may explain why Table 7 showed Black male drivers to be the most common drivers of luxury vehicles. Black males driving new luxury brand cars purchase a benefit in reduced probability of search of .013 whereas 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 4 also demonstrates that for racial minorities, the luxury benefit diminishes significantly as vehicles age. The slopes for Black and Latinx male drivers in Figure 4 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 4 are consistent for female drivers as well, although at a smaller magnitude. Minority drivers can purchase some significant privilege, but only for a time.

Conclusion

Traffic stops are the most common forms of interaction between citizens and the police, and Americans experience them in vastly different ways. For the majority of middle-class White drivers, a traffic stop is the opportunity to attempt to persuade the officer to issue a warning rather than a ticket for the speeding or other violation of the law that generated the stop. For many other drivers, the encounter is fraught with anxiety and fear. We have analyzed here 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 Hispanic 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.

Our analysis of approximately 10 million traffic stops conducted by the Texas Highway Patrol is consistent with findings in other states and by other agencies; there appears nothing special about the results we have reported here. They do have some special characteristics, however, that allow us to add to the literature: Vehicle type matters. Texas state troopers, like police officers nationwide, make use of every cue available to them when assessing a driver for potential involvement in criminal activity. Some of these cues are sent before the traffic stop (and may therefore be a partial cause of the stop itself); others are sent after the stop has been initiated. The decision to search the driver is a clear indication of this suspicion. We have shown how this varies in systematic and troubling ways.

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 types of vehicles benefit from lower rates of officer suspicion than other drivers. These factors, however, are highly dependent on race and gender, and 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.

Police officers and state troopers throughout the nation are called upon to make quick decisions about the odds that a given driver is engaged in criminal behavior while driving on the highway. We should develop methods to discourage the use of inaccurate heuristics based on race or race-related characteristics and we should recognize that the stakes are higher than they have been assumed to be, just as the benefits may be lower than they have been assumed to be. The stakes are higher than assumed because we have not traditionally given much importance to the message received by the driver when an agent of the state indicates by the demand to search the car that the driver is a criminal suspect, usually falsely. The benefits are lower because the vast majority of these searches yield no contraband, and an even lower share lead to the arrest of the driver. 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.

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 Contraband Hits by Race-Gender Categories

Race	Gender	Stops	Searches	Search Rate	Search Rate Ratio
Black	Male	742,879	31,234	4.20	2.28
Latinx	Male	2,325,886	62,934	2.71	1.47
White	Male	3,875,289	71,427	1.84	1.00
Black	Female	349,548	7,840	2.24	1.85
Latinx	Female	752,400	12,613	1.68	1.39
White	Female	1,916,323	23,121	1.21	1.00
Total		9,962,325	209,169	2.10	-

Note: Search rates are per 100 stops. Ratios are the rate for the minority driver of a given gender divided by the rate for the White driver of that same gender. Values for Whites are therefore 1.00 by construction.

Table 2: Vehicle Type Categories

Collapsed	Original	Stops
Passenger Car	Passenger Car	3,740,175
Pickup Truck	Pickup Truck	2,675,862
SUV	Jeep, Passenger Van, SUV, Van	2,175,531
Motorcycle	Motorcycle	40,447
Utility Van	Utility Van (UPS, Bread Truck, etc.)	14,087
Bus	Bus, School Bus	8,878
Tractor-Trailers	Full Trailer Refrigerator, Truck Tractor, Straight Truck/Dump Truck/Flatbed/ Cement Mixer, Truck Tractor/Semi-Trailer, Semi-Trailer Livestock, Pole Trailer Log, Tank	1,307,345
Other	Emergency Vehicle, Motor Scooter/Moped, NULL, Other, None, Unknown, Motor Coach, Limousine, Dolly Converter, Crib Log Trailer, Intermodal No Owner, Train, Intermodal Owner, Road Tractor, Recreational Vehicle	38,963
Total		10,001,288
Total for Analysis	(Note: this excludes "other" from the list above.)	9,962,325

Note: See Table A2 for results replicating our findings from Table 4, below, using the original vehicle type categories provided, not the collapsed ones displayed here. This robustness check demonstrates that coefficients within each category are consistent. Further, categories within the "Other" category are for the most part insignificant, justifying our decision to exclude them in the main analysis.

Table 3. 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 4. Predicting Searches.

	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 5. 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.

Table 6: Luxury and Non-luxury Vehicle Makes

Luxury	Non-luxury
Acura, Audi, BMW, Buick, Cadillac, Land Rover, Lexus, Lincoln, Infiniti, Jaguar, Mercedes-Benz, Porsche, Volvo	Chevrolet, Chrysler, Dodge, Fiat, Ford, GM, GMC, Honda, Hummer, Hyundai, Isuzu, Jeep, Kia, Mazda, Mercury, Mini Cooper, Mitsubishi, Nissan, Oldsmobile, Plymouth, Pontiac, Saab, Saturn, Scion, Smart Car, Subaru, Suzuki, Toyota, Volkswagen

Source: Derived from Trotter 2020.

Table 7. 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

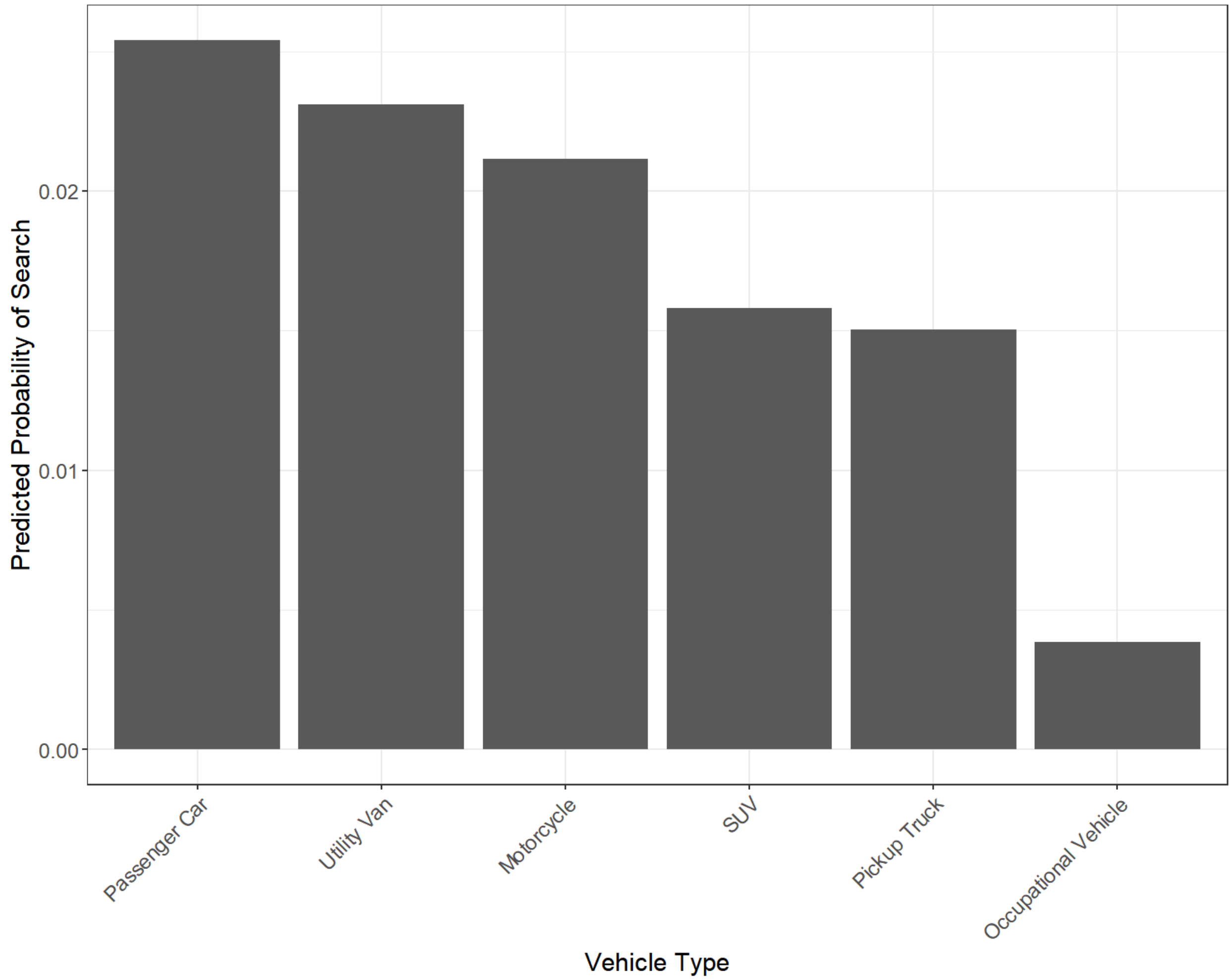
Note: Includes passenger cars and SUVs only. SUV includes passenger vans.

Table 8. 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	

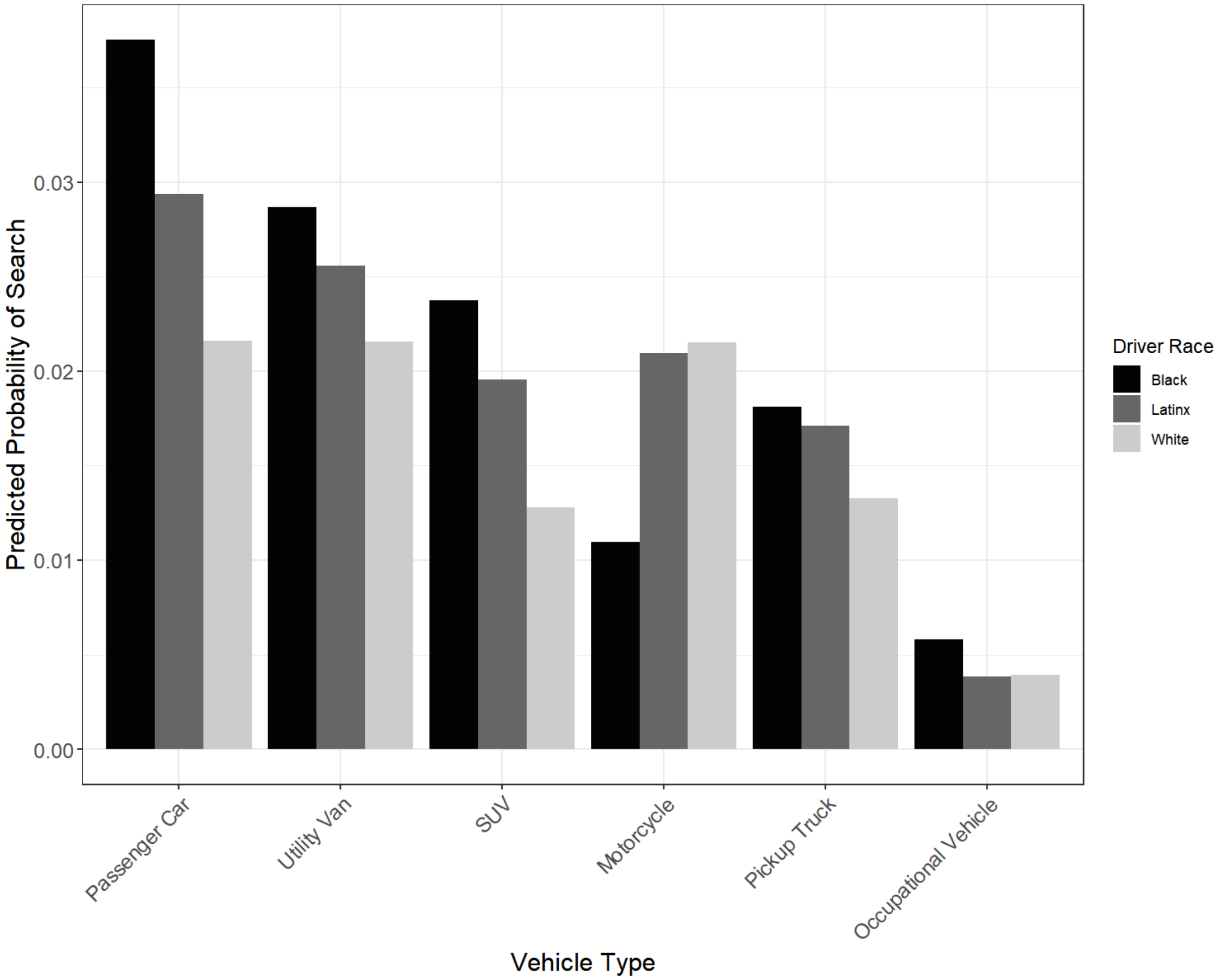
Note*:* $^{*}p<.1$, $^{**}p<.05$, $^{***}p<0.01$; Omitted categories are: Driver Race-Gender, "White Female"; Vehicle Type, "SUV". Logit coefficients are shown in the first column for each model with standard errors in parentheses. Odds ratios are presented in the second column for each model. Vehicle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

Figure 1: Predicted Probability of Search by Vehicle Type



Note: Predicted probability for vehicle type category derived from Table 3 Model 3 logit results. Estimates are calculated holding all other control variables at their observed value. See Table A3 for values.

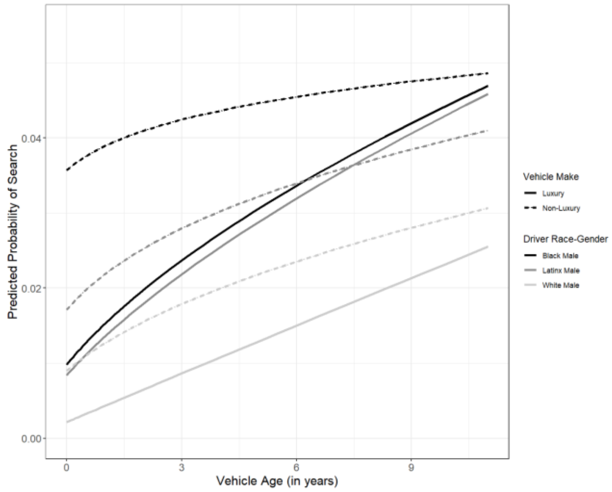
Figure 2: Predicted Probability of Search by Race and Vehicle Type.



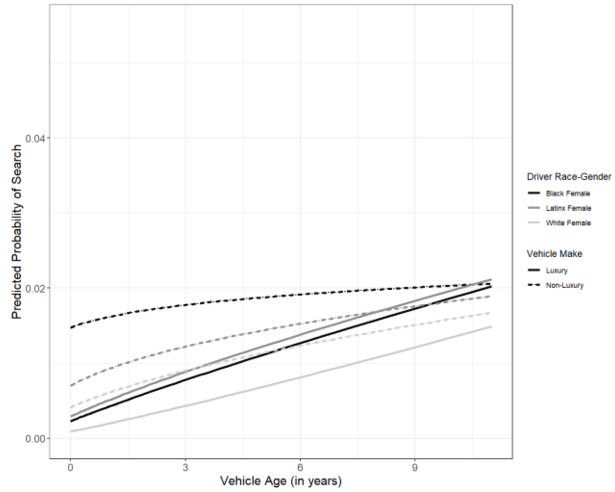
Note: Predicted probability for vehicle type category derived from Table 5. Estimates are calculated holding all other control variables at their observed value. See Table A4 for values.

Figure 3: Predicted Probability of Search by Driver Race-Gender, Luxury Vehicle Status, and Vehicle Age.

Part A. Male Drivers.

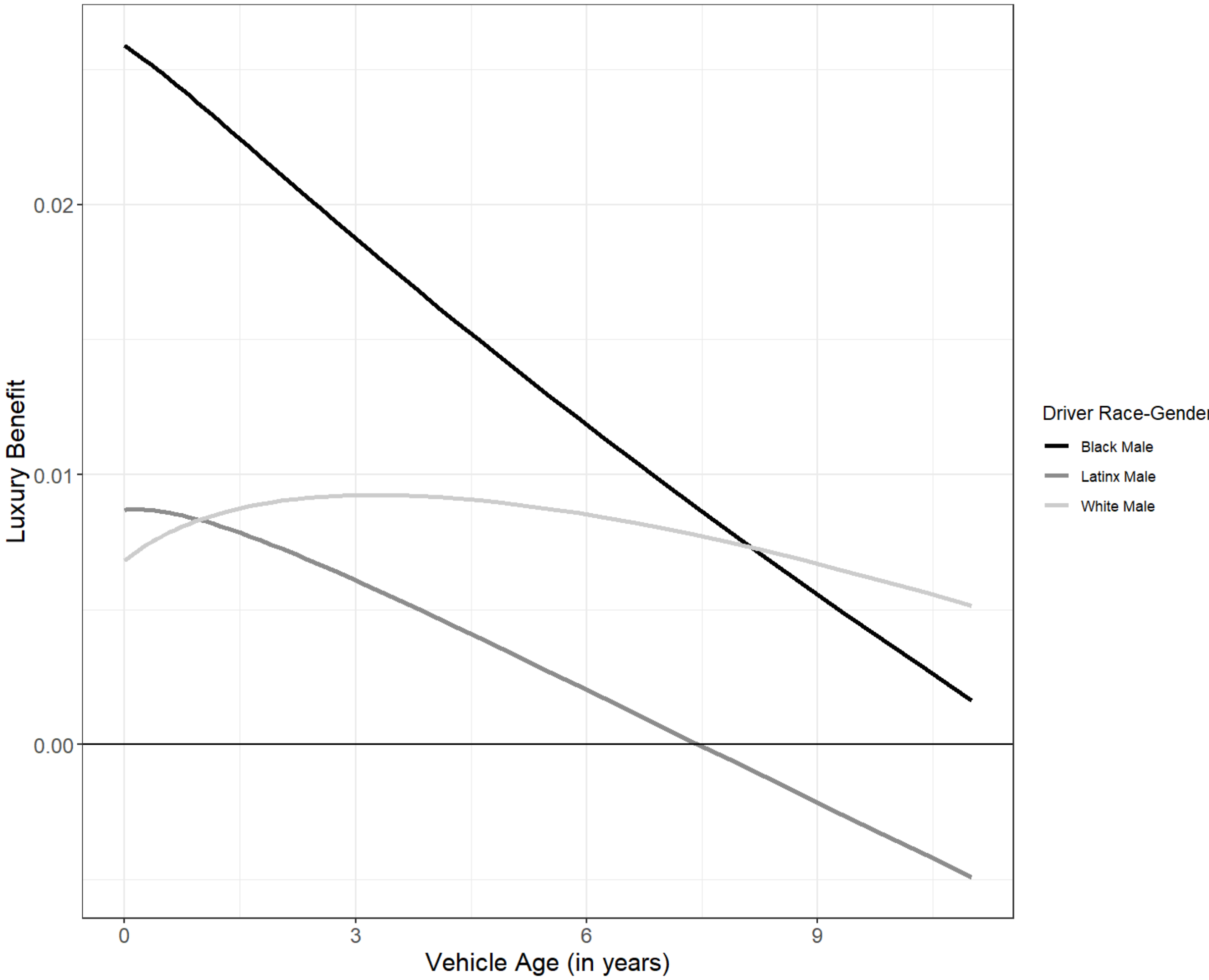


Part B. Female Drivers



Note: Predicted probabilities derive from Model 2 of Table 8. Estimates are calculated holding all other control variables at their observed value. See Tables A5 and A6 for values.

Figure 4: 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.