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Endogenous Driving Behavior in Tests of Racial Profiling in Police Traffic Stops

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Abstract African-American motorists may adjust their driving in response to increased scrutiny by law enforcement. We develop a model of police stop and motorist driving behavior and demonstrate that this behavior biases conventional tests of discrimination. We empirically document that minority motorists are the only group less likely to have fatal motor vehicle accidents in daylight when race is more easily observed by police, especially within states with high rates of police shootings of African-Americans. Using data from Massachusetts and Tennessee, we also find that African-Americans are the only group of stopped motorists whose speed relative to the speed limit slows in daylight. Consistent with the model prediction, these shifts in the speed distribution are concentrated at higher percentiles of the distribution. A calibration of our model indicates substantial bias in conventional tests of discrimination that rely on changes in the odds that a stopped motorist is a minority.

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1. Introduction

The possibility that police treat minority motorists differently than other groups has become a source of protest and social unrest.[1] The public's most frequent interaction with police is through motor vehicle enforcement, which can serve as the precipitating event for more serious actions like searches, arrests or use-of-force. Many states have mandated the collection and analysis of traffic stop data for assessing racial differences in police stops.[2] However, these analyses may provide misleading statistics if minority motorists rationally choose to drive more slowly and carefully in response to real or perceived discrimination. Such behavioral changes would reduce minority representation in samples of traffic stops and bias estimates of racial disparities. Similar responses to adverse treatment are documented in several contexts including labor market, health, and orchestra auditions (see Arcidiacono, Bayer and Hizmo 2010; Institute of Medicine 2003; and Goldin and Rouse 2000). However, work on behavioral responses to police discrimination is mostly absent in the existing literature.[3] Research documents decreasing criminal behavior as police enforcement rises, and if discrimination is interpreted as increased scrutiny by police, our paper also contributes to this literature.[4]

We develop a simple model of motorist infractions and police stops in which some motorists choose not to commit infractions. Although discrimination is typically assumed to

[1] See Arthur et al. (2017), Goff et al. (2015), and Nix et al. (2017) for recent media coverage on police shootings.

[2] 23 states collect and analyze traffic stop data. Also see policy initiatives like Obama's Task Force on 21st Century Policing as well as funding made available via the National Highway Safety Traffic Authority (NHTSA). See NHTSA SAFETEA-LU and Fast Act S. 1906 funding for FY 2006 to 2019.

[3] The key exception is Knowles, Persico and Todd (1999) and Persico and Todd (2008) who develop models of carrying contraband, also see discussion in Persico (2009). The key difference between our model and theirs is that carrying contraband is a choice that is unobserved by police, while infraction severity is observed.

[4] For example, see notably Levitt (1997), Evans & Owens (2007), Chalfin and McCrary (2018), and Mello (2019).

increase the minority share of stops, we demonstrate that discrimination actually has an *ambiguous* effect on the share of minority traffic stops in models that capture motorist driving behavior. The ambiguity arises because the higher probability of stop induces motorists with relatively weak preferences for committing infractions to become inframarginal and choose not to infract. Under reasonable assumptions, the effect of motorists choosing to not infract can dominate the increased likelihood of being stopped as discrimination rises. Inframarginal motorists also impact the distribution of stopped motorists over infraction level because those motorists would have committed less severe infractions. Nonetheless, by imposing additional assumptions on the distribution of motorists, we demonstrate that the direct effect of motorists decreasing their infraction level as discrimination rises dominate the effect of an increasing share of inframarginal motorists at more severe infraction levels. We utilize this result by examining the entire distribution of stopped motorist speeds in our empirical work.

Any empirical analysis of motorist response to police behavior must account for the role that the police stop decision itself plays in shaping the available data. Traffic stop data represents samples of motorists who have committed an infraction of some sort *and* who have been stopped by police. Thus, the composition of the sample is selected based on police decisions. We attempt to separate motorist behavior from selection issue in three ways: (1) We examine the racial composition of fatal traffic accidents using lower accident rates as an indicator of safer driving because accidents are not selected based on police decision making; (2) We exploit our second theoretical result pertaining to unambiguous downward shift in infraction severity at higher percentiles in the infraction distribution by examining the upper portion of the speed distribution of stopped motorists, and (3) We calibrate our model to the speed distribution and racial composition of traffic stops and then calculate police stop costs. We also simulate counterfactual test statistics where motorists are not allowed to respond to changes in stop costs.

In addition to selection, we must also address a classic challenge faced by nearly all traffic stop studies where we do not observe the distribution of motorists who are committing traffic infractions.[5] We address this counterfactual problem using a popular approach developed by Grogger and Ridgeway (2006), the "Veil of Darkness" (VOD). VOD leverages seasonal variation in daylight to compare stops made at the same time of day and day of week where some stops were in daylight and others in darkness. The VOD operates under the premise that motorist race is less easily identified by police after sunset, but that the distribution of motorists committing infractions at a given time of day is unaffected by the timing of sunset. With over 22 applications across the country, VOD has quickly become the gold standard for assessing racial differences in police traffic stops, and so the validity of this approach has significant policy implications.[6] Regardless, our findings are broadly applicable to any test of discrimination in the decision to stop a minority motorist.

For our first empirical analysis, we use accident data to obtain a population that is not directly impacted by traffic stop decisions following Alpert, Smith, and Dunham (2003).[7]

[5] Exceptions exist where researchers observe a representative sample of motorists (Lamberth 1994; Lange et al. 2001; McConnell and Scheidegger 2004; Montgomery County MD 2002), but such approaches are considered prohibitively expensive (Kowalski and Lundman 2007; p. 168; Fridell et al. 2001, p. 22). Many studies examine vehicle searches where the counterfactual, motorists stopped, is observed (Knowles et al. 2001; Dharmapala and Ross 2004; Anwar and Fang 2006; Antonovics and Knight 2009; Marx 2018; Gelbach 2018). Also see Arnold, Dobbie and Yang (2018) and Fryer (2019) who examine bail and use-of-force, respectively.

[6] Applications include Grogger and Ridgeway (2006) in Oakland, CA; Ridgeway (2009) Cincinnati, OH; Ritter (2017) in Minneapolis, MN; Worden et al. (2012) as well as Horace and Rohlin (2016) in Syracuse, NY; Renauer et al. (2009) in Portland, OR; Taniguchi et al. (2016a, 2016b, 2016c, 2016d) in Durham Greensboro, Raleigh, and Fayetteville, North Carolina; Masher (2016) in New Orleans, LA; Chanin et al. (2016) in San Diego, CA; Ross et al. (2019, 2017) in Connecticut and Rhode Island; Criminal Justice Policy Research Institute (2017) in Corvallis PD, OR; Milyo (2017) in Columbia, MO; Smith et al. (2017) in San Jose, CA; and Wallace et al. (2017) in Maricopa, AZ.

[7] We use all accidents, not just not-at-fault, because West (2018) reports evidence that the determination of fault in traffic accidents is itself potentially subject to police discrimination.

The U.S. National Highway Traffic Safety Authority's Fatality Analysis Reporting System (FARS) contains race/ethnicity and information on the circumstances surrounding all automobile accidents that result in one or more fatalities.[8] We estimate models that are similar to VOD tests regressing motorist race on whether the fatal accident occurred in daylight/darkness conditional on time of day, day of week, and year by location. Consistent with minority motorists driving more carefully during daylight because they expect to face more scrutiny by police, we find a smaller share of minorities in the accident sample in daylight relative to darkness. Fatalities are 1.5 percentage points less likely to involve an African-American motorist in daylight relative to a share of 13 percent in the overall sample. Further, these effects are largest in states with larger racial disparities in police shootings and in those that rank highly on a Google trends racism index. The fatal accident sample also exhibits balance between daylight and darkness over available motorist and vehicle attributes.

In our second empirical analysis, we examine data on police speeding stops in Massachusetts and Tennessee. We focus on speeding stops because the motorist's speed provides a convenient variable for assessing infraction severity.[9] To our knowledge, these samples are the only statewide data available with information on the speed of traffic stops resulting in a warning rather than tickets/fines alone.[10] We first conduct VOD tests using the racial composition of speeding stops. We find that daylight stops are more likely to be of African-American motorists than darkness stops in Massachusetts and West Tennessee with the largest differences in Massachusetts, but observe no differences in East Tennessee.[11]

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[8] We thank Jesse Shapiro for pushing us to identify a sample that would not be selected on police stop decisions. See Knox, Lowe and Mummolo (2019) for discussion of concerns about relying on administrative data collected in response to police enforcement decisions.

[9] Darkness may also affect traffic stops for non-moving violations, like cell phone use or equipment failures (Grogger and Ridgeway 2006; Kalinowski, Ross and Ross 2019a). Researchers might use fines to measure severity for a broader set of moving violations.

[10] In Tennessee, the data explicitly identifies warnings and tickets. In Massachusetts, many speeding tickets have zero fine, which we interpret as somewhat equivalent to a warning.

[11] Tennessee is divided at the time zone boundary removing counties on the boundary.

We then examine changes in the relative speed of motorists stopped between daylight and darkness using an unconditional quantile regression. As noted above, our theoretical model implies that the overall effect of discrimination on stopped motorist infraction levels is unambiguously negative at higher points in the infraction distribution. We find no effect on stopped motorist speeds at the 10th and 20th percentiles for Massachusetts and West Tennessee, and only a 1 to 1.5 percentage point shift in the speed distribution for East Tennessee. However, the negative shift in the minority motorist speed distribution from daylight to darkness increases in magnitude at higher percentiles. Massachusetts has a decrease of speed in daylight of 11 to 12 percentage points at the 80th and 90th percentile and East Tennessee has a decrease of 3 percentage points at the 70th percentile. In West Tennessee, the maximum shift in the speed distribution is less than one percentage point.

The much larger shift in Massachusetts appears reasonable given the higher rates of minority motorist stops in the Massachusetts data. The next largest shift in speed occurs in East Tennessee. Notably, this finding occurs even though the VOD test revealed no evidence of racial discrimination in stops for East Tennessee. East Tennessee is consistent with the change in motorist behavior in darkness having dominated the change in police stop behavior, preventing the VOD test from detecting discrimination. Further, we find no evidence of speed distribution shifts for white motorists between daylight and darkness or over available motorist and vehicle attributes.

Finally, we calibrate a model to the speed distribution of stopped motorists and the share of stops made of African-Americans motorists in daylight and darkness.[12] Overall, the calibrated models do a very good job of matching the empirical moments. Most significantly, the calibration for East Tennessee is able to match both the shift in the speed distribution of stopped African-American Motorists between daylight and darkness and produce a VOD test statistic that is near one in magnitude, which is typically interpreted as evidence of equal treatment. In East Tennessee, the daylight stop cost for African-American motorists is substantially below the darkness stop costs, and the daylight decrease in stop cost is similar to

[12] We calibrate to aggregate moments, more common in macroeconomics, rather than estimating the structural model using micro data due to the large computational requirements.

the increase in officer pay-off arising from a two standard deviation increase in motorist speed. The calibrated racial differences in Massachusetts are very large implying pay-off differences similar to a five standard deviation increase in the speed. In West Tennessee, the small shift in the speed distribution implies much smaller racial differences in stop costs equivalent to only one-half of a standard deviation change in speed. Finally, we simulate the model while forcing motorist behavior to remain unchanged in daylight, which implies an increase in the VOD test statistic from 1.00 to 1.22 in East Tennessee, a noticeably smaller increase of 1.09 to 1.17 in West Tennessee, and a very large increase of 1.38 to 2.74 in Massachusetts.

The racial differences in speeding stops against African-Americans by Massachusetts and Tennessee police contributes to the literature examining racial differences in the legal system including police stops (Grogger and Ridgeway 2006; Ridgeway 2009, Horrace and Rohlin 2016, Ritter 2017, and Kalinowski, Ross and Ross 2019b), fines (Goncalves and Mello 2017, 2018), searches (Knowles, Persico, and Todd 2001; Dharmapala and Ross 2004; Anwar and Fang 2006; Antonovics and Knight 2009; Marx 2018), use-of-force (Fryer 2019; Knox, Lowe and Mummolo 2019), bail (Ayres and Waldfogel 1994; Arnold, Dobbie and Yang 2018) and jury trials (Anwar, Bayer, and Hjalmarsson 2012; Flanagan 2018). Further, our model of minority responses to discrimination is relevant to theoretical models of statistical discrimination (Lundberg and Startz 1983; Lundberg 1991; Coates and Loury 1993; Moro and Norman 2003, 2004), decisions on investment in skills and education (Lang and Manove 2011; Arcidiacono, Bayer and Hizmo 2010) and the interpretation of audit/correspondent studies (Heckman 1998; 2004, National Research Council 2004 p109-113).

2. Simple Model of Police-Motorist Interaction

We develop a model of police traffic stops and consider the effect of discrimination on the driving behavior of minority motorists. We impose two key requirements based on important aspects of police and motorist behavior: (1) While motorists committing severe infractions, e.g. higher speeds, are overall more likely to be stopped, motorists are sometimes stopped (not stopped) for more modest (severe) infractions; (2) Some motorists may also choose not to commit infractions. Specifically, we specify a model where the cost faced by police to stop a motorist depends upon a both race and an additional stochastic component capturing circumstance costs. Circumstance costs might include environmental factors, officers' idiosyncratic preferences, and current officer enforcement activities. As a result, motorists always faces a positive probability of a stop even when committing a low-level infraction, but are never stopped with certainty even when committing severe infractions. In response, heterogeneous motorists select an optimal infraction level by trading off benefits against the expected costs of committing an infraction. Some motorists with very low returns from infractions choose not to infract. Thus, changes in stop costs have both intensive and extensive effects on the distribution of motorist infractions and police stops.

This approach differs from models of police search like Knowles, Persico and Todd (1999) or Persico and Todd (2008). In those models, motorist uncertainty about being stopped for an infraction arises because in equilibrium motorists adjust their decision to carry contraband until police are indifferent between searching and not based on the share of motorists carrying contraband. As a result, police randomize their search decision.[13] Models of police search must depend upon the equilibrium likelihood of guilt because guilt is unobserved prior to search. In our case, however, the severity of the moving violation is observed by police prior to determining whether to stop the motorist, and so the individual's behavior is the most relevant information on which to base the police stop decision.[14]

2.1. The Police Officer's Problem

The officer's decision to stop a motorist $\gamma(i, d, \phi)$ is made after observing a non-negative infraction severity i (e.g. speed above the limit) that would yield a pay-off from stop of $u(i)$, motorist type/demography d, and circumstances surrounding the stop ϕ. The officer's utility maximization problem takes the form

$$\max_{\gamma(i, s_d, \phi)} [u(i) - h(\phi) - s_d] \gamma(i, s_d, \phi) \quad (1)$$

[13] Dharmapala and Ross (2004) and Bjerk (2007) extend these models so motorists may not be observed by police. In our model, being unobserved would raise circumstance specific stop costs and prevent stops.

[14] In principle, police may also care about aggregate stop patterns and adjust to changes in motorist driving behavior. However, our results on the ambiguity of stop-rate based tests would still hold since our model is a special case of this possible generalization.

where we define s_d as a fixed component of stop costs associated with a motorist type while $h(\phi)$ represents circumstantial costs.

We make the following assumptions about police pay-offs and costs

Assumption 1.1 u *is continuous and twice differentiable over positive values of its argument,* $\frac{du(i)}{di} > 0$ *and* $\frac{d^2u(i)}{di^2} > 0 \; \forall \; i > 0$, $lim_{i \to 0^+} u(i) = u_0 > 0$, *and* $u(i) = 0 \;\; \forall \;\; i \leq$

Assumption 1.2 $\phi \sim Uniform(0,1)$*;*

Assumption 1.3 h *is a continuous, twice differentiable function defined over* $[0,1)$, $\frac{dh(\phi)}{d\phi} > 0 \; \forall \; 0 \leq \phi \leq 1$, $lim_{\phi \to 1} h(\phi) = \infty$, *and* $h(0) = 0$*;*

Assumption 1.4 $u_0 - s_d > 0, \; u_0 > 0, \;\; s_d > 0 \;\; \forall \;\; d$

In Assumption 1.1, we assume u is discontinuous at zero so that the officer receives no pay-off for stopping a non-infracting motorist, but has a pay-off bounded away from zero for any positive infraction level. We also assume that u has increasing total and marginal pay-off with respect to infraction severity. These assumptions are consistent with the penalty structures in many states. In Assumption 1.2, we assume circumstances are drawn from a uniform $(0,1)$ distribution and allow the monotonically increasing function $h(\phi)$ to capture possible non-linearities in the mapping between circumstances and costs. Therefore, Assumption 1.3 does not directly impose sign restrictions on the second derivative of h to allow for generality over circumstance costs. However, the assumption $lim_{\phi \to 1} h(\phi) = \infty$ implies that the second derivative of h must be positive as ϕ approaches one. Finally, Assumption 1.4 requires a positive net pay-off of stop under favorable circumstances, sufficiently low ϕ, even for small positive infraction levels. Therefore, the probability of stop is bounded away from zero for any non-zero infraction level creating a situation where motorists might choose to not commit infractions (modeling requirement 2 above).

The solution to the officer's problem implies an optimal infraction threshold above which the officer makes a stop with certainty and below which the officer does not make a stop.[15] Given the officer's net utility of $u(i) - h(\phi) - s_d \; \forall \, i$, the solution to her utility maximization problem is simply

$$\gamma(i, s_d, \phi) = \begin{cases} 1, & \text{if } u(i) > h(\phi) + s_d \\ 0, & \text{otherwise.} \end{cases}$$

Solving for the infraction level with zero net pay-off implies a threshold severity of

$$i^*(\phi, s_d) = u^{-1}(h(\phi) + s_d) \tag{2}$$

where u^{-1} maps from stop costs (u_0, ∞) to stop thresholds within $(0, \infty)$.[16]

Conditional on infraction severity and stop costs, we can solve Equation (2) for the circumstances $\phi^*(i, s_d)$ when net pay-off is zero by exploiting the monotonicity of $h(\phi)$.

$$\phi^*(i, s_d) = h^{-1}(u(i) - s_d) \tag{3}$$

Based on Assumption 1.3, h^{-1} maps from stop costs $(0, \infty)$ to stop circumstances $(0,1)$.[17] ϕ is distributed uniform, and so Equation (3) represents the unconditional (i.e. circumstances not observed) probability that an officer stops a motorist with infraction level i.

Lemma 1. *(i) The infraction level representing the optimal stop-threshold,* $i^*(\phi, s_d) = u^{-1}(h(\phi) + s_d)$*, is increasing in officer circumstances and demographic stop cost, and these derivatives are finite for a finite* ϕ*. (ii) The probability of an officer making a stop,* $\phi^*(i, s_d) = h^{-1}(u(i) - s_d)$*, is decreasing in stop cost and increasing in the level of infraction, and these derivatives are finite for finite* i*. (iii) The* $\lim_{i \to 0} \phi^*(i, s_d) > 0$ *for all* s_d.

The results in Lemma 1 arise directly from the assumptions above. Formal proofs for all Lemmas and Propositions are provided in Appendix B of the supplemental materials.

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[15] In principle, γ could be a probability between zero and one if the net return were zero, but since ϕ follows a continuous distribution and h is a monotonic, continuous function zero return to stop only arises on a set of measure zero. Unlike Knowles, Persico, and Todd (1999) and Persico and Todd (2006), circumstantial costs imply that motorists' adjustment no longer yields police indifference between stopping and not stopping motorists.

[16] We also note that $h(\phi) + s_d$ is always greater than u_0 for all combinations i and ϕ where $u(i) = h(\phi) + s_d$.

[17] We note that based on Assumption 1.4 $u(i) - s_d$ is always greater than zero for positive i.

In this model, discrimination arises if police officers have lower demographic cost of stopping a minority *(m)* relative to the majority *(w)*, $s_m < s_w$. A standard statistic for evaluating racial discrimination in stops is the relative share of stops involving minority motorists, or

Definition 1. $K_f \equiv \frac{p[m|stopped, s_m, f(i,m)]}{p[w|stopped, s_w, f(i,w)]} = \frac{\int_0^\infty f(i,m)\phi^*(i,s_m)di}{\int_0^\infty f(i,w)\phi^*(i,s_w)di}$

where $f(i,d)$ is the distribution of infraction severity by motorist type. Holding majority motorist stop costs fixed, discrimination (or an increase in discrimination) can be represented as a decrease in minority stop costs. Proposition 1 is consistent with the typical assumption that discrimination increases the relative stop rate of minority motorists (K_f).

Proposition 1. *A decrease in the stop costs of minority motorists,* s_m*, will increase the relative stop rate of minority motorists,* K_f.

This proposition is established by simply examining the derivative of K_f with respect to s_m.

2.2. The Motorist's Problem

The motorist problem can be characterized as a trade-off between the benefit of committing an infraction $b(i,c)$, which depends on motorist preferences c, e.g. recklessness, criminality, stress, timing of trip, sleep deprivation, etc. and the expected cost of being stopped, or

$$\max_{i(c,s_d)} b(i,c) - \tau(i)\phi^*(i,s_d)d\phi \quad (4)$$

where the cost of being stopped for committing an infraction is $\tau(i)$ and the probability of being stopped is $\phi^*(i,s_d)$.

We make the following assumptions about motorist's constraints and preferences

Assumption 2.1 b *is a continuous, twice differentiable, non-negative function,* $\frac{\partial b}{\partial i} > 0$ *and* $\frac{\partial^2 b}{\partial i^2} < 0 \;\forall\; c$ *and* $i \geq 0$, $b(0,c) = 0$, *and* $lim_{c\to-\infty} b(i,c) = 0 \;\forall\; i$*;*

Assumption 2.2 $\frac{\partial b}{\partial c} > 0$ *and* $\frac{\partial^2 b}{\partial c \partial i} \geq 0 \;\forall\; c$ *and for* $i \geq 0$*;*

Assumption 2.3 τ *is a continuous, twice differentiable, positive function,* $\frac{d\tau}{di} > 0$ *and* $\frac{d^2\tau}{di^2} > 0$ *for* $i \geq 0$, *and* $\tau(0) > 0$*;*

Assumption 2.4 $\frac{\partial b}{\partial i}|_{i=0} \geq \frac{d\tau}{di}|_{i=0} h^{-1}(u_0 - s_d) + \tau(0) h^{-1'}(u_0 - s_d) \;\forall\; c$ *and* $\lim_{i\to\infty} \frac{d\tau}{di} > \frac{db}{di}$

Assumption 2.5 $\frac{\frac{d^2u}{di^2}}{\frac{du}{di}} \geq \frac{-h^{-1''}}{h^{-1'}}\frac{\partial u}{\partial i}$ *and* $\frac{\frac{\partial \tau}{\partial i}}{\tau(i)} > \frac{-h^{-1''}}{h^{-1'}}\frac{\partial u}{\partial i} = \frac{\partial^2 \phi^*}{\partial i \partial s_d}\left(-\frac{\partial \phi^*}{\partial s_d}\right)^{-1}$ *for* $i \geq 0$

Assumptions 2.1-2.4 are relatively standard assumptions. In Assumption 2.1, we assume that the motorist benefit or pay-off is an increasing function of infraction severity and that marginal benefit is diminishing. In Assumption 2.2, we assume that both the benefit and the marginal benefit of infracting rise with c, which simply initializes the effect direction of the preference parameter. In Assumption 2.3, we assume that the motorist's cost and marginal cost are increasing in infraction severity. In the last part of Assumption 2.3, we assume that motorist's cost is bounded away from zero for small infraction levels, consistent with fine schedules. This assumption combined with Lemma 1 allows for the existence of inframarginal motorists who do not commit an infraction (modeling requirement 2). To assure an interior optimal infraction level for motorists who choose to commit an infraction, Assumption 2.4 requires that the slope of the cost function is less than the slope of the benefit function when i equals zero and greater than the slope of the benefit function at large i.

Assumption 2.5 imposes two technical assumptions that the curvature (relative to the slope) of the officer's utility function and the relative slope of the cost function both exceed in magnitude the cross partial derivative of ϕ^* relative to the first derivative of ϕ^* with respect to s_d. Effectively, this restriction places a limit on how quickly the negative relationship between the probability of a stop and stop costs can fall as infraction severity increases. In terms of the primitives, the positive slope of h^{-1} cannot decrease too quickly, or equivalently the positive relationship between circumstances and stop costs cannot increase too quickly in percentage terms. The first restriction allows us to sign the second order condition of the motorist's problem assuring a unique, interior optimum infraction level.[18] The second restriction assures that infraction severity responds to stop costs in the expected manner, i.e. increasing when police find it more costly to stop motorists.

Based on these assumptions, we derive the properties of the optimal motorist infraction level.

[18] As shown in the proof of Lemma 2, this assumption is only required to establish uniqueness, not existence.

Lemma 2. (*i) There exists a unique optimal infraction level* i' *on* R^+ *for a motorist of type* $\{c, d\}$. *(ii) The optimal infraction level is increasing in preferences* c, *increasing in stop costs* s_d, *and the first derivatives of this infraction level function are finite.*

The curvature restrictions imposed on h^{-1} by Assumption 2.5 are required to establish Lemma 2 because motorists are making decisions based on the expected cost of committing an infraction, $\tau(i)\phi^*(i, s_d)$. As i becomes large, the curvature of $\tau(i)$ dominates as $\phi^*(i, s_d)$ approaches a constant, but at low infraction levels rapid changes in the relationship between stop probability and infraction level as stop costs change can dominate the changes in the infraction penalty function $\tau(i)$. Without the curvature assumptions, motorists could decrease their infraction level as stop costs rise and the likelihood of stop falls, creating the possibility of multiple interior, infraction-level optima.

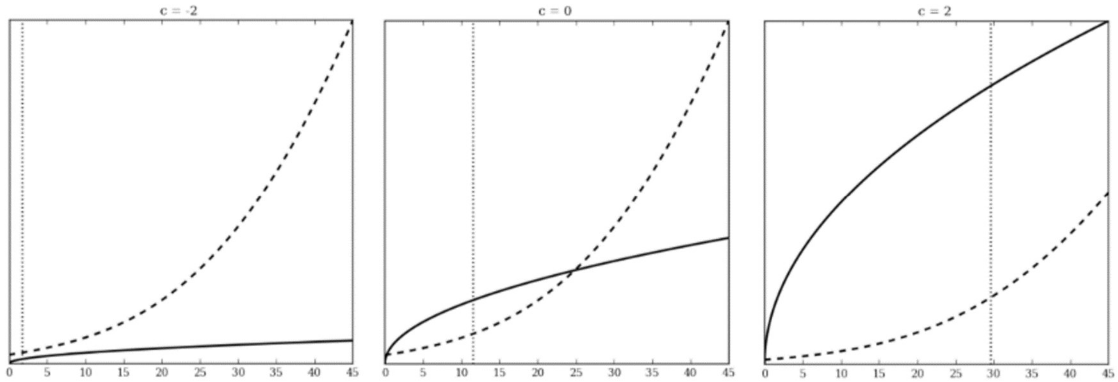
Next, we define i^{**} as the actual infraction level of the motorist. If the pay-off from the interior, optimal infraction level is positive then $i^{**} = i'$, but if negative then $i^{**} = 0$ and if zero motorists are indifferent between infracting and not. Then, motorists with sufficiently low values of c will choose not to commit an infraction (modeling requirement 2).

Lemma 3. (*i) As long as some motorists chose to commit infractions at finite* c, *there exists a threshold* c^* *on* R *above which motorists commit a traffic infraction at the optimal level* i' *and below which motorists do not commit an infraction or* $i' = 0$. *(ii)* $lim_{c \to c^{*+}} i^{**} > 0$ *where the plus sign indicates the limit from above. (iii) If* c^* *exists, it is decreasing in* s_d.

The non-convexity in the police pay-off and motorist penalty at $i = 0$ leads to a situation where the motorist benefit at the optimal, positive infraction level can be smaller than the expected cost of stop. Figure 1 illustrates the optimization problem presenting benefits and costs over infraction level for different values of the preference parameter.[19] Starting on the left with a low value of $c = -2$, the benefit curve lies below the expected cost curve and motorists choose not to infract. As c increases, the benefit function increases and crosses the expected cost function yielding an positive optimal infraction level above a threshold c^*.

[19] Note that the data used to generate this figure and the two figures that follow comes from the calibrated simulation of the model for Massachusetts that is described in Section 5.

Figure 1: Motorist Benefits and Expected Costs by the Preference Parameter



As above, discrimination arises when police officers have a lower cost of stopping a minority $s_m < s_w$. However, the standard statistic for racial discrimination in police stops can now be written utilizing the distribution of motorists over preferences $g(c, d)$.

Definition 2. $K_g \equiv \frac{p[m|stopped, s_m, g(c,m)]}{p[w|stopped, s_w, g(c,w)]} = \frac{\int_{c^*(s_m)}^{c_h} g(c,m)\tilde{\phi}(c,s_m)di}{\int_{c^*(s_w)}^{c_h} g(c,w)\tilde{\phi}(c,s_w)di}$

where $\tilde{\phi}(c, s_d) \equiv \phi^*(i'(c, s_d), s_d)$. As in Proposition 1, discrimination against minority motorists can be interpreted as a decrease in minority motorist stop costs. However, a decrease in stop costs now operates through two effects: 1. a change in the probability of stop $\tilde{\phi}$ for motorist's who were infracting and 2. an increase in the threshold at which motorists begin to commit infraction.

The purpose of this model is to allow us to examine whether the behavioral adjustments of motorists can reverse Proposition 1 that decreases in minority motorist stop costs lead to a higher share of minorities among stopped motorists. In fact, both of these effects can potentially work against Proposition 1. Unlike the prior case where we considered motorist behavior as exogenous, the derivative of $\tilde{\phi}$ is ambiguous in sign

$$\frac{d\tilde{\phi}}{ds_d} = \frac{\partial \phi^*}{\partial s_d} + \frac{\partial \phi^*}{\partial i}\frac{\partial i'}{\partial s_d} <> 0 \tag{8}$$

A decrease in stop costs directly raises the likelihood of stop, first term of Equation (8), but it also reduces the equilibrium infraction level of motorists which in turn reduces stop likelihood, the second term. Without a closed form solution for i', we cannot sign the derivative. Intuitively, motorists who travel slower in response to a decreased stop costs will likely not travel so much slower that the effect of their behavioral response is larger than the direct effect of the change in stop cost.[20] This belief is consistent with stops costs and relative stop rates moving in opposite directions, as in Proposition 1. Thus, we expect that violations of Proposition 1 will be driven primarily by the second effect arising from changes in the share of motorists who choose not to infract.

Proposition 2. *Given the general motorist and officer problems defined above, equilibria exist where a decrease in s_m leads to a decrease in K_g.*

As with Proposition 1, this proposition is established by examining the derivative of K_g with respect to s_m. A decrease in stop costs will lead to a direct change in the equilibrium stop probability that likely raises the share of minorities stopped, as well as decreasing the share of minority motorists who commit infractions and are at risk of being stopped. This second negative effect can dominate the direct effect if either the density of inframarginal motorists at c^* or the change in c^* with stop cost is large enough to counteract changes in stop probabilities. Any parameters that change the responsiveness of c^* to stop costs also influence stop probabilities, and so the proof in the appendix creates a counterexample by modifying the density of motorists at c^*. Figure 2 illustrates the response of motorists to discrimination using daylight stop costs calculated from the model calibrations presented later in the paper. Lower stop costs lead to a large increase in the threshold for committing infractions and a modest decline in severity for motorists who commit infractions.

2.3. Equilibrium Distribution of Infraction Levels

Finally, we examine the infraction distribution of stopped motorists. We demonstrate that discrimination shifts the distribution of stopped motorist infraction severity downwards to less severe infractions above a certain percentile threshold. We rely on this property of our

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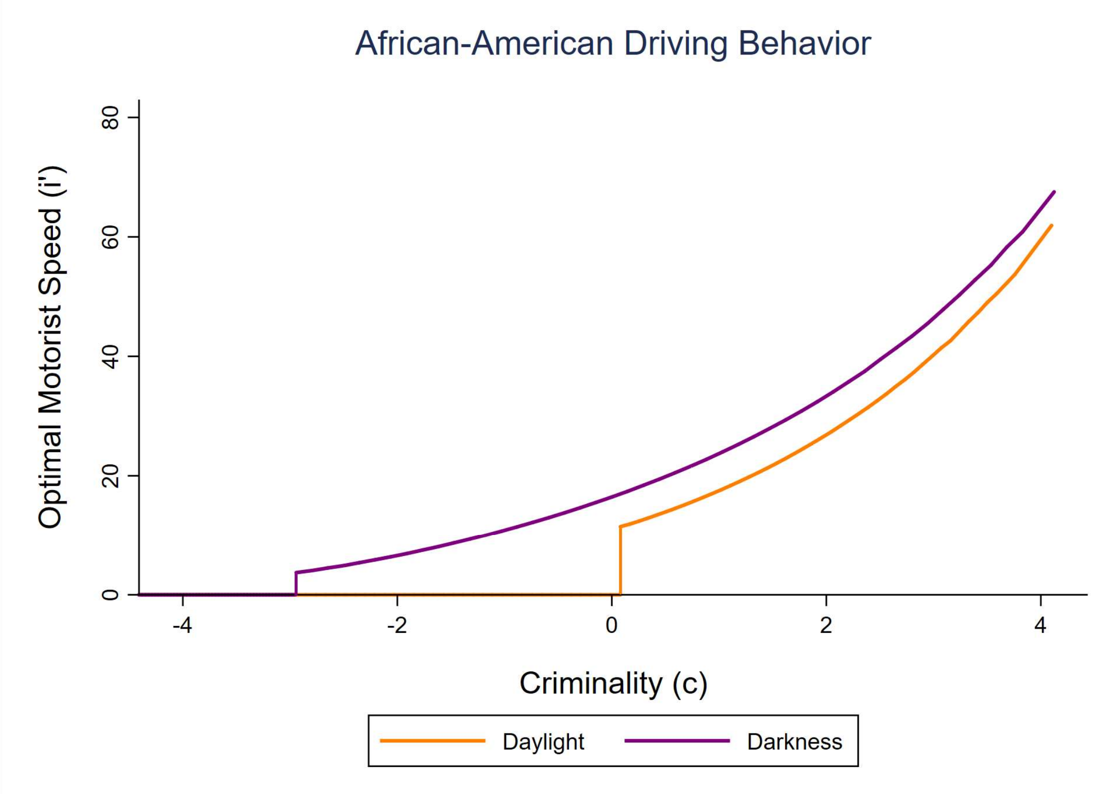
[20] This belief will be satisfied if $\frac{\partial u}{\partial i}\frac{di'}{ds_d} < 1$. In other words, the utility from police stops must rise sufficiently slowly with infraction level that the effect of stop-cost on infraction does not reverse the direct effect on the likelihood of a stop. This condition can be derived from the following equation $\frac{d\tilde{\phi}}{ds_d} = -h^{-1'}(u(i) - s_d) * \left(1 - \frac{\partial u}{\partial i}\frac{di'}{ds_d}\right)$.

Figure 2: Speeding Violations of Motorists by Preference Parameters and Visibility



model for our empirical analyses of the speed distribution of stopped motorists. For convenience, we suppress the minority indicator on the probability distribution $g(c, m)$.

We characterize changes in the observed infraction severity distribution by examining the effect of a change in s_m on severity level i_x of motorists at a specific percentile x in the speed distribution of stopped motorists. Conditional on s_m and motorist preference $c \geq c^*(s_m)$, we write a stopped motorist percentile by integrating over the product of the pdf of c and the equilibrium probability of stop $\tilde{\phi}(c, s_m) = \phi^*(i'(c, s_m), s_m)$, or

$$x(c, s_m) = \frac{\int_{c^*(s_m)}^{c} g\,(c')\phi^*(i'(c', s_m), s_m)\, dc'}{\int_{c^*(s_m)}^{\infty} g\,(c')\phi^*(i'(c', s_m), s_m)\, dc'}$$

where the numerator captures the mass of stopped motorists below c and the denominator captures all stopped motorists. Similarly, we can pick a percentile x and write the preference parameter of the motorist as an implicit function c_x of the percentile.

$$\int_{c^*(s_m)}^{c_x(x,s_m)} g\,(c')\phi^*(i'(c',s_m),s_m)\,dc' = x\int_{c^*(s_m)}^{\infty} g\,(c')\phi^*(i'(c',s_m),s_m)\,dc' \tag{9}$$

Finally, we define the equilibrium infraction level of stopped motorists at each percentile by substituting c_x into i'.

Definition 3. $i_x(x,s_m) \equiv i'(c_x(x,s_m),s_m)$

Next, we impose several assumptions to assure that the motorist problem is well behaved as x limits to one. If the density of c is positive over R, c limits to infinity as x limits to one, $x < 1$ for all finite c, and infraction level i may limit to infinity as x limits to one. So, we strengthen the second part of Assumption 2.5 on the relative curvature of h^{-1}.

Assumption 3.1 $\lim_{i\to\infty}\left(\frac{\partial\tau}{\partial i}h^{-1'} + \tau(i)h^{-1''}\frac{\partial u}{\partial i}\right) = L > 0$ *where* L *is finite and the derivatives of* h^{-1} *are evaluated at* $(u(i) - s_m)$.

Assumption 2.5 assures that this expression is positive on R^+, and Assumption 3.1 extends this condition on the curvature of h^{-1} so that this expression does not limit to zero as infraction level increases. Next, we impose assumptions on the police and motorist problems as c and $i'(c,s_m)$ limit to infinity.

Assumption 3.2 $\lim_{i\to\infty}\frac{d^2u}{di^2} = 0$, $\lim_{i\to\infty}\frac{d^2\tau}{di^2} > 0$, $\lim_{c\to\infty}\frac{\partial^2 b}{\partial i^2} \geq 0$, $\lim_{i\to\infty}\left(\tau(i)h^{-1'}\right) \neq \infty$ *where* $h^{-1'}$ *is evaluated at* $(u(i) - s_m)$, $\lim_{c\to\infty}\frac{\partial^2 b}{\partial c\partial i} \geq 0$, *and all limits listed in the assumption plus* $\lim_{i\to\infty} h^{-1''}$ *exist and are finite.*[21]

The restriction on the second derivative of u assures that the limit of the first and second derivatives of ϕ^* are both zero, consistent with ϕ^* asymptotically approaching one or some

[21] The existence requirement of assumption 3.2 eliminates situations where the second derivative of functions could oscillate in sign. Such oscillation allows the first derivative to limit to zero even if the second derivative does not exist. The classic example of this is $f'(x) = 1 + \sin(x^2)/x$ where $\lim_{x\to\infty} f(x) = 1$, a horizontal asymptote, but $f''(x) = 2cos(x^2) - \sin(x^2)/x^2$ and the limit of the second derivative does not exist.

upper limit as i approaches infinity and assuring that stop is never certain for a finite i. The restrictions on the limits of the second derivatives of τ and b and on the limit of $\tau(i)h^{-1'}$ are required so that the limit of the second order condition is finite and non-zero as i increases. Note that a finite, non-zero second derivative of τ implies that the first derivative of τ limits to infinity based on a finite, non-zero rate of change. Therefore, we also restrict the cross-partial derivative of b to be finite so that the first derivative of b will also limit to infinity with c based on a finite rate of change. So, in cases i' limits to infinity with c, the marginal costs and benefits of the first order condition from the motorist's problem will both move together.

Lemma 4. *(i)* $\lim_{i\to\infty}\frac{\partial\phi^*}{\partial i}=0$ *and* $\lim_{i\to\infty}\frac{\partial^2\phi^*}{\partial i^2}=0$, *(ii) if* $\lim_{c\to\infty}\frac{\partial^2 b}{\partial c\partial i}=0$ *then* $\lim_{c\to\infty} i'(c,s_d)=I(s_d)$, *while if* $\lim_{c\to\infty}\frac{\partial^2 b}{\partial c\partial i}>0$ *then* $\lim_{c\to\infty} i'(c,s_d)=\infty$ *, (iii).* $\lim_{c\to\infty}(SOC)_{i=i'}\neq 0$ *and finite.*

Finally, we impose a key restriction on the distribution of c. The intuition behind the proposition below is based on fact the that adding population to the bottom of a distribution has a much larger effect on the bottom of the distribution than on the top. For example, increasing the total population by 11 percent by adding people to the bottom will shift the person who was originally at the bottom to the 10th percentile, while only moving someone originally at the 90th percentile to about the 91st percentile. The difficulty arises if the density over the preference parameter approaches zero as the preference parameter becomes large requiring larger and larger changes in c to move the percentile as c approaches infinity. Then, small percentile changes at the top of the distribution could have large impacts on preferences and infraction levels. To rule this out, we first require the distribution be continuous, and then place restrictions on how quickly the probability density can limit to zero.

*A**ssumption 3.3*** *The domain of the non-zero values of the probability distribution of* c *is continuous, or equivalently for any* c *where* $g(c)\neq 0$ *if there exists* $c_h>c$ *where* $g(c_h)=0$ *then* $g(c')=0$ *for all* $c'>c_h$ *and if there exists* $c_l<c$ *where* $g(c_l)=0$ *then* $g(c')=0$ *for all* $c'<c_l$. *Given this continuity assumption, if the domain of* g *is not bounded above, i.e. there exists a* c_l *such that* $g(c)\neq 0$ *for all* $c>c_l$, *then* $\lim_{c\to\infty}{(1-G(c))}/{g(c)}=0$. *On the other hand, if the non-zero domain of* g *ends at* c_h, *i.e. there* *exists a* c_h *such that* $G(c) \neq 0$ *for* $c_l < c < c_h$ *for some* $c_l \neq c_h$ *and* $G(c) = 0$ *for* $c > c_h$*, then either* $g(c_h) \neq 0$ *or* $\lim_{c \to c_h} {(1 - G(c))}/{g(c)} = 0$.

One can verify manually that this assumption encompasses several well-known probability distributions by applying L'hopital's rule to the limit in Assumption 3.3

$$\lim_{c \to \infty} {(1 - G(c))}/{g(c)} = \lim_{c \to \infty} {-g(c)}/{g'(c)} = 0$$

The generalized normal distribution $g(c) = k(\beta, \sigma)e^{-\sigma^{-1}|c|^{\beta}}$ satisfies these requirements for all $\beta > 1$ including the normal distribution, but excluding the Laplace distribution where $\beta = 1$. The assumption is also satisfied for the skew normal distribution $g(c) = 2(2\pi\sigma)^{-1}e^{-\sigma^{-1}c^2}\Phi(c)$ where Φ is the CDF of the normal distribution, and the generalized gamma distribution $g(c) = l(\beta, \sigma, \delta)c^{\delta-1}e^{-b(c/\sigma)^{\beta}}$ for $\beta > 1$ including the Weibull distribution where $\delta = \beta$ if $\beta > 1$, but excluding the gamma distribution where $\beta = 1$. Assumption 3.3 tends to hold for probability distributions that include an exponential function and have a light tail, but does include distributions with heavier tails than the normal. However, the condition fails for distributions that contain an exponential that is linear in c, such as the Laplace or gamma distributions, or for distributions based only on powers of c, such as the pareto or Cauchy distributions.

Under these assumptions, discrimination will decrease the infraction levels of stopped motorists above some percentile $\tilde{x}$ of the infraction level distribution.

Proposition 3. *For all* s_m *there exists* $\tilde{x}$ *such that* $\frac{di_x}{ds_m} > 0$ *for all* $x > \tilde{x}$.

The proof in the appendix proceeds by differentiating $i_x(x, s_m)$ in Definition 3

$$\frac{di_x}{ds_m} = \frac{di'}{ds_m} + \frac{di'}{dc}\frac{dc_x}{ds_m}$$

Assumptions 2.5 and 3.1 imply that optimal motorist infraction level increases as stop costs rise. However, changes in the distribution of infraction severity are ambiguous because additional motorists who had chosen not to infract due to weak preferences may now choose to commit an infraction given higher stop costs and c_x falls as those additional motorists are added to the bottom of the distribution.

However, this phenomenon grows weaker as we move further out the speed distribution. Additional infracting motorists added at the bottom of the distribution result in only a fraction of motorists at a fixed preference level c being shifted across any percentile. As the percentile x approaches one (top of the speed distribution), the first term in the derivative of i_x (the partial derivative of i') remains bounded away from zero, while the share shifted across the percentile, i.e. the derivative of c_x, approaches zero.

$$\frac{dc_x}{ds_m} = \frac{1}{\phi^*(i'(c_x, s_m), s_m)g(c_x)}\left((1-x)\frac{dc^*}{ds_d}g(c^*)\phi^*(i'(c^*, s_m), s_m) + -(1-x)\int_{c^*(s_m)}^{c_h} g(c')\frac{d\tilde{\phi}}{ds_m}\,dc' + \int_{c_x}^{c_h} g(c')\frac{d\tilde{\phi}}{ds_m}\,dc'\right)$$

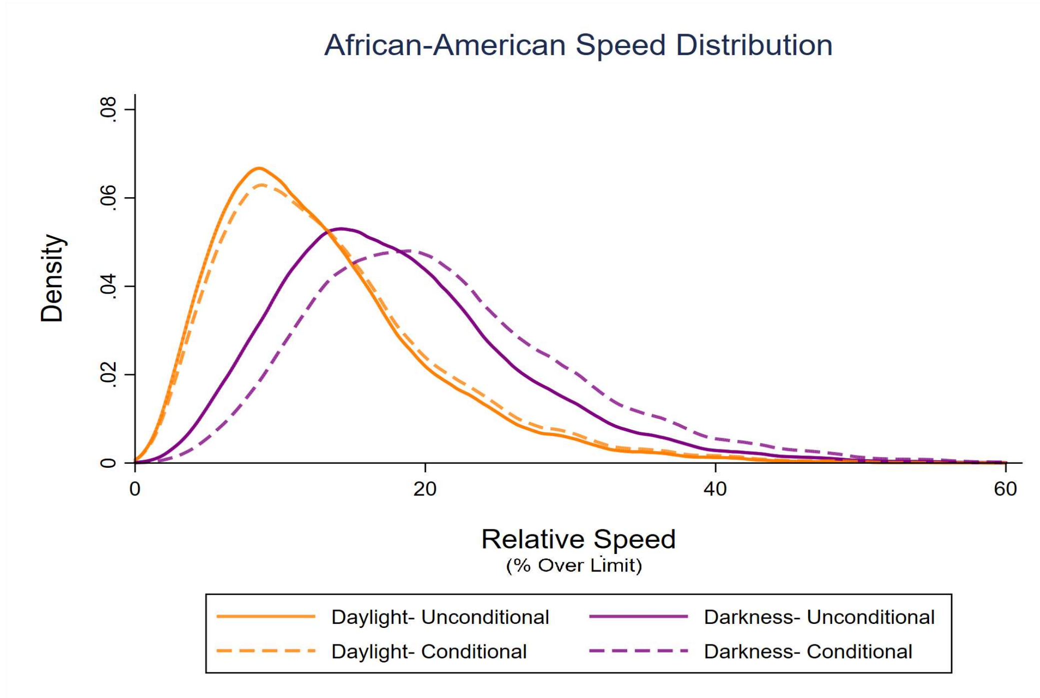
The first two terms in parentheses are proportional to $(1-x)$ and the last term is shown in the proof of the proposition to be bounded by an expression that is proportional to $(1-x)$, and so the derivative limits to zero. As a result, any significant increase in the speed of stopped minority motorists near the top of the speed distribution is suggestive that minority motorists may be responding to real or perceived discrimination.

Note that the effects discussed above are driven primarily by the selection of motorists into committing infractions, rather than selection into stop. Figure 3 illustrates this by plotting the empirical distribution of minority speeders (solid lines) and minority motorists stopped for speeding (dashed lines) with discrimination (daylight) and without (darkness) using the model calibration for Massachusetts from below. The speed distribution is substantially slower with discrimination whether based on all speeders or stopped motorists only.

3. Evidence from Accident Data

In the empirical work below, we exploit the logic of the Veil of Darkness (VOD) examining motorist race in daylight and darkness at the same time of day in order to circumvent the problem that racial composition of motorists at risk of an accident is unknown. We examine a national sample of traffic accidents for evidence of whether minority motorists adjust their driving behavior in response to lighting conditions, possibly driving more conservatively and safely in daylight when race can be observed. Unlike the data on police stops, accident data provides evidence on the driving behavior of minority motorists where the racial composition

Figure 3. Speed Distribution of Motorists who Commit Infractions by Visibility



is not directly affected by the composition of police stops. Therefore, we believe that the patterns uncovered in the accident data can be attributed to changes in motorist driving behavior, presumably in response to actual or perceived discrimination.

Our sample is drawn from the National Highway Traffic Safety Authority's Fatality Analysis Reporting System (FARS) data, which documents all automobile accidents in the United States involving one or more fatalities. This dataset documents the race and ethnicity of fatalities, and we restrict our sample to accidents where the motorist died and were either an African-American or a Non-Hispanic white. The overall sample consists of 282,924 motorist fatalities from a total of 615,826 accidents involving a fatality that occurred in the contiguous United States from 2000 to 2017.[22]

Following Grogger and Ridgeway (2006), we further limit our sample to 39,076 traffic fatalities where the accident occurred within a window of time between the earliest and

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[22] Observations are weighted by the inverse number of fatalities involved in a given accident. For instance, when both drivers from a two-car accident die, we give each of those fatalities a weight of one-half.

latest sunset of the year, the so-called inter-twilight window (ITW). Changes to the timing of sunset occur within this window due to both seasonal variation and the discrete spring/fall daylight savings time (DST) shifts. We identify accidents occurring within the ITW based on data from the United States Naval Observatory (USNO) denoting the bounds of the ITW using the eastern and westernmost coordinates of each county where the accident occurred. The lower bound of the county-specific window is the earliest annual easternmost sunset and the upper bound is the latest westernmost end to civil twilight. Unlike many VOD studies of traffic stops, the FARS data also contains detailed reporting on the lighting conditions when an accident occurred. We use this self-reported measure rather than estimates of daylight based on USNO data to minimize measurement error in visibility. For a more thorough discussion of measurement error in VOD daylight measures, see Kalinowski et al (2019).[23]

Table 1 presents descriptive statistics with column 1 showing the means for the entire ITW sample, column 2 for the sample of accidents involving fatalities of African-American motorists and column 3 for the sample of white motorist fatalities. The African-American population is more male, older, drives newer vehicles, more likely to drive imported vehicles, and more likely to be involved in accidents that occur on weekends and in darkness.

We follow the standard logic of the VOD test by placing race (R_i) on the left-hand side of the equation and testing whether accidents occurring in daylight ($\overline{v}_i$) are more likely to be of African-American motorists using a linear probability model. We condition on day of the week (d) and hourly time of the day (t) fixed effects to assure that the effect of daylight is identified by comparing stops that were made when the composition of the drivers is expected to have been the same. The resulting estimation equation is

$$R_{idt} = \beta \overline{v}_{idt} + \delta_d + \gamma_t + \varepsilon_{idt} \tag{10}$$

where δ_d is the vector of day of the week fixed effects and γ_t contains the time of the day fixed effects. We also add state and year or state by year fixed effects. Since many models involve high dimensional fixed effects, we estimate linear probability models rather than

[23] In Appendix B Table B1, we present comparable results using USNO definitions of daylight and darkness and results are robust. As is standard, we disregard stops occurring each day during actual twilight when visibility is somewhere between daylight and darkness.

Table 1: Descriptive Statistics for the FARS Accident Data

Total Accidents		615,826		
Fatal Accidents		282,924		
Inter-Twilight		39,076		
Sample		All	AA	White
Daylight		53.44%	49.93%	53.95%
Motorist	African-American	12.83%	100.00%	0.00%
	Male	67.67%	72.22%	66.99%
	Young	42.74%	38.92%	43.31%
Auto.	Domestic	66.36%	62.25%	66.97%
	Old	22.05%	19.10%	22.48%
Day of Week	Sunday	14.03%	15.19%	13.86%
	Monday	13.49%	12.96%	13.57%
	Tuesday	12.91%	11.49%	13.11%
	Wednesday	13.50%	12.90%	13.59%
	Thursday	14.01%	13.52%	14.08%
	Friday	16.52%	16.15%	16.58%
	Saturday	15.54%	17.79%	15.21%
Hour of Day	4:00 PM	5.70%	3.23%	6.07%
	5:00 PM	22.97%	21.79%	23.14%
	6:00 PM	24.83%	24.83%	24.83%
	7:00 PM	21.53%	23.83%	21.19%
	8:00 PM	18.06%	19.64%	17.82%
	9:00 PM	4.87%	3.93%	5.01%
States + DC		49	49	49

Note: The overall sample includes only traffic stops involving African-American or Non-Hispanic white motorists.

logistic regression as used in Grogger and Ridgeway (2006). Kalinowski et al. (2019) demonstrate the equivalence of the linear probability and logistic regression tests in Grogger and Ridgeway (2006).[24] Standard errors are clustered at the state level in columns 1 and 2, but at the state by year level when the model includes state by year fixed effects.

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[24] Starting with Equation (6) in Grogger and Ridgeway (2006), they set the second term to zero (in the equation prior to taking the log) based on the assumption that motorist composition does not change between daylight and darkness. Then, one can replace the conditional probabilities for a representative motorist with the predicted probabilities arising from a linear probability model. For positive β in Equation (10) above, the test statistic is greater than one consistent with discrimination, and the statistic increases with increases in β.

Panel 1 of Table 2 reports the results from estimating Equation (10) using our sample of fatal accidents. Column 1 presents estimates for a model containing the controls in Equation (10) plus state and year fixed effects, while column 2 presents estimates for models that contain state by year fixed effects. Column 3 presents estimates after adding controls for motorist and vehicle attributes including motorist age and gender and vehicle age and whether the vehicle was an import. The estimates imply that the likelihood of a fatal accident involving an African-American decreases by 1.5 to 1.6 percentage points in daylight, relative to a mean of 12.8%. Lower fatality rates of African-Americans in daylight are consistent with African-American motorist driving more conservatively in daylight when race can be observed.

The behavior of minority motorists is also likely to be shaped by their perceptions of police behavior. Panels 2 and 3 present estimates based on interacting daylight with one of two different measures that might capture African-American perceptions about police treatment of minority motorists. The first proxy is the odds that an unarmed individual involved in a police shooting in a given state is African-American divided by the fraction of state residents who are African-American, where the values range from 0.04 (odds of 1.04) in Connecticut to 16.76 in Rhode Island..[25] The second proxy is a measure of real and perceived racism constructed using Google Trends data in a similar manner as Stephens-Davidowitz (2014).[26] The index that google trends produces is between 0 and 100, but has been

[25] Police shootings data comes from Mesic et al. (2018). However, findings are robust to shootings ratios from Fatal Encounters (https://fatalencounters.org/) or Mapping Violence (https://mappingpoliceviolence.org/).

[26] Stephens-Davidowitz (2014) uses the frequency of searches for racial slurs to capture the sentiment of whites about minorities. In our case, we are interested in the opposite, i.e. the sentiment of minorities in terms of real or perceived discrimination, particularly by police. Thus, we construct an index using Google Trends from 2004-20 by searching for the following words: police shooting, discrimination, racial profiling, prejudice, racism, and police complaint. Similar results arise using an index developed by Mesic et al. (2018) based on residential segregation, incarceration rates, and disparities in education and employment status.

Table 2: Estimated Change in the Accidents Rate for Minority Motorists in Daylight

LHS: African-American		(1)	(2)	(3)	(4)
Baseline					
Daylight		-0.01752*** (0.00412)	-0.01663*** (0.00392)	-0.01566*** (0.00399)	-0.01525*** (0.00398)
Observations		39076	39076	39076	39076
Interaction – Black-White Police Shootings Odds Ratio					
Daylight x Police Shootings		-0.00193 (0.00150)	-0.00356** (0.00150)	-0.00415*** (0.00159)	-0.00429*** (0.00158)
Observations		39063	39063	39063	39063
Interaction – Google Search Racism Index					
Daylight x Racism Index		-0.00886** (0.00364)	-0.01169*** (0.00345)	-0.01131*** (0.00358)	-0.01182*** (0.00355)
Observations		39063	39063	39063	39063
VOD Inconclusive States					
Daylight		-0.04642*** (0.01217)	-0.03559*** (0.01085)	-0.03324*** (0.01080)	-0.03381*** (0.01071)
Observations		6587	6587	6587	6587
Controls	Hour of Day	X	X	X	X
	Day of Week	X	X	X	X
	Year	X	X		
	State		X		
	State x Year			X	X
	Motorist/Vehicle				X

Notes: Coefficient estimates are presented where * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance. Standard errors are clustered at the state by year level. The sample includes only fatal accidents involving African-American or Non-Hispanic white motorists which occurred within the ITW in the contiguous U.S. from 2000 to 2017 involving at least one or more non-commercial automobiles (no motorcycle or pedestrian). Observations are weighted by the inverse number of observations per accident included within the sample. Panel 2 adds an interaction between daylight and the odds that an unarmed individual involved in a police shooting in a given state is African-American divided by the fraction of residents in the state who are African-American. Panel 3 adds an interaction between daylight and a statewide, standardized google trends index using the terms: "police shooting", "discrimination", "racial profiling", "prejudice", "racism", and "police complaint". Panel 4 repeats panel 1 for the subsample of states where the VOD test was conducted and results were inconclusive: Arizona, California, Connecticut, Louisiana, Missouri, North Carolina, Ohio, Oregon, and Rhode Island.

standardized and so ranges from –2.16 (index of 48.6) in Montana to 2.38 (index of 89) in Maryland. Both variables are cross-sectional characterizing states over the period from 2004 to 2020. The proxy for the perception of discrimination is positively associated with the reduction in the share of fatal accidents involving African-Americans in daylight relative to darkness. A doubling of the black-white odds of police shooting from even odds to odds of 2 to 1 implies an increase in racial differences associated with daylight fatalities of 0.4 percentage points, while a one standard deviation increase in the racism index implies a 1.2 percentage point increase in differences.

Next, in Panel 4, we restrict our FARS sample to the 9 states where the VOD test has been conducted on police traffic stops and either failed to find or found mixed evidence of discrimination.[27] We find even larger racial differences in this subsample. Daylight motorist fatalities are over 3 percentage points more likely to involve African-American motorists relative to a dependent mean of 13.2%, as compared to 1.5 percentage points relative to a mean of 12.8 for the entire sample. While these fatality differences do not imply discrimination in police stops, the data is suggestive that minority motorists are concerned about such stops, potentially affecting previous tests for discrimination.[28]

Lastly, we address the concern that the overall composition of motorists might change in response to daylight. Formal tests of balance are wholly absent in existing applications of the VOD test because traffic stop data alone cannot be used to disentangle changes in enforcement activity from compositional changes in traffic patterns. In our accident data, however, we can reasonably expect that police traffic stop behavior did not directly affect the composition of motorists and vehicle attributes associated with traffic

[27] The states are Arizona, California, Connecticut, Louisiana, Missouri, North Carolina, Ohio, Oregon, and Rhode Island. For convenience and to maintain a reasonably sized sample, we do not restrict our accident sample to the exact same time periods of VOD traffic stop studies in these states.

[28] We cluster standard errors by state by year due to the small number of states. This decision is conservative empirically in that clustering at the state level yields smaller standard errors than arise with state by year clustering.

fatalities, at least for those fatalities involving white motorists. We examine the composition of white non-Hispanic motorists involved in fatal accidents in Table 3. Columns 1-4 present models where daylight is regressed on whether the vehicle is domestic rather than import, the age of the vehicle in years, whether the motorist was male and whether the motorist was under the age of 30. Column 5 presents a model that includes all four of the motorist and vehicle attributes available. All models included hour of day, day of week and state by year fixed effects. The composition of fatal accidents for Non-Hispanic white motorists does not vary between daylight and darkness for these variables. No t-statistics are significant, and in the full

Table 3: Balancing Test of Accidents for White Motorists within the ITW

LHS: Daylight		(1)	(2)	(3)	(4)	(5)
Domestic Vehicle		0.00428 (0.00510)				0.00487 (0.00512)
Vehicle Age			-0.00589 (0.00547)			-0.00575 (0.00548)
Male Motorist				-0.00629 (0.00490)		-0.00668 (0.00491)
Young Motorist					0.00572 (0.00470)	0.00571 (0.00471)
Controls	Hour of Day	X	X	X	X	X
	Day of Week	X	X	X	X	X
	State x Year	X	X	X	X	X
R^2		0.35243	0.35243	0.35245	0.35244	0.35252
Observations		34050	34050	34050	34050	34050

Notes: Coefficient estimates are presented where * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance. Standard errors are clustered at the state by year level but robust to clustering on just state or year. The sample includes only fatal accidents involving Non-Hispanic white motorists which occurred within the ITW in the contiguous U.S. from 2000 to 2017 involving at least one or more non-commercial automobiles (no motorcycle or pedestrian). Observations are weighted by the inverse number of observations per accident included within the sample. Results are robust to restricting the sample to not-at-fault accidents as well as weighting the fatal accidents based on the likelihood of experiencing a fatality, estimated using detailed vehicular characteristics and restraint use. The F-statistic for the main variables of interest in specification five is 1.4 and a p-value of 77.82 percent.

model the F-statistic associated with the four estimates is 1.37 (p=0.24). Motorist race appears to be the only motorist or vehicle characteristic available for which differences in fatality rates correlate with daylight.[29]

In this section, we present evidence that minority motorists are involved in accidents at a lower rate during periods of daylight relative to equivalent periods of darkness. These changes in minority accident rates are larger in states with more police shootings and where there is a higher perception of racism. Further, these responses are especially large in states where VOD analyses of traffic stops have failed to find evidence of discrimination. This evidence is supportive of a view that African-American motorists realize that their race can be identified by police in daylight, and so choose to drive more conservatively and carefully during daylight hours. We also found that the accidents rates of non-Hispanic white motorists are invariant to changes in visibility across several motorist and vehicle characteristics, suggesting that this responsiveness to daylight is a phenomenon that is primarily about race.

4. Evidence from Traffic Stop Data

In this section, we present the results from an analysis of police traffic stops. Following previous studies, we focus on a subsample of stops made for moving violations, in our case speeding, since other violations (e.g. headlights, seatbelt, and cellphones) are possibily correlated with both visibility and race. Our focus on speeding stops also has the added advantage of providing a clear measure of infraction severity that we can use to assess changes in motorist driving behavior, i.e. speed relative to the speed limit. We analyze speeding stops in Massachusetts from April 2001 to January 2003 made by either the State Police or large

[29] Motorists might differ in their selection into the sample of fatalities. We have detailed data on all accidents involving a fatality, but only race and ethnicity for the fatalities themselves. Therefore, we also estimate inverse probability weighted models based on the likelihood that the motorist dies during a fatal traffic accident using vehicle attributes and information on restraints, i.e. airbags and seatbelt usage. The results presented above are robust to selection on these observables (Appendix Table B2). We do not include controls for airbags and seatbelt use in the models above because those controls may be endogenous to motorist risk-taking behavior.

municipal police departments in Massachusetts and by Tennessee State Police from 2006 to 2015.[30] As noted above, we selected these two states because the stop records contain information on the speed traveled for stops in which a warning was issued.[31] In Massachusetts, we observe stops by local and state police. In order to focus on stop populations containing a reasonable number of African-Americans, we restrict our analysis to state police stops and stops made by town police departments of the 10 largest towns.[32] In Tennessee, we make a distinction between patrol districts lying on the Eastern and Western side of the time zone border that bisects the state.[33] As before, we select only traffic stops that occur within the Inter-Twilight window (ITW) which we bound between the earliest recorded Easternmost sunset and latest Westernmost end to civil twilight in each county.[34]

[30] Massachusetts data was collected by Bill Dedman for the Boston Globe and used by Antonovics and Knight (2009) to study police searches. Tennessee data was obtained from the Stanford Open Policing Project.

[31] In Tennessee, warnings are explicitly included in the data. In Massachusetts, there are a large number of traffic stops with zero-dollar fines listed which we believe represent warnings.

[32] These towns include Boston, Worcester, Springfield, Lowell, Cambridge, Brockton, New Bedford, Quincy, Lynn, and Newton of which Newton is the smallest with a population of under 90,000. Restrictions based on omitting towns with African-American shares below the state average yields a similar sample of towns and similar results. Smaller towns in Massachusetts tend to be more rural and have very few African-American residents.

[33] We exclude three rural patrol districts (of eight total) that lie adjacent to or on top of the time zone boundary. A significant portion of those traffic stops occur on opposing sides of the time zone from the patrol district's headquarters creating ambiguity about the time of the stop. We find that estimates using the overall sample are less precise, but quantitatively similar to our preferred specification which excludes these patrol districts.

[34] The ITW occurred in Massachusetts between 4:09 PM and 9:08 PM while in Tennessee it falls within 5:15 PM and 9:48 PM. The Massachusetts traffic stop data only contains the hour of the day that the stop was made. So, only traffic stops that occurred during the ITW in an hour of complete daylight or darkness were included.

Table 4 presents descriptive statistics for the ITW speeding stop samples, excluding actual twilight. The Massachusetts sample numbered 10,203 speeding stops, while samples in East and West Tennessee, respectively, contain 23,515 and 102,054 stops. In Massachusetts, speeding stops were more likely to involve African-American motorists in daylight, for female drivers, for imported vehicles, and on Saturdays. In Tennessee, weekend stops were more likely to be African-Americans, but stops of males were less likely to be African-Americans in east Tennessee and more likely to be African-Americans in west Tennessee.

Table 4: Descriptive Statistics for Massachusetts and Tennessee Traffic Stop Data

		MA		East TN		West TN	
Total Stops		401,408		489,313		1,658,611	
Speeding Stops		80,471		143,014		541,667	
Inter-Twilight		10,203		23,515		102,054	
Sample		AA	White	AA	White	AA	White
	Daylight	71.05%	65.78%	67.59%	68.63%	63.15%	65.03%
Motorist	African-American	100.00%	0.00%	100.00%	0.00%	100.00%	0.00%
	Male	69.82%	73.42%	58.54%	62.07%	73.33%	65.21%
	Young	50.62%	52.27%	-	-	-	-
Auto.	Domestic	28.62%	33.75%	34.12%	36.77%	30.61%	31.85%
	Old	50.62%	49.54%	-	-	-	-
	Red	11.88%	10.01%	-	-	-	
Day of Week	Sunday	13.48%	14.99%	16.04%	12.98%	14.67%	11.85%
	Monday	12.04%	14.24%	12.96%	13.30%	16.04%	14.17%
	Tuesday	15.78%	14.84%	11.50%	13.03%	10.54%	12.69%
	Wednesday	13.43%	13.51%	11.48%	13.54%	11.82%	13.34%
	Thursday	15.84%	13.70%	12.99%	14.10%	11.73%	13.71%
	Friday	12.68%	14.66%	18.92%	19.58%	19.62%	20.50%
	Saturday	16.75%	14.05%	16.11%	13.48%	15.58%	13.73%
Hour of Day	5:00 PM	33.87%	37.51%	22.69%	23.97%	24.84%	26.44%
	6:00 PM	38.26%	33.05%	27.29%	28.94%	21.91%	23.61%
	7:00 PM	17.50%	16.02%	22.57%	21.90%	20.81%	20.60%
	8:00 PM	10.38%	13.43%	15.65%	14.53%	19.62%	17.27%
	9:00 PM			11.79%	10.67%	12.83%	12.08%
Counties/Towns		18		13		44	

Note: The overall sample includes only traffic stops involving African-American or Non-Hispanic white motorists. MA is used in this and the following tables as an abbreviation for Massachusetts and TN is used in the following tables as an abbreviation for Tennessee.

Table 5 presents the VOD model estimates for all three samples of speeding violations. The model follows Equation (10) from the traffic fatality data except that the geographic fixed effects are within state. To control for geography, we use town and state police barracks fixed effects because counties are quite large relative to the size of Massachusetts. In Tennessee, models include county fixed effects because counties are small in size relative to state police patrol districts. Standard errors are clustered at the town/state police barracks level for Massachusetts, and at the county by year level for Tennessee.[35] Columns 1, 3 and 5 present estimates for models that include time of day, day of week, geographic and in Tennessee year fixed effects. Columns 2, 4 and 6 present estimates adding the available motorist and vehicle controls that include whether the motorist is male or female and whether the vehicle is

Table 5: Canonical Veil of Darkness Estimates

LHS: African-American		(1)	(2)	(3)	(4)	(6)	(7)
		MA		East TN			West TN
Daylight		0.0458** (0.0185)	0.0441** (0.0193)	-0.00116 (0.00397)	-0.000921 (0.00395)	0.0105*** (0.00384)	0.00972** (0.00382)
Controls	Day of Week	X	X	X	X	X	X
	Time of Day	X	X	X	X	X	X
	County (or Town)	X	X	X	X	X	X
	Year			X	X	X	X
	Motorist/Vehicle		X		X		X
Observations		10203	10203	23515	23515	102054	102054

Notes: Coefficient estimates are presented where * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance. Standard errors are clustered on county by year in East and West Tennessee (TN) and town or state highway patrol districts in Massachusetts (MA) but robust in Tennessee to clustering on county and year separately and robust in Massachusetts to clustering by town. The sample includes only traffic stops for speeding violations involving African-American or Non-Hispanic white motorists. The models using the Tennessee samples also include controls for year in the first two specifications of each panel and county by year fixed effects in the last.

[35] We could cluster by county for the Tennessee models in columns 3, 4, 6 and 7 where we do not include county by year FE's. However, East Tennessee only contains 13 counties. We have confirmed that the standard errors based on clustering at the county level are smaller than those clustered at the county by year level. Standard errors in West Tennessee are very similar when comparing clustering at the county and at the county by year level.

domestic or import for both states plus whether the driver is under the age of 30, whether the vehicle is older than 5 years and whether the vehicle is red for Massachusetts. Estimates for east and west Tennessee are very similar including county by year fixed effects.

In Massachusetts and West Tennessee, we find evidence suggesting that the odds that stops involves a minority motorist increases in daylight relative to darkness. A daylight stop in Massachusetts is approximately 4.5 percentage points more likely to involve an African-American motorist, while in west Tennessee daylight stops are 1 percentage point more likely to involve African-Americans. The magnitude of these estimates are stable as we add controls for motorist and vehicle attributes and as we add county by year fixed effects for Tennessee. However, we find no evidence of differences in East Tennessee. The classic interpretation of these results is that Massachusetts and West Tennessee show evidence of discriminatory policing, but that East Tennessee does not. Appendix Table B3 presents similar estimates using the logistic regression as in Grogger and Ridgeway.

Next, we explore our motivating hypothesis that the speed of stopped minority motorists decreases in daylight in response to real or perceived discrimination at higher percentiles of the speed distribution. We calculate a relative speed based on both our intuition that the same absolute speed limit violation will be more concerning to police when speed limits are low and the empirical fact that fine schedules in both states apply more severe penalties for the same absolute speed violation at lower speed limits. Specifically, we define S_{idt} as $speed/speed\ limit$. We then estimate marginal effects at each decile using unconditional quantile regressions following Firpo, Fortin, and Lemieux (2009) and using a software package described in Borgen (2016).

The estimation follows a three-step procedure where we (1) construct a transformed speed variable using kernel density estimation, (2) define the re-centered influence function (RIF) variable for each quantile in the transformed distribution, and (3) use RIF as the outcome in a linear model to obtain the quantile estimates (Firpo, Fortin, and Lemieux 2009). We kernel smooth speeds to obtain an estimated density at discrete points in the distribution.

$$\widehat{f_K}(S_i) = \sum_{j=1}^{n} K\left(\frac{S_i - S_j}{h}\right)$$

The bandwidth parameter h is selected following a standard procedure that minimizes the mean integrated squared error under a Guassian Kernal if the data is Gaussian.[36] The results are robust to a variety of alternative functional forms for K, but is specified as Epanechnikov in our estimates. We estimate the relative speed and density at each numeric decile τ of the distribution, and then calculate the Recentered Influence Function (RIF) for each decile in the kernel smoothed speeding data within the inter-twilight sample as follows

$$RIF\left(S_i: q_\tau, F_{\widehat{spd}}\right) = q_\tau + \frac{\tau - \mathbb{I}\{S_i \leq q_\tau\}}{f_{spd}(q_\tau)}$$

where q_τ and f_{spd} are the estimated speed and density at decile τ, and $\mathbb{I}$ is an indicator function. Using the decile RIF's for each i observation, we estimate changes in the speeding distribution using linear models for the RIF at each decile.

$$RIF_{\tau,idt} = \beta_{\tau,0} + \beta_{\tau,1} R_{idt} + \beta_2 \overline{v}_{idt} + \beta_{\tau,3}(R_{idt} \cdot \overline{v}_{idt}) + \delta_{\tau,d} + \gamma_{\tau,t} + \varepsilon_{\tau,idt} \tag{11}$$

where the variable R_{idt} is a dichotomous indicator variable equal to unity when the motorist was of African-American descent and $\overline{v}_{idt}$ is a binary variable indicating the presence of the daylight during the traffic stop. The parameter of interest $\beta_{\tau,3}$ is the coefficient on the interaction of these two variables, which captures racial heterogeneity in speed distribution shift. As above, we add geographic fixed effects, and for the Tennessee samples we also include year or county by year fixed-effects.

Table 6 presents the results from applying Equation (11) to the same sample of speeding stops used for the VOD estimates in Table 5. We find evidence of slower speeds in daylight for African-American motorists, but as suggested by our model the speed distribution shift in all three sites arises primarily for the higher percentiles. In Massachusetts, the shift is quite large starting near zero at the 10th percentile and rising to over 10 percentage points at the 80th and 90th percentiles. The next largest speed distribution shift is in East Tennessee starting around 1 percentage point at the 10th percentile and reaching a maximum of 3 percentage points at the 70th percentile. The shift in West Tennessee is smaller starting at zero

[36] The precise calculation is $h = (9m/10n)^{1/5}$ where $m = min\left(\sqrt{var(S)}, IQR(S)/1.349\right)$ and IQR is the interquartile range.

Table 6: Estimated Change in Speed Distribution for Stopped Minority Motorists in Daylight

LHS: Rel. Speed		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		10 pct	20 pct	30 pct	40 pct	50 pct	60 pct	70 pct	80 pct	90 pct
MA	Daylight	0.00519	0.114	1.847	0.628	-0.415	-0.120	0.449	-0.749	-1.372
		(1.092)	(1.140)	(1.221)	(0.904)	(1.130)	(1.247)	(1.351)	(2.177)	(2.819)
	African-American	0.664	0.548	2.551**	2.187***	1.551**	1.728*	1.477	5.959***	6.514**
		(1.029)	(0.993)	(1.202)	(0.720)	(0.685)	(0.850)	(1.672)	(1.816)	(2.946)
	Daylight*African-American	-0.273	-0.213	-1.718	-2.228**	-5.032**	-6.839**	-7.783***	-10.99***	-12.24**
		(1.298)	(1.286)	(1.376)	(1.004)	(1.946)	(2.585)	(2.682)	(2.803)	(4.239)
	Obs.	10203	10203	10203	10203	10203	10203	10203	10203	10203
East TN	Daylight	-0.200	0.00734	-0.186	-0.123	-0.0979	-0.0470	0.181	0.210	-0.113
		(1.094)	(0.806)	(0.471)	(0.351)	(0.336)	(0.411)	(0.565)	(0.835)	(1.116)
	African-American	-2.116**	-1.861*	-1.254*	-0.909	-0.795	-1.039	-0.178	-1.029	-1.732
		(0.763)	(0.903)	(0.688)	(0.804)	(0.824)	(1.063)	(1.402)	(1.827)	(2.132)
	Daylight*African-American	-1.158	-1.384**	-1.070**	-0.965**	-1.419***	-1.560**	-3.069**	-2.232	-2.117
		(0.842)	(0.629)	(0.465)	(0.365)	(0.440)	(0.589)	(1.084)	(1.542)	(2.248)
	Obs.	23515	23515	23515	23515	23515	23515	23515	23515	23515
West TN	Daylight	0.0879	0.174	-0.0740	-0.137	-0.205*	-0.0470	0.00219	-0.168	-0.176
		(0.120)	(0.212)	(0.109)	(0.140)	(0.110)	(0.183)	(0.250)	(0.341)	(0.472)
	African-American	0.182	0.606**	0.676**	0.671*	0.296	0.664	0.671	0.546	0.170
		(0.249)	(0.272)	(0.259)	(0.378)	(0.344)	(0.428)	(0.514)	(0.607)	(0.723)
	Daylight*African-American	-0.102	-0.176	-0.545***	-0.867***	-0.536***	-0.843***	-0.996***	-0.802	-0.948
		(0.151)	(0.202)	(0.172)	(0.258)	(0.188)	(0.243)	(0.328)	(0.511)	(0.668)
	Obs.	102054	102054	102054	102054	102054	102054	102054	102054	102054

Notes: Coefficient estimates are presented such that * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance. Standard errors are clustered on county by year in East and West Tennessee (TN) and patrol districts in Massachusetts (MA). The sample includes only traffic stops for speeding violations involving African-American or Non-Hispanic white motorists. Controls include time of day, day of week, and geographic location fixed-effects. The two Tennessee samples also include controls for year. Relative speed is calculated as speed relative to the speed limit and multiplied by one hundred.

and reaching a maximum below 1 percentage point at the higher percentiles. Notably, the coefficients on daylight are always insignificant consistent with no shift in the speed distribution of non-Hispanic white motorists.

The quantile regressions yield multiple estimates and raise concerns about multiple hypothesis testing. We follow Bifulco et al. (2008) and conduct a simulation exercise for each site to assess the likelihood that the pattern of results arose by chance. Bifulco et al. (2008) exploit the logic of a Fisher's exact permutation test in a resampling framework 1) ordering the t-statistics arising from the coefficients for each quantile by magnitude, 2) drawing 10,000 bootstrap samples of the same size as the original sample with replacement under the null of no correlation between speed and daylight (randomizing daylight), 3) re-estimating the quantile model for and ordering the t-statistics from each bootstrap sample, and 4) calculating the fraction of bootstrap samples where the set of ordered t-statistics dominate the actual set of t-statistics. While the t-tests above are two-sided, this permutation test is one-sided where a vector of signed and ordered bootstrap t-statistics lies below the actual signed and ordered t-statistics if all the elements of the bootstrap vector have a lower value than the corresponding elements of the actual vector. We strongly reject the null hypothesis of no negative shift for all three sites. In Massachusetts, the likelihood of this pattern arising by chance is 0.013 percent. In East and West Tennessee, the likelihoods are 0.005 and 0.001, respectively. We also re-estimate these models adding the motorist and vehicle controls, and in Tennessee adding county by year fixed effects (Appendix Table B4). The addition of motorist and vehicle controls has no impact. The county by year fixed effects erode the speed shift in East Tennessee somewhat with upper percentile point estimates between 15 and 20 percent smaller, but the pattern remains significant with a 0.04 likelihood of a type 1 error.

Next, as we did for the fatality analysis, we examine the speed distribution for non-Hispanic White motorists over other factors. In both Massachusetts and Tennessee, we observe whether the motorist is male and whether the vehicle is either a domestic or imported vehicle. We re-estimate the models in Table 6 replacing race in Equation (11) with either motorist male or whether domestic vehicle. Repeating our bootstrap analysis, we find that the likelihood that these results could have arisen by chance was 0.89 for Massachusetts, 0.59 for East Tennessee and 0.37 for West Tennessee for gender; and 85.7 percent for Massachusetts, 72.3 percent for East Tennessee, and 91.1 percent for West Tennessee for vehicle type, see Appendix Table B5.[37] For Massachusetts, we also conduct these analyses for whether the driver is younger than 30, the vehicle is older than 5 years and whether the vehicle is red. As above, we find no evidence of a change in speeds with daylight, see Appendix Table B6.

In this section, we present evidence on the speed distribution of stopped motorists. African-American motorists in the upper half of the speed distribution travel more slowly in daylight, when presumably race is observed. The largest differences in the speed distribution arise in the Massachusetts sample where we also observed the largest composition differences between daylight and darkness stops. In Tennessee, we observed that the largest shift in the speed distribution of stopped African-American motorists arose in East Tennessee where the VOD tests did not identify any evidence of discrimination, consistent with behavioral changes potentially confounding the VOD test. Further, we find no evidence of speed distribution shifts for whites or shifts over other motorist or vehicle attributes.

5. Calibration and Simulation

In this section, we calibrate our model to the data on stopped motorists from Massachusetts and East and West Tennessee to calculate racial differences in police stop costs in daylight and darkness. We also use the darkness police stop costs to calculate counterfactual VOD test statistics that would have arisen if African-American motorists did not respond to increased scrutiny by police in daylight by driving more slowly. We note that we choose to conduct a macro-style calibration using the aggregate moments, rather than a structural estimation using micro data. This decision is based on computational demands given that each calibration takes several weeks to run.[38] Due to the use of calibration rather than structural estimation, we rely on the quantile regressions above for inference.

[37] We follow the same permutation strategy except that the test is two-sided using the absolute value of the t-statistics because we have no priors concerning how these attributes might shift the speed distribution. For Tennessee, we repeat the analyses including county by year fixed effects, and the negative findings are robust.

[38] Beyond the increase in computation time required for just using micro data, we also approximate the relationship between infraction level and the preference parameter. This

We assume that motorist preferences c follow a skew-normal distribution with skewness a, location e and scale w and separate parameters for whites and African-Americans

$$f(t) = 2\phi(t)\Phi(at)$$

where ϕ and Φ are the normal PDF an CDF respectively, and $t = (x - e)/w$

Next, we parameterize the probability of being stopped $\phi^*(i, s_d)$ as a function of speed/infraction severity and police stop costs. We begin by specifying the police return from a stop as a monotonic function of motorist speed. Specifically,

$$u(i) = i^\eta + u_0 \quad \text{for } i > 1 \text{ and } u(0, s_d) = 0$$

where $\eta > 1$ allows the return to stop to increase non-linearly with infraction severity and $u_0 > \max(s_{v,d})$ for all $\{v, d\}$ assures that $u(i) > 0$ for all positive infraction levels.

Next, we need specify h^{-1} as a monotonic mapping from a priori net pay-off to stop probability ϕ^* between zero and one. Specifically,

$$\phi^*(i, s_d) = h^{-1}(u(i) - s_d) \text{ where } h^{-1}(\omega) = \begin{cases} \frac{\omega^a}{\omega^a + K} & \omega > 0 \\ 0 & otherwise \end{cases}, a > 0,\ K > 0$$

The function limits to one as $\omega \to \infty$. If $a < 1$, the function has a negative second derivative for $h > 0$. Otherwise, the second derivative can change sign with i but is negative as $h \to \infty$.

To specify the motorist problem, we assume a stop penalty of

$$\tau(i) = i^\mu + \tau_0 \quad for\ \ i > 0$$

where $\mu > 1$ and $\tau_0 > 0$ so costs are bounded away from zero and are convex in infraction level. The benefit function from committing the infraction depends on both i and c

$$b(i, c) = b_0 i^{\alpha_1} e^{\alpha_2 c}$$

where $b_0 > 0$, $0 < \alpha_1 < 1$ so that marginal returns are diminishing with infraction level, and the direction of the preference parameter is initialized by $\alpha_2 > 0$. The motorist solves

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approximation represents most of the computational requirements for each optimization step. With aggregate moments, a relatively fine grid of 10,000 points provides reasonable accuracy, but micro data estimation implies the comparison of individual motorist speed levels to predicted speed levels at their percentile in the distribution requiring a much finer grid.

$$\max_{i'(c,s_d)} b(i,c) - \tau(i)\, \phi^*(i,s_d)$$

to find the optimal speed $i'(c,s_d)$.

While a closed-form solution does not exist for $i'(c,s_d)$, we exploit the monotonicity of $i'(c,s_d)$ to define $c'(i,s_d) = i'^{-1}(i,s_d)$, and derive a closed-form solution for

$$c'(i,s_d) = \frac{1}{\alpha_2} ln\left(\mu\phi^*(i,s_d) i^{\mu-\alpha_1} + \frac{\partial\phi^*}{\partial i}\frac{(i^\mu + \tau_0)}{i^{\alpha_1 - 1}}\right) - \frac{\ln(\alpha_1 b_0)}{\alpha_2}$$

We calculate $c'(i,s_d)$ over a fine grid of values of i and create a piece-wise approximation of $i'(c,s_d)$ by linearly interpolating between the two nearest points in the grid.

For a given set of parameters, we can calculate the motorist's optimal speed for each c, and then solve for the value $c^*(s_d)$ where net benefits at the optimal speed are equal to zero. With $\phi^*(i,s_d)$, $i'(c,s_d)$ and $c^*(s_d)$, we can solve for the equilibrium speed distribution and the speed distribution of stopped motorists by drawing a large sample of motorists from the distribution of c and using the probability of stop as a weight. Assuming a common police stop cost $s_{\underline{v}}$ in darkness and separate daylight police stop costs for white and minority motorists, $s_{\overline{v},w} > s_{\underline{v}}$ and $s_{\overline{v},m} < s_{\underline{v}}$; we can use the same sample over c to simulate white and minority speed distributions in daylight and in darkness. Finally, we vary the share of minority motorists in the population by applying a weight to the minority distribution to calibrate the share of stops in daylight and darkness that involve minority motorists.

To calibrate the model, we calculate six speed percentiles (20^{th}, 40^{th}, 60^{th}, 80^{th}, 90^{th}, and 95^{th}) in miles per hour over the speed limit for each combination of daylight/darkness and minority/non-minority, the fraction of motorists stopped during daylight who are minority, and the fraction of motorists stopped in darkness who are minority. Beyond the quintiles, we add moments for the 90^{th} and 95^{th} percentiles to help capture the skewed nature of the speed distribution. Further, to better fit the model, we calibrate using 12 moments associated with the speed distribution of white and minority motorists in daylight, 12 moments associated with the difference between the daylight and darkness speed at each percentile in the white and minority speed distributions. Similarly, we calibrate to one moment for the percentage (fraction times 100) of motorists stopped during the darkness who are minority and one moment for the VOD test statistic in Definition 3 again times 100. To assure that the speed moments are comparable to the estimations above, we remove the time of day, day of week and geographic fixed effects in our relative speed model and add the sample means back to the residuals yielding motorists with effectively common observables. Finally, we convert these relative speeds back to miles per hour using the mode speed limit in each sample. Given that the number of speed moments is arbitrary, we place a weight of 0.070 on the share minority stops and VOD test statistic moments and a smaller weight of approximately 0.036 on each speed distribution moments.

The functional forms above contain ten parameters shared by both white and minority simulated motorists. The Mean, variance, and skewness of our preference distribution, and daylight stop costs, must be determined separately for white and minority motorists. We initialize the darkness stop cost $s_{\underline{v}}$ to 44 allowing both the daylight stop cost of both groups and the minimum return to a stop u_0 to vary relative to this fixed value. Finally, we must calibrate the fraction of minority motorists for the simulated population. Therefore, in total 18 free parameters are calibrated for each site. We minimize a mean squared error (MSE) optimization function of the weighted moments. Because the surface of this function is highly non-linear, we first use a derivative-free Simplex-based optimization algorithm, Subplex (Rowan, 1990), to identify a series of local minima. We use these minima to set broad bounds on parameters and the best local minima as a starting value for a modified evolutionary-based optimization routine, ESCH (da Silva Santos et al., 2010), to identify a global minimum. Once we have identified the global minimum, we use a third optimization routine based on quadratic approximations to the surface, BOBYQA (Powell 2009), to precisely locate that minimum and verify that the gradient is approximately zero. The step by step process is detailed in Appendix B, and the specific limits for each parameter are shown in Appendix Table C1.

Table 7 presents the results of the calibration with the first two columns presenting the empirical and the simulated moments for Massachusetts and the next four columns presenting the same results for East and West Tennessee (majority motorist moments are shown in Appendix Table C2). At the bottom, the table also presents the fraction not infracting for minority and the majority motorists in daylight and in darkness. The model does a very good job of matching both the daylight speed distribution and the change in the speed distribution between daylight and darkness. The model also closely matches both the fraction

Table 7: Calibration Results

	Massachusetts		East Tennessee		West Tennessee	
	Data	Simulation	Data	Simulation	Data	Simulation
African-American Speed Distribution Daylight						
20th Percentile	13.3835	13.3344	12.1763	12.8364	11.5419	11.1629
40th Percentile	14.8568	15.5537	15.2878	14.9840	13.5632	13.4064
60th Percentile	18.3094	18.5776	17.8090	17.5080	15.7624	15.8768
80th Percentile	23.9418	23.6617	20.7542	21.5682	19.3593	19.5268
90th Percentile	28.4176	28.5276	25.3446	25.0375	22.8966	23.1396
95th Percentile	33.3009	33.1861	28.6582	28.4432	26.8071	26.5863
Difference Daylight and Darkness						
20th Percentile	-0.0899	0.2458	0.5273	-0.2437	0.0830	0.3135
40th Percentile	2.2735	2.3309	0.3049	0.3068	0.2845	0.4916
60th Percentile	3.8130	3.5311	0.7094	0.6952	0.4227	0.5726
80th Percentile	4.7673	4.6565	1.6052	0.9309	0.4644	0.6492
90th Percentile	5.6541	5.1206	1.2012	1.3029	0.7023	0.6702
95th Percentile	5.1922	5.3577	1.3253	1.4398	1.0512	0.7007
Minority Share of Stops						
Minority Share of Stops Darkness	0.1664	0.1665	0.0466	0.0466	0.1771	0.1771
VOD Test Statistic	1.3769	1.3793	0.9924	0.9973	1.0908	1.0899
Percent Minority						
Motorists	NA	0.1638	NA	0.0552	NA	0.1771
Not Infracting in Daylight	NA	0.4959	NA	0.3197	NA	0.0773
Not Infracting in Darkness	NA	0.0056	NA	0.1673	NA	0.0063

Notes: Empirical speed distribution in miles per hour based on regressing relative speed on day of week, time of day, geographic and for Tennessee year controls, calculating the residual, adding the means of controls back and then calculating miles per hour based on the mode speed limit of traffic stops for each site. The simulated moments arise from the global optimum identified by applying an evolutionary based optimization routine called ESCH and precisely located by applying second optimization routine based on quadratic approximations to the surface BOBYQA. The calibrated parameters used to calculate these moments are shown in Appendix Table B2.

of stops in darkness that involve minority motorists and the VOD test statistic. The results for East Tennessee are notable in that the model fits both the empirical VOD test statistic that is just below one, and the speed distribution with stopped minority motorists at upper speed percentiles driving substantially slower in daylight. The calibrated parameters are shown in Appendix Table C3.

Table 8 summarizes impact of race on police stop behavior in the calibration. The first row presents the minority stop cost in daylight, which is 0.006 in Massachusetts, 30.113 in East Tennessee, and 37.753 in West Tennessee all in comparison to a darkness stop cost of

Table 8: Calibration Results Related to Racial Differences in Police Stop Behavior

	Massachusetts	East Tennessee	West Tennessee
Police Return and Cost of Stops			
Minority Stop Cost Diff	43.994	13.887	6.247
Return to Increase in Speed			
0.5 SD Increase			6.405
2.0 SD Increase		13.002	
5.0 SD Increase	42.940		
VOD Test Statistics			
Simulated VOD Test	1.379	0.997	1.090
Adjusted VOD Test	2.736	1.223	1.173

Notes The minority stop cost difference is calculated by subtracting the calibrated stop cost for minorities in daylight from the darkness stop cost of 44. The return to a specific number $\boldsymbol{\alpha}$ of standard deviations $\boldsymbol{\sigma}$ increase in miles per hour over the speed limit is calculated relative to the mean speeding violation $\boldsymbol{\mu}$ by $(\boldsymbol{\mu} + \boldsymbol{\alpha\sigma})^{\boldsymbol{\eta}} - (\boldsymbol{\mu_i})^{\boldsymbol{\eta}}$ using the calibrated parameters and the simulated speed distribution for each site. Finally, the simulated VOD test statistics is the statistic implied by the simulated speed distributions based on the calibrated parameters, and the adjusted VOD test statistic is calculated using the darkness minority speed distribution for daylight stops, but having police stop motorists based on their daylight stop costs.

44.0. White stop costs in daylight are all near the darkness stop cost, consistent with the quantile regression estimates that showed no change in the speed distribution in daylight for white motorists. Consistent with previous studies and the large shift in the speed distribution, we find evidence of high levels of police prejudice in Massachusetts, i.e. a daylight stop cost far below the darkness stop cost. We observe higher levels of prejudice (lower stop costs) for East Tennessee than West Tennessee, based on the shift in the speed distribution in East Tennessee, even though the VOD test statistic for East Tennessee was near 1.0.

Further, we can use the calibrated parameters for police stop costs and $u(i)$ to compare the lower minority stop costs in daylight to the police pay-offs that arise from stopping a motorist whose speeding infraction is more severe. The next three rows show the change in return to a police stop if the speed of the motorist increases by ½, 2 or 5 standard deviations relative to the simulated mean level of infractions among stopped motorists. Specifically, we find the mean μ and standard deviation σ of the number of miles per hour over the speed limit within the simulation for motorists committing infractions, and calculate $(\mu + \alpha\sigma)^{\eta} - (\mu)^{\eta}$ where α takes on the values of ½, 2 and 5 and η is the exponent parameter in $u(i)$. Daylight raises the effective net returns to stopping minority motorists in Massachusetts by more than the effect of raising speed by five standard deviations above the mean. In East Tennessee, daylight raises the return to stopping minority motorists by an amount comparable to a 2 standard deviation increase in speed, but in West Tennessee where the speed distribution shift is smaller daylight raises the return by ½ a standard deviation.

The second panel of Table 8 presents the VOD test statistic from the calibration and a counterfactual VOD statistic that would arise if minority motorists did not change their infraction behavior in daylight, i.e. behaved in daylight as if they faced the police costs for stops in darkness. Following Grogger and Ridgeway (2006), the VOD test statistic is

Definition 4. $K_{VOD} \equiv \frac{p[m|stopped,\overline{\upsilon}]}{p[w|stopped,\overline{\upsilon}]} \frac{p[w|stopped,\underline{\upsilon}]}{p[m|stopped,\underline{\upsilon}]}$

We can calculate the alternative statistic K_{ADJ} by calculating the above probabilities in K_{VOD} except c^* and i' in daylight $\overline{\upsilon}$ are assumed to depend on the darkness $\underline{\upsilon}$ police stop cost.

Definition 5. $K_{ADJ} \equiv \frac{\int_{c^*(s_{\underline{\upsilon}})}^{c_h} g(c,m)\phi^*\left(i'\left(c,s_{\underline{\upsilon}}\right),s_{\overline{\upsilon},m}\right)di}{\int_{c^*(s_{\underline{\upsilon}})}^{c_h} g(c,w)\phi^*\left(i'\left(c,s_{\underline{\upsilon}}\right),s_{\overline{\upsilon},w}\right)di} \frac{\int_{c^*(s_{\underline{\upsilon}})}^{c_h} g(c,w)\phi^*\left(i'\left(c,s_{\underline{\upsilon}}\right),s_{\underline{\upsilon}}\right)di}{\int_{c^*(s_{\underline{\upsilon}})}^{c_h} g(c,m)\phi^*\left(i'\left(c,s_{\underline{\upsilon}}\right),s_{\underline{\upsilon}}\right)di}$

The counterfactual VOD test statistic increases the most in Massachusetts from 1.38 to 2.74, the next most in East Tennessee from 1.00 to 1.22, and has the smallest increase in West Tennessee to 1.17 from the calibrated value of 1.09. The results in Table 8 are repeated for alternative weights in Appendix Table C4, see Table C5 for calibration parameters.

6. Conclusion

The VOD test uses seasonal variation to compare the racial composition of police stops in daylight and darkness at the same time of day and has quickly become a gold standard for evaluating administrative data on police stops. This paper observes that, even if the composition of motorists is the same between daylight and darkness, the behavior of motorists may change when they face discrimination. If race is only observable in daylight, minority motorists might rationally choose to drive more conservatively and commit fewer infractions or less severe infractions in daylight, if they anticipate being stopped for infractions at higher rates when race can be observed. Our model implies that the standard test statistics for racial discrimination in police stops may not increase with discrimination, and that motorists at the top of the speed distribution of stopped minority motorists will drive slower in daylight

We document empirical evidence of behavioral changes using both national data on traffic fatalities and data on traffic stops from the states of Massachusetts and Tennessee. Using the national accident fatality data, we find that the likelihood of a motorist fatality being an African-American as opposed to white motorist decreases by about 1.5 percentage points in daylight. In the traffic stop data, we find a large shift in the speed distribution of African-Americans between daylight and darkness near the top of the distribution for Massachusetts, 7 to 12 percent slower in daylight relative to the speed limit. We find a smaller, but sizable, shift for East Tennessee, 1.5 to 3 percent slower, but very little shift in West Tennessee, one percent slower or less. We do not observe similar changes in fatalities or speeding over any observable motorist or vehicle characteristics, nor do we observe such changes in speeding for white motorists.

We calibrate our theoretical model of police stop and motorist infraction behavior. The model matches the empirical moments well including capturing the fact that the observed decreases in the infraction level of African-Americans in daylight is largest at the highest percentiles of the speed distribution. The calibrated differences in police stop costs for minority motorists between daylight and darkness is very large in Massachusetts, equivalent to the return to police of increasing the motorist speed above the speed limit by 5 standard deviations relative to the mean. These larger differences are consistent with both the high VOD test statistic and the large speed distribution shift. On the other hand, the VOD test statistic in East Tennessee is near one and yet we observe substantially lower calibrated police stop costs for minority motorists in daylight, equivalent to an increase in motorist speed of 2 standard deviations. The failure of the VOD test statistic to detect discrimination in East Tennessee appears attributable to the substantial shift in the minority speed distribution between daylight and darkness.

In summary, the VOD test remains one of the best techniques available for providing convincing evidence of discrimination in police stops. However, this paper has documented substantial empirical evidence that minorities likely adjust their behavior in daylight to reflect actual or perceived police discrimination in stops. Our model calibrations suggest that the bias in the VOD test arising from changes in minority motorist behavior can be large, and in East Tennessee this bias appears to have completely eliminated any observable evidence of discrimination. Researchers should consider such behavioral responses to discrimination when testing for discrimination in police stops. Going forward, states and localities that collect data on traffic stops should also attempt to collect objective information on the severity of the infraction where possible including the disposition of the stop, e.g. citation vs. warning.

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Appendix

A. Theoretical Appendix

A.1. The Police Officer's Problem

Officer's choice $\gamma(i, d, \phi)$ observing non-negative infraction severity i, motorist type/demography d, and circumstances surrounding the stop ϕ.

$$\max_{\gamma(i,s_d,\phi)} [u(i) - h(\phi) - s_d]\gamma(i, s_d, \phi) \tag{1}$$

where s_d as a fixed component of stop costs and $h(\phi)$ represents circumstantial costs.

Assumption 1.1 u is continuous and twice differentiable over positive values of its argument, $\frac{du(i)}{di} > 0$ and $\frac{d^2u(i)}{di^2} > 0 \; \forall \; i > 0$, $\lim_{i\to 0^+} u(i) = u_0 > 0$, and $u(i) = 0 \;\forall\; i \leq 0$;

Assumption 1.2 $\phi \sim Uniform(0,1)$;

Assumption 1.3 h is a continuous, twice differentiable function defined over $[0,1)$, $\frac{dh(\phi)}{d\phi} > 0 \;\forall\; 0 \leq \phi \leq 1$, $lim_{\phi\to 1} h(\phi) = \infty$, and $h(0) = 0$;

Assumption 1.4 $u_0 - s_d > 0,\; u_0 > 0,\quad s_d > 0 \;\forall\; d$

The solution to the officer's problem is

$$\gamma(i, s_d, \phi) = \begin{cases} 1, & \text{if } u(i) > h(\phi) + s_d \\ 0, & \text{otherwise.} \end{cases}$$

Officer will stop all motorists at any infraction level above some threshold severity level

$$i^*(\phi, s_d) = u^{-1}(h(\phi) + s_d) \tag{2}$$

Solve Equation (2) for the circumstances $\phi^*(i, s_d)$ where the net pay-off of a stop is zero as

$$\phi^*(i, s_d) = h^{-1}(u(i) - s_d) \tag{3}$$

Equation (3) represents the probability that an officer stops a motorist with infraction level i.

Lemma 1. *(i) The infraction level representing the optimal stop-threshold,* $i^*(\phi, s_d) = u^{-1}(h(\phi) + s_d)$*, is increasing in officer circumstances and demographic stop cost, and these derivatives are finite for a finite* ϕ*. (ii) The probability of an officer making a stop,* $\phi^*(i, s_d) = h^{-1}(u(i) - s_d)$*, is decreasing in stop cost and increasing in the level of infraction, and these derivatives are finite for finite* i*. (iii) The* $\lim_{i\to 0} \phi^*(i, s_d) > 0$ *for all* s_d.

Proof of Lemma 1. *(i) Assumption 1.1 and the Implicit Function Theorem imply that the derivative* $u^{-1\prime}(\cdot) > 0$ *and finite over its domain* (u_0, ∞). *Then by Assumption 1.3 and inspection it is clear the derivative of Equation (2) implies* $\frac{\partial i^*}{\partial \phi} = u^{-1\prime} \frac{dh}{d\phi} > 0$, *and* $\frac{\partial i^*}{\partial s_d} = u^{-1\prime} > 0$.

(ii) Assumption 1.3 and the Implicit Function Theorem imply that the derivative $h^{-1\prime}(\cdot) > 0$ *and finite over its domain, and by Assumption 1.1 and inspection it is clear the derivative of Equation (3) implies* $\frac{\partial \phi *}{\partial s_d} = -h^{-1\prime} < 0$, *and* $\frac{\partial \phi^*}{\partial i} = h^{-1\prime} \frac{du}{di} > 0$.

(iii) Based on Equation (3) and the continuity of h, *we can rewrite* $\lim_{i \to 0} \phi^*(i, s_d)$ *as* $\lim_{i \to 0} h^{-1}[u(i) - s_d] = h^{-1}\left[\lim_{i \to 0} u(i) - s_d\right] = h^{-1}(u_0 - s_d) > 0$, *which is greater than zero based on Assumption 1.4 and the definition of* h *(Assumption 1.3).* ***QED***

Standard statistic for evaluating racial discrimination in stops is the relative share of stops involving minority motorists, or

Definition 1. $K_f \equiv \frac{p[m|stopped, s_m, f(i,m)]}{p[w|stopped, s_w, f(i,w)]} = \frac{\int_0^\infty f(i,m)\phi^*(i, s_m) di}{\int_0^\infty f(i,w)\phi^*(i, s_w) di}$

where $f(i, d)$ is the joint distribution of infraction severity and motorist type.

Proposition 1. *A decrease in the stop costs of minority motorists,* s_m, *will increase the relative stop rate of minority motorists,* K_f.

Proof of Proposition 1. *The theorem is established by taking the derivative of* K_f *with respect to* s_m.

$$\frac{dK_f}{ds_m} = \frac{1}{p[w|stopped, s_w, f(i,w)]} \int_0^\infty f(i, m) \frac{\partial \phi^*}{\partial s_m} di < 0$$

The derivative is negative based on part ii of Lemma 1. ***QED***

A.2. The Motorist's Problem

The motorist problem is

$$\max_{i'(c, s_d)} b(i, c) - \tau(i)\phi^*(i, s_d) \tag{4}$$

Where benefit of committing an infraction $b(i, c)$ depends on motorist preferences c and cost of being stopped for committing an infraction $\tau(i)$ times the probability of being stopped ϕ^*.

Assumption 2.1 b is a continuous, twice differentiable, non-negative function, $\frac{\partial b}{\partial i} > 0$ and $\frac{\partial^2 b}{\partial i^2} < 0 \ \forall \ c$ and $i \geq 0$, $b(0, c) = 0$, and $\lim_{c \to -\infty} b(i, c) = 0 \ \forall \ i$;

Assumption 2.2 $\frac{\partial b}{\partial c} > 0$ and $\frac{\partial^2 b}{\partial c \partial i} \geq 0 \; \forall \; c$ and for $i \geq 0$;

Assumption 2.3 τ is a continuous, twice differentiable, positive function, $\frac{d\tau}{di} > 0$ and $\frac{d^2\tau}{di^2} > 0$ for $i \geq 0$, and $\tau(0) > 0$;

Assumption 2.4 $\frac{\partial b}{\partial i}|_{i=0} \geq \frac{d\tau}{di}|_{i=0} h^{-1}(u_0 - s_d) + \tau(0) h^{-1'}(u_0 - s_d) \; \forall \; c$ and $\lim_{i \to \infty} \frac{d\tau}{di} > \frac{db}{di}$

Assumption 2.5 $\frac{\frac{d^2u}{di^2}}{\frac{du}{di}} \geq \frac{-h^{-1''}}{h^{-1'}} \frac{\partial u}{\partial i}$ and $\frac{\frac{\partial \tau}{\partial i}}{\tau(i)} > \frac{-h^{-1''}}{h^{-1'}} \frac{\partial u}{\partial i} = \frac{\partial^2 \phi^*}{\partial i \partial s_d} \left(-\frac{\partial \phi^*}{\partial s_d}\right)^{-1}$ for $i \geq 0$

Lemma 2. (*i) There exists a unique optimal infraction level* i' *on* R^+ *for a motorist of type* $\{c, d\}$. *(ii) The optimal infraction level is increasing in preferences* c, *increasing in stop costs* s_d, *and the first derivatives of this infraction level function are finite.*

Proof of Lemma 2. *(i) The motorist can chooses an infraction level that satisfies the following first-order condition*

$$FOC \equiv \frac{\partial b(i,c)}{\partial i} - \frac{d\tau(i)}{di} \phi^*(i, s_d) - \tau(i) \frac{\partial \phi^*(i, s_d)}{\partial i} = 0 \qquad (6)$$

By Assumption 2.1, the first term in Equation (6) is positive on R^+, *and by Assumption 2.3 and Lemma 1 the second and third terms are negative when including the subtraction signs. The first part of Assumption 2.4 implies that the right-hand side of Equation (6) is positive at* $i = 0$. *Turning back to the officer's problem, we know that* $\lim_{i \to \infty} u(i) = \infty$ *due to* $u(i)$ *having a positive slope and a non-negative second derivative (Assumption 1.1), and by Assumption 1.3* $\lim_{\omega \to \infty} h^{-1}(\omega) = 1$. *Therefore, based on Equation (3),* $\lim_{i \to \infty} \phi^*(i, s_d) = 1$, *and so by the second part of Assumption 2.4 the negative second term becomes larger in magnitude than the first term as* i *limits to infinity. These results imply that the FOC is negative for some positive values of* i. *Therefore, by continuity of all functions over* R^+, *a positive FOC value at zero and negative FOC value as infinity is approached, solutions* i' *to Equation (6) must exist on* R^+ *and an odd number of those solutions must maximize the objective function in Equation (5).*

In order to assure a unique solution over R^+, *we examine the second-order condition of the motorist's problem*

$$SOC \equiv \frac{\partial^2 b(i,c)}{\partial i^2} - \frac{d^2\tau(i)}{di^2}\phi^*(i,s_d) - 2\frac{d\tau(i)}{di}\frac{\partial\phi^*(i,s_d)}{\partial i} - \tau(i)\frac{\partial^2\phi^*(i,s_d)}{\partial i^2} > 0 \tag{7}$$

The first term in Equation (7) is negative based on Assumption 2.1, the second and third terms (again including the minus signs) are negative based on Assumption 2.3 and Lemma 1. If the final term is negative, the SOC is unambiguously negative. In order to show why the final term is negative, we draw on the solution of the officer's problem and the monotonicity of $h^{-1}(x)$. *Recall that* $\phi^*(i,s_d) = h^{-1}[u(i) - s_d]$; *we use this expression to expand the second derivative of* ϕ^* *from Equation (3)*

$$\frac{\partial^2\phi^*(i,s_{v,d})}{\partial i^2} = \left(\frac{du(i)}{di}\right)^2 h^{-1''}(u(i) - s_d) + \frac{d^2u(i)}{di^2}h^{-1'}(u(i) - s_d) \geq 0.$$

The first term is ambiguous and the second term is positive. If the first term is negative, the second term is at least as large in magnitude as the first term based on Assumption 2.5. Therefore, the last term in Equation (7) is negative, and there exists a unique positive value of i' *that maximizes motorist payoff over* R^+. *Finally, by the continuity of all functions, this solution varies continuously with* c *and* s_d. *The continuity of* i' *assures the derivatives are finite.*

(ii) Next, we turn to signing the derivatives of i'. *By total differentiation of the first order condition in Equation (6), we show that the optimal infraction level* i' *is increasing in criminality. Specifically,*

$$\frac{di'}{dc} = -\frac{1}{SOC}\frac{\partial(FOC)}{\partial c} = -\frac{\frac{\partial^2 b}{\partial c \partial i}}{SOC} > 0 \; \forall \; c \; and \; s_d > 0,$$

where the sign of the numerator is positive based on Assumption 2.2 and the SOC *is the expression for the second-order condition in Equation (7) and is negative when motorists are maximizing their net benefits from infracting on* R^+.

A similar exercise signs the derivative with respect to stop costs s_d *where the derivative of the FOC or the numerator is*

$$\frac{di'}{ds_d} = -\frac{1}{SOC}\frac{\partial(FOC)}{\partial s_d} = \frac{1}{SOC}\left(\frac{\partial\tau}{\partial i}\frac{\partial\phi^*}{\partial s_d} + \tau(i)\frac{\partial^2\phi^*}{\partial i \partial s_d}\right) > 0$$

The first term in parentheses is negative by Assumption 2.3 and Lemma 1, but the second term is ambiguous in sign. Rearranging the expression in the second part of Assumption 2.5 demonstrates that the *first term is larger in magnitude than the second term. The negative sign of the SOC implies that the total derivative is positive.* ***QED***

Next, we define i^{**} as the actual infraction level. If the pay-off from the interior, optimal infraction level is positive then $i^{**} = i'$, but if negative then $i^{**} = 0$.

Lemma 3. (*i) As long as some motorists chose to commit infractions at finite* c*, there exists a threshold* c^* *on* R *above which motorists commit a traffic infraction at the optimal level* i' *and below which motorists do not commit an infraction or* $i' = 0$*. (ii)* $lim_{c \to c^{*+}} i^{**} > 0$ *where the plus sign indicates the limit from above. (iii) If* c^* *exists, it is decreasing in* s_d*.*

Proof of Lemma 3. (*i) The last part of Assumption 2.1, the last part of Assumption 2.3 and part (iii) of Lemma 1 implies that* $\lim_{c \to -\infty} (b(i', c) - \tau(i')\phi^*(i', s_d)) < 0$ *since benefits limit to zero regardless of the optimal infraction level* i' *and stop costs and stop probability are bounded above zero for any positive* i*. If some motorists infract, then there exist values of* c *for which* $(b(i', c) - \tau(i')\phi^*(i', s_d)) > 0$*, and by the continuity of* i' *over* c *this establishes the existence of a* c^* *where* $(b(i', c^*) - \tau(i')\phi^*(i', s_d)) = 0$*.*

We can differentiate the motorist net benefits expression (NB) from Equation (5) at any c*. We then cancel out derivative terms involving* i' *since the FOC is zero at the optimal infraction level (envelope theorem), and show that*

$$\frac{dNB}{dc} = \frac{\partial}{\partial c}(b(i', c) - \tau(i')\phi^*(i', s_d)) = \frac{\partial b(i', c)}{\partial c} > 0$$

Therefore, with NB of zero at c^**, NB must be negative for* $c < c^*$ *and positive for* $c > c^*$

(ii) In the proof of Lemma 2, we show that the optimal infraction level i' *is positive for all* c *and that the function* i' *is continuous and monotonically increasing in* c*. Therefore, if* c^* *exists for a given equilibrium based on part (i) above,* i' *is positive for* c *equal to* c^**, and the continuity of* i' *implies that the optimal infraction level at* c *must approach that positive value as* c *approaches* c^* *from above or equivalently* $lim_{c \to c^{*+}} i^{**} > 0$.

(iii) We calculate the total derivative of the equation that defines c^**,* $NB = 0$*, with respect to* s_d *and* c^**. We again exploit the envelop theorem cancelling out terms that involve the derivative of* i' *at the optimal infraction level.*

$$\left(\frac{d}{dc}(b(i', c) - \tau(i')\phi^*(i', s_d))dc^* + \frac{d}{ds_d}(b(i', c) - \tau(i')\phi^*(i', s_d))ds_d\right)_{c=c^*} = 0$$

Accordingly,

$$\left(\frac{\partial b}{\partial c}dc^* - \tau(i')\frac{\partial \phi^*}{\partial s_d}ds_d\right)_{c=c^*} = 0 \;\; or \;\; \frac{dc^*}{ds_d} = \tau(i')\left(\frac{\partial \phi^*}{\partial s_d}\right)\left(\frac{\partial b}{\partial c}\right)^{-1}_{c=c^*} < 0$$

where the terms in parentheses are evaluated at c^* *and* $i'(c^*, s_d)$. *Finally,* c^* *falls with* s_d *based on Lemma 1 part (ii) and Assumption 2.2.* ***QED***

The share of stop motorist who are minority can be rewritten as

Definition 2. $K_g \equiv \frac{p[m|stopped,s_m,g(c,m)]}{p[w|stopped,s_w,g(c,w)]} = \frac{\int_{c^*(s_m)}^{c_h} g(c,m)\tilde{\phi}(c,s_m)di}{\int_{c^*(s_w)}^{c_h} g(c,w)\tilde{\phi}(c,s_w)di}$

where $\tilde{\phi}(c, s_d) \equiv \phi^*(i'(c, s_d), s_d)$ and g(c,d) is the distribution of motorists.

Unlike the ϕ^*, the derivative of $\tilde{\phi}$ is ambiguous in sign

$$\frac{d\tilde{\phi}}{ds_d} = \frac{\partial \phi^*}{\partial s_d} + \frac{\partial \phi^*}{\partial i}\frac{\partial i'}{\partial s_d} <> 0 \tag{8}$$

Proposition 2. *Given the general motorist and officer problems defined above, equilibria exist where a decrease in* s_m *leads to a decrease in* K_g.

Proof of Proposition 2. *As in Proposition 1, we examine the impact of decreasing* s_m.

$\frac{dK_g}{ds_m} = \frac{1}{p[w|stopped,s_w,g(c,w)]}\left(-\left(\frac{dc^*}{ds_m}\right)_{c=c^*} g(c^*, m)\tilde{\phi}(c^*, s_m) + \right.$

$\left.\int_{c^*}^{\infty} g(c,m)\frac{d\tilde{\phi}}{ds_m}dc\right)$

A positive derivative is consistent with the existence of equilibria that satisfy Proposition 2.

The first term in paratheses is positive by Lemma 3 part (i) as stop costs rise new motorists with lower values of c *begin to commit infractions raising minority motorists' share in the population of stops. The second term is generally ambiguous. The proposition will hold if equilibria exist when the inequality below is satisfied.*

$$-\left(\frac{dc^*}{ds_m}\right)_{c=c^*} g(c^*, m)\tilde{\phi}(c^*, s_m) > -\int_{c^*}^{\infty} g(c,m)\frac{d\tilde{\phi}}{ds_m}dc$$

The rest of the proof will proceed by constructing an example of an equilibrium by selecting primitives where the inequality above holds. We can bound the integral on the right hand side of the inequality from above by first exploiting the fact that the partial derivative of ϕ^* *with respect to* s_m *must be less than the total derivative of* $\tilde{\phi}$ *with respect to* s_m *because the second term in Equation (8) is always positive.*

$$-\int_{c^*}^{\infty} g(c,m)\frac{\partial\phi^*}{\partial s_m}di > -\int_{c^*}^{\infty} g(c,m)\frac{d\tilde{\phi}}{ds_m}di$$

Second, select h *so that the second derivative of* h^{-1} *is always negative. Now, we can bound the resulting expression from above because the negative second derivative of* h^{-1} *implies that the derivative of* ϕ^* *with respect to* s_m *is always increasing in* c*. Specifically, Equation (3) replacing* i *with* $i'(c, s_d)$ *yields.*

$$\frac{\partial^2\phi^*}{\partial c\partial s_d} = -h^{-1\prime\prime}\frac{du}{di}\frac{\partial i'}{\partial c} > 0$$

or equivalently that the negative derivative of ϕ^* *with respect to* s_d *is falling in magnitude with* c*. Therefore, the partial derivative of* ϕ^* *takes its maximum value within the intergral at* c^**, and so this derivative can be replaced by a constant equal to its value at* $i'(c^*, s_m)$ *and then factored out of the integral.*

$$-\left(\frac{\partial\phi^*}{\partial s_m}\right)_{i=i'(c^*,s_m)}\left(1-G(c^*,m)\right) \geq -\int_{c^*}^{\infty} g(c,m)\frac{\partial\phi^*}{\partial s_m}di$$

where $G(c^*, m)$ *is the cumulative distribution function of* $g(c, m)$ *at* c^**.*

Using this inequality, we replace the right-hand side of the inequality required for Proposition 2 to hold yielding a sufficient condition for a positive derivative of K_g*.*

$$-\left(\frac{dc^*}{ds_m}\right)_{c=c^*} g(c^*,m)\tilde{\phi}(c^*,s_m) > -\left(\frac{\partial\phi^*}{\partial s_m}\right)_{i=i'(c^*,s_m)}\left(1-G(c^*,m)\right)$$

Next, we replace the derivative of c^* *using the equation from the proof of Lemma 3 part (iii)*

$$\frac{dc^*}{ds_d} = \tau(i')\left(\frac{\partial\phi^*}{\partial s_d}\right)\left(\frac{\partial b}{\partial c}\right)_{c=c^*}^{-1}$$

then the proposition holds if

$$g(c^*,m)\tilde{\phi}(c^*,s_m) > \frac{1}{\tau(i')}\frac{\partial b}{\partial c}\left(1-G(c^*,m)\right)$$

where the negative of the derivatives of ϕ^* *with respect to* s_m *on both sides of the inequality were evaluated at* $i'(c^*, s_m)$ *and so cancel out of the expression, and* τ *and the derivative of* b *are evaluated at* $i'(c^*, s_m)$ *and* c^**.*

Now, let $g(c, m)$ *be a symmetric, unimodal probability distribution centered on* c^* *with a maximum density of* $\bar{g}$ *at* c^* *and rewrite the inequality based on this distribution.*

$$\bar{g}\,\tilde{\phi}(c^*,s_m) > \frac{1}{\tau(i')}\frac{\partial b}{\partial c}\frac{1}{2}$$

The solutions for c^*, $i'(c^*, s_m)$, $\tilde{\phi}(c^*, s_m)$ and the derivative of b do not depend upon the probability distribution, and $\tilde{\phi}(c^*, s_m)$ is bounded away from zero. By construction, $\bar{g}$ must limit to infinity as the variance of the distribution of c limits to zero. Therefore, by continually reducing the variance of the distribution, we can obtain a density $\bar{g}$ that is sufficiently large to satisfy the inequality above. ***QED***

A.3. Equilibrium Distribution of Infraction Levels

We write a stopped motorist percentile by integrating over the product of the pdf of c and the equilibrium probability of stop $\tilde{\phi}(c, s_m) = \phi^*(i'(c, s_m), s_m)$, or

$$x(c, s_m) = \frac{\int_{c^*(s_m)}^{c} g\,(c')\phi^*(i'(c', s_m), s_m)\, dc'}{\int_{c^*(s_m)}^{\infty} g\,(c')\phi^*(i'(c', s_m), s_m)\, dc'}$$

We next write the preference parameter as an implicit function c_x of the percentile.

$$\int_{c^*(s_m)}^{c_x(x,s_m)} g\,(c')\phi^*(i'(c', s_m), s_m)\, dc' = x \int_{c^*(s_m)}^{\infty} g\,(c')\phi^*(i'(c', s_m), s_m)\, dc' \qquad (9)$$

Finally, we define the equilibrium infraction level of stopped motorists at each percentile.

Definition 3. $i_x(x, s_m) \equiv i'(c_x(x, s_m), s_m)$

Assumption 3.1 $\lim_{i\to\infty}\left(\frac{\partial\tau}{\partial i}h^{-1'} + \tau(i)h^{-1''}\frac{\partial u}{\partial i}\right) = L > 0$ where L is finite and the derivatives of h^{-1} are evaluated at $(u(i) - s_m)$.

Assumption 3.2 $\lim_{i\to\infty}\frac{d^2u}{di^2} = 0$, $\lim_{i\to\infty}\frac{d^2\tau}{di^2} > 0$, $\lim_{c\to\infty}\frac{\partial^2 b}{\partial i^2} \geq 0$, $\lim_{i\to\infty}\left(\tau(i)h^{-1'}\right) \neq \infty$ where $h^{-1'}$ is evaluated at $(u(i) - s_m)$, $\lim_{c\to\infty}\frac{\partial^2 b}{\partial c\partial i} \geq 0$, and all limits listed in the assumption plus $\lim_{i\to\infty} h^{-1''}$ exist and are finite. [1]

[1] The existence requirement of assumption 3.2 eliminates situations where the second derivative of functions could oscillate between positive and negative. Such oscillation creates the possibility that the first derivative can limit to zero even though the second derivative does not exist. The classic example of this type of problem is $f'(x) = 1 + \sin(x^2)/x$ where $\lim_{x\to\infty} f(x) = 1$, a horizontal asymptote, but $f''(x) = 2cos(x^2) - \sin(x^2)/x^2$ and so the limit of the second derivative does not exist.

Lemma 4. *(i)* $\lim_{i\to\infty}\frac{\partial\phi^*}{\partial i}=0$ *and* $\lim_{i\to\infty}\frac{\partial^2\phi^*}{\partial i^2}=0$, *(ii) if* $\lim_{c\to\infty}\frac{\partial^2 b}{\partial c\partial i}=0$ *then* $\lim_{c\to\infty} i'(c,s_d)=I(s_d)$, *while if* $\lim_{c\to\infty}\frac{\partial^2 b}{\partial c\partial i}>0$ *then* $\lim_{c\to\infty} i'(c,s_d)=\infty$ *, (iii).* $\lim_{c\to\infty}(SOC)_{i=i'}\neq 0$ *and finite.*

Proof of Lemma 4. *(i) Since the second derivative of* u *limits to zero, the first derivative of* u *must approach a horizontal asymptote and so be finite. Using Equation (3),*

$$\lim_{i\to\infty}\frac{\partial\phi^*}{\partial i}=\lim_{i\to\infty}h^{-1'}\frac{du}{di}=0$$

The first term of the product limits to zero based on the definition of h *in Assumption 1.3 and the first derivative of* u *is finite as noted above and so the limit of the derivative equals zero. Next, we can write*

$$\lim_{i\to\infty}\frac{\partial^2\phi^*}{\partial i^2}=\lim_{i\to\infty}\left(h^{-1''}\left(\frac{du}{di}\right)^2+h^{-1'}\frac{d^2u}{di^2}\right)=0$$

The second term limits to zero based on the definition of h *and Assumption 3.2. Turning to the first term, the fact that* $h^{-1'}$ *limits to zero requires that* $h^{-1''}$ *also limit to zero under the assumption that its limit exists. Specifically, if* $h^{-1''}$ *limits to a negative value, there exists an* i *large enough that* $h^{-1''}$ *will always be within* ε *of that limiting value. Then, for any finite, positive value of* $h^{-1'}$ *at this* i*, we can divide this positive value by the lower bound of the magnitude of* $h^{-1''}$ *(its current value at* i *plus* ε*) and increasing* i *by this amount leads to a negative value of* $h^{-1'}$ *and a contradiction. Therefore,* $h^{-1''}$ *must limit to zero, and since the limit of the derivative of* u *is finite the first term of the expression above also limits to zero.*

(ii) If the cross-partial derivative of b *limits to zero with* c*, then the limit of the first derivative of* b *in the first order condition must limit to a constant with* c *holding* i *fixed. Further, because the second derivative of b with respect to* i *is negative, this limit must be larger than the limit that arises when the limit of the derivative is evaluated for* $i'(c)$ *so that* i *increases as* c *increases, and so the limit of the first derivative of* b *evaluated at* $i'(c)$ *is also finite*

$$\lim_{c\to\infty}\frac{\partial b}{\partial i}=B(i)>\lim_{c\to\infty}\left(\frac{\partial b}{\partial i}\right)_{i=i'}=B$$

Therefore,

$$\lim_{c\to\infty}FOC=B-\lim_{c\to\infty}\left(\frac{d\tau}{di}\phi^*(i,s_m)+\tau(i)\frac{\partial\phi^*}{\partial i}\right)_{i=i'}=0$$

The non-zero second derivative of τ *implies that the second term in the FOC limits to infinity as* i *limits to infinity because the first derivative of* τ *is always increasing with* i *by some value that is bounded away from zero. Therefore, since the first term is finite in the limit at* B, *the FOC can only be satisfied if* i' *limits to a finite value as* c *limits to infinity,* $\lim_{c\to\infty} i'(c, s_m) = I(s_m)$.

If the cross-partial of b *limits to a positive value, then the first derivative of* b *must limit to infinity with* c. *Now, rewriting the limit of the FOC*

$$\lim_{c\to\infty} FOC = \lim_{c\to\infty}\left(\frac{\partial b}{\partial i}\right)_{i=i'} - \lim_{c\to\infty}\left(\frac{d\tau}{di}\phi^*(i,s_m) + \tau(i)\frac{\partial \phi^*}{\partial i}\right)_{i=i'} = 0$$

It is clear by inspection that the first order condition can only be satisfied in the limit if the second term limits to infinity and this will only occur if $\lim_{c\to\infty} i'(c, s_d) = \infty$.

(iii) The second order condition based on primitive functions is

$$SOC \equiv \frac{\partial^2 b(i,c)}{\partial i^2} - \frac{d^2\tau(i)}{di^2}\phi^*(i,s_d) - 2\frac{d\tau(i)}{di}h^{-1\prime}\frac{\partial u}{\partial i} - \tau(i)\left(h^{-1\prime\prime}\left(\frac{du}{di}\right)^2 + h^{-1\prime}\frac{d^2u}{di^2}\right)$$

If $\lim_{c\to\infty} i'(c, s_m) = I(s_m)$, *then all of the terms in the SOC are evaluated in the limit for a finite value of* i. *The first term is finite based on Assumption 3.2 and all other terms are finite based on the finite value of* i. *Similarly, all terms except for the first term are non-zero at any finite* i.

If $\lim_{c\to\infty} i'(c, s_m) = \infty$, *then we must evaluate each term in the SOC individually. The first term is zero. In order to see this, remember that the first derivative is unambiguously positive and the second derivative is unambiguously negative for any finite* i *and* c. *As* i *limits to infinity for any finite* c, *the second derivative as long as it exists must limit to zero for any finite c. Otherwise, we could find a value of* i *large enough that the second derivative is within* ε *of its limiting negative value, and then an increase of* i *by the current value of the first derivative divided by the lower bound of the second derivative (the limiting value plus epsilon) will result in a negative first derivative and a contradiction. If the first term limits to zero for any finite* c, *then it must limit to zero as* c *and* $i'(c)$ *limit to infinity. The second term is finite and non-zero based directly on Assumption 3.2. The third term is finite and non-zero because the first derivative of* u *is finite and non-zero and Assumption 3.1 implies that the first two terms in this product are finite and non-zero. The fourth term is zero because Assumption 2.5 implies that the second half of this term dominates the first half and Assumption 3.2 implies that* $\tau(i)h^{-1\prime}$ *is finite and that the second derivative of* u *limits to zero.* ***QED***

Assumption 3.3 The domain of the non-zero values of the probability distribution of c is continuous, or equivalently for any c where $g(c) \neq 0$ if there exists $c_h > c$ where $g(c_h) = 0$ then $g(c') = 0$ for all $c' > c_h$ and if there exists $c_l < c$ where $g(c_l) = 0$ then $g(c') = 0$ for all $c' < c_l$. Given this continuity assumption, if the domain of g is not bounded above, i.e. there exists a c_l such that $g(c) \neq 0$ for all $c > c_l$, then $\lim_{c \to \infty} {(1 - G(c))}/{g(c)} = 0$. On the other hand, if the non-zero domain of g ends at c_h, i.e. there exists a c_h such that $G(c) \neq 0$ for $c_l < c < c_h$ for some $c_l \neq c_h$ and $G(c) = 0$ for $c > c_h$, then either $g(c_h) \neq 0$ or $\lim_{c \to c_h} {(1 - G(c))}/{g(c)} = 0$.

Proposition 3. *For all s_m there exists $\tilde{x}$ such that $\frac{di_x}{ds_m} > 0$ for all $x > \tilde{x}$.*

Proof of Proposition 3. *Differentiation of $i_x(x, s_m)$ in Definition 3 yields*

$$\frac{di_x}{ds_m} = \frac{di'}{ds_m} + \frac{di'}{dc}\frac{dc_x}{ds_m}$$

The derivative of $c_x(x, s_m)$ can be found by differentiating Equation (9) with respect to s_m and replacing x with $G(c_x)$.

$$\frac{dc_x}{ds_m} g(c_x)\phi^*(i'(c_x, s_m), s_m) = (1 - G(c_x))\frac{dc^*}{ds_d} g(c^*)\phi^*(i'(c^*, s_m), s_m) + G(c_x)\int_{c^*(s_m)}^{c_h} g(c')\frac{d\phi^*}{ds_m}\, dc' - \int_{c^*(s_n)}^{c_x} g(c')\frac{d\phi^*}{ds_m}\, dc'$$

where c_h is the maximum value of c within the domain of the probability distribution, which could be positive infinity.

The first term on the right-hand side of the equation above is negative based on Lemma 3 leading to an ambiguous derivative of i_x. This first term represents the same source of ambiguity discussed in Proposition 2. As stop costs increase, c^* falls and more minority motorists commit infractions. These new infracting motorists have lower values of c shifting the distribution of infracting motorists to lower infraction levels.

However, as we increase c and move to higher percentiles (x or $G(c_x)$ approaches 1), the first term goes to zero. Further, as c_x approaches the c_h, $G(c_x)$ approaches 1, and the second and third terms exactly cancel out when $c_x = c_h$. Therefore, if $g(c_h) \neq 0$, then the derivative of c_x with respect to s_m is zero at $x = 1$.

If $\lim_{c \to c_h} g(c) = 0$ *whether* c_h *is finite or infinite, we must evaluate the limit of the derivative of* c_x.

$$\lim_{c_x \to c_h} \frac{dc_x}{ds_m} = \lim_{c_x \to c_h} \frac{1}{\phi^*(i'(c_x, s_m), s_m) g(c_x)} \Bigg((1-x) \frac{dc^*}{ds_d} g(c^*) \phi^*(i'(c^*, s_m), s_m) +$$

$$x \int_{c^*(s_m)}^{c_h} g\,(c') \frac{d\tilde{\phi}}{ds_m}\, dc' - \int_{c^*(s_n)}^{c_x} g\,(c') \frac{d\tilde{\phi}}{ds_m}\, dc' \Bigg)$$

Now, we can rewrite last two terms in parentheses by extending the limit of the second integral from c_x *to* c_h *and adding a new term to offset that extentions.*

$$\lim_{c_x \to c_h} G(c_x) \int_{c^*(s_m)}^{c_h} g\,(c') \frac{d\tilde{\phi}}{ds_m}\, dc' - \int_{c^*(s_n)}^{c_x} g\,(c') \frac{d\tilde{\phi}}{ds_m}\, dc'$$

$$= \lim_{c_x \to c_h} -(1 - G(c_x)\,) \int_{c^*(s_m)}^{c_h} g\,(c') \frac{d\tilde{\phi}}{ds_m}\, dc' + \int_{c_x}^{c_h} g\,(c') \frac{d\tilde{\phi}}{ds_m}\, dc'$$

Since the derivative of $\tilde{\phi}$ *is finite, we can bound the magnitude of the last term by replacing this derivative with the maximum of its absolute value and factoring this out of the integral.*

$$\lim_{c_x \to c_h} \left| \int_{c_x}^{c_h} g\,(c') \frac{d\tilde{\phi}}{ds_m}\, dc' \right| < \lim_{c_x \to c_h} \max_{c} \left| \frac{d\tilde{\phi}}{ds_m} \right| |(1 - G(c_x)\,)|$$

As a result, the first term and revised second term only depend upon c_x *through a linear function of* $(1 - G(c_x)\,)$ *and the revised third term is bounded by a function that also depends linearly on* $(1 - G(c_x)\,)$. *Based on Assumption 3.3, the limit of the ratio of* $(1 - G(c)\,)$ *to* $g(c)$ *is zero and so the derivative of* c_x *with respect to* s_m *limits to zero as* c *limits to* c_h *even if* $g(c)$ *limits to zero.*

Using the equations for the derivatives from part (ii) of Lemma 2, we note that

$$\frac{di'}{dc} = -\frac{\frac{\partial^2 b}{\partial c \partial i}}{SOC}$$

$$\frac{di'}{ds_m} = \frac{1}{SOC} \left(\frac{\partial \tau}{\partial i} \frac{\partial \phi^*}{\partial s_m} + \tau(i) \frac{\partial^2 \phi^*}{\partial i \partial s_m} \right) = \frac{-1}{SOC} \left(\frac{\partial \tau}{\partial i} h^{-1'} + \tau(i) h^{-1''} \frac{\partial u}{\partial i} \right)$$

If the cross-partial of b *limits to zero and based on Lemma 4* $\lim_{c \to \infty} i'(c, s_d) = I(s_d)$ *or alternatively if the probability distribution of* c *has zero density above some finite value of* c_h, *then* $i'(c)$ *is finite in the limit. As a result, both derivatives of* i' *are positive and finite. Therefore, the second term in the derivative of* i_x *limits to zero and the first term is finite so that the derivative of* i_x *must limit to a positive value as* x *approaches one.*

On the other hand, if $\lim_{c\to\infty} i'(c, s_d) = \infty$ *and the density is non-zero for any finite* c*, we must evaluate these two derivatives in the limit as* i *approaches infinity. Assumption 3.2 assures that the limit of the derivative of* i' *with respect to* c *is finite because the limit of the cross-partial of* b *is finite and based on* Lemma *4 the SOC does not limit to zero. Assumption 3.1 assures that the limit of the derivative of* i' *with respect to* s_d *is bounded away from zero. Therefore, the first term in the derivative of* i_x *limits to a positive value and the second term limits to zero.* ***QED***

Appendix B. Empirical Appendix

Table B1: Estimated Change in the Accidents Rate for Minority Motorists in Daylight, USNO Daylight Definition

LHS: African-American		(1)	(2)	(3)	(4)
Baseline					
Daylight		-0.01107*** (0.00413)	-0.01019*** (0.00389)	-0.00986*** (0.00392)	-0.00960*** (0.00391)
Observations		39076	39076	39076	39076
Interaction – Black-White Police Shootings Odds Ratio					
Daylight x Police Shootings		-0.00268* (0.00152)	-0.00399*** (0.00146)	-0.00437*** (0.00152)	-0.00451*** (0.00151)
Observations		39063	39063	39063	39063
Interaction – Google Search Racism Index					
Daylight x Racism Index		-0.00779** (0.00348)	-0.01167*** (0.00337)	-0.01125*** (0.00347)	-0.01196*** (0.00345)
Observations		39063	39063	39063	39063
VOD Inconclusive States					
Daylight		-0.04334*** (0.01162)	-0.03245*** (0.01052)	-0.03235*** (0.01037)	-0.03277*** (0.01031)
Observations		6587	6587	6587	6587
Controls	Hour of Day	X	X	X	X
	Day of Week	X	X	X	X
	Year	X	X		
	State		X		
	State x Year			X	X
	Motorist/Vehicle				X

Table B2: Estimated Change in the Accidents Rate for Minority Motorists in Daylight, Fatality Risk Weighted

LHS: African-American		(1)	(2)	(3)	(4)
Baseline					
Daylight		-0.00879 (0.00690)	-0.01296** (0.00634)	-0.01328** (0.00648)	-0.01353** (0.00650)
Observations		39076	39076	39076	39076
Interaction – Black-White Police Shootings Odds Ratio					
Daylight x Police Shootings		-0.00107 (0.00156)	-0.00240 (0.00157)	-0.00312* (0.00164)	-0.00323** (0.00163)
Observations		39063	39063	39063	39063
Interaction – Google Search Racism Index					
Daylight x Racism Index		-0.00937*** (0.00381)	-0.01138*** (0.00373)	-0.01056*** (0.00389)	-0.01109*** (0.00385)
Observations		39063	39063	39063	39063
VOD Inconclusive States					
Daylight		-0.04623*** (0.01242)	-0.03683*** (0.01082)	-0.03601*** (0.01077)	-0.03640*** (0.01072)
Observations		6587	6587	6587	6587
Controls	Hour of Day	X	X	X	X
	Day of Week	X	X	X	X
	Year	X	X		
	State		X		
	State x Year			X	X
	Motorist/Vehicle				X

Table B3: Canonical Veil of Darkness Estimates, Logit

LHS: African-American		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		MA		East TN			West TN		
Daylight		0.409*** (0.0703)	0.416*** (0.0989)	0.0104 (0.0958)	-0.0150 (0.0943)	0.00300 (0.0981)	0.0706** (0.0289)	0.0637** (0.0288)	0.0817*** (0.0286)
Controls	Day of Week	X	X	X	X	X	X	X	X
	Time of Day	X	X	X	X	X	X	X	X
	County (or Town)	X	X	X	X		X	X	
	Year			X	X		X	X	
	Motorist/Vehicle		X		X	X		X	X
	County x Year					X			X
Observations		10203	10203	23515	23515	23515	102054	102054	102054

Notes: Coefficient estimates are presented where * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance. Standard errors are clustered on county by year (TN) and patrol districts (MA) but robust to clustering on county and year separately (TN), patrol district (TN), or town (MA). The sample includes only traffic stops involving African-American or Non-Hispanic white motorists. The two Tennessee samples also include controls for year in the first two specifications of each panel.

Table B4: Estimated Change in Speed Distribution for Stopped Minority Motorists in Daylight, Demographic Controls and County by Year Fixed Effects for Tennessee

LHS: Rel. Speed		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		10 pct	20 pct	30 pct	40 pct	50 pct	60 pct	70 pct	80 pct	90 pct
MA	Daylight	0.0811	0.196	1.938	0.727	-0.318	-0.0289	0.482	-0.560	-1.260
		(1.117)	(1.174)	(1.260)	(0.931)	(1.128)	(1.251)	(1.389)	(2.252)	(2.918)
	African-American	0.712	0.555	2.479*	2.164***	1.467**	1.601*	1.262	5.639***	6.154**
		(1.054)	(1.053)	(1.243)	(0.738)	(0.687)	(0.860)	(1.669)	(1.801)	(2.891)
	Daylight*African-American	-0.324	-0.221	-1.683	-2.230**	-5.000**	-6.748**	-7.616**	-10.79***	-11.93**
		(1.308)	(1.311)	(1.392)	(1.011)	(1.974)	(2.624)	(2.680)	(2.739)	(4.133)
	Obs.	10203	10203	10203	10203	10203	10203	10203	10203	10203
East TN	Daylight	0.372	0.327	0.0145	0.00964	0.0284	0.0854	0.374	0.459	-0.100
		(0.695)	(0.454)	(0.274)	(0.273)	(0.318)	(0.354)	(0.461)	(0.699)	(0.991)
	African-American	-2.008	-1.807**	-1.190**	-0.877	-0.780	-0.989	-0.180	-1.187	-1.958
		(1.236)	(0.868)	(0.551)	(0.535)	(0.614)	(0.711)	(0.892)	(1.322)	(1.682)
	Daylight*African-American	-0.822	-1.023	-0.812	-0.700	-1.113	-1.324*	-2.757***	-1.697	-1.684
		(1.334)	(0.980)	(0.629)	(0.574)	(0.681)	(0.738)	(0.989)	(1.486)	(2.028)
	Obs.	23515	23515	23515	23515	23515	23515	23515	23515	23515
West TN	Daylight	0.153	0.277*	0.0104	-0.0326	-0.0999	0.0761	0.138	-0.0119	-0.0466
		(0.108)	(0.156)	(0.108)	(0.146)	(0.121)	(0.171)	(0.235)	(0.296)	(0.397)
	African-American	0.193	0.600***	0.665***	0.685***	0.331*	0.738***	0.754**	0.637*	0.319
		(0.131)	(0.164)	(0.135)	(0.200)	(0.180)	(0.240)	(0.309)	(0.347)	(0.502)
	Daylight*African-American	-0.115	-0.214	-0.538***	-0.865***	-0.543***	-0.854***	-1.015***	-0.781**	-0.903
		(0.146)	(0.193)	(0.153)	(0.218)	(0.184)	(0.265)	(0.356)	(0.395)	(0.572)
	Obs.	102054	102054	102054	102054	102054	102054	102054	102054	102054

Notes: Coefficient estimates are presented such that * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance. Standard errors are clustered on county by year in East and West Tennessee (TN) and patrol districts in Massachusetts (MA). Bootstrapping one-thousand random samples, we find that the p-value for a one-sided permutation test of joint significance on all nine quantiles is equal to 1.4 percent for Massachusetts, 0.4 percent for East Tennessee, and 0.1 percent for West Tennessee. The sample includes only traffic stops involving African-American or Non-Hispanic white motorists. Controls include observed motorist and vehicle attributes, time of day, day of week, and geographic location fixed-effects. The two Tennessee samples also include controls for county by year fixed effects. Relative speed is calculated as speed relative to the speed limit and multiplied by one hundred.

Table B5: Falsification Test over Gender (Panel 1) and over Vehicle Type (Panel 2) with White Motorists

LHS: Rel. Speed		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Motorist Gender								
		10 pct	20 pct	30 pct	40 pct	50 pct	60 pct	70 pct	80 pct	90 pct
MA	Daylight*Male	-1.265	-0.516	-0.267	-0.752	-0.226	0.0118	0.850	0.179	0.348
		(0.847)	(0.789)	(0.801)	(1.061)	(1.293)	(1.628)	(1.842)	(2.076)	(4.474)
	Obs.	8334	8334	8334	8334	8334	8334	8334	8334	8334
		(0.602)	(0.359)	(0.254)	(0.227)	(0.189)	(0.267)	(0.284)	(0.646)	(1.202)
East TN	Daylight*Male	-0.471	-0.186	0.260	0.314*	0.110	-0.0347	-0.265	-0.306	-1.004
		(0.493)	(0.353)	(0.274)	(0.158)	(0.336)	(0.431)	(0.513)	(0.841)	(1.314)
	Obs.	22424	22424	22424	22424	22424	22424	22424	22424	22424
		(0.0957)	(0.162)	(0.137)	(0.145)	(0.125)	(0.172)	(0.171)	(0.254)	(0.319)
West TN	Daylight*Male	-0.00342	0.0480	-0.00976	-0.0928	-0.0347	-0.307	-0.285	-0.779**	-0.285
		(0.151)	(0.197)	(0.193)	(0.193)	(0.160)	(0.187)	(0.219)	(0.333)	(0.452)
	Obs.	83076	83076	83076	83076	83076	83076	83076	83076	83076
		Domestic vs. Imported Vehicle								
LHS: Rel. Speed		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		10 pct	20 pct	30 pct	40 pct	50 pct	60 pct	70 pct	80 pct	90 pct
MA	Daylight*Domestic	-0.147	-0.554	-0.910	0.118	0.654	0.576	0.280	1.457	-1.389
		(1.158)	(1.234)	(0.914)	(1.098)	(1.007)	(0.942)	(1.302)	(2.182)	(2.221)
	Obs.	8334	8334	8334	8334	8334	8334	8334	8334	8334
		(0.411)	(0.490)	(0.238)	(0.245)	(0.251)	(0.316)	(0.538)	(0.865)	(1.489)
East TN	Daylight*Domestic	0.104	-0.655	-0.338	0.00464	-0.192	-0.146	-0.451	-0.556	-1.559
		(0.649)	(0.718)	(0.302)	(0.323)	(0.303)	(0.372)	(0.532)	(0.866)	(1.711)
	Obs.	22424	22424	22424	22424	22424	22424	22424	22424	22424
		(0.118)	(0.177)	(0.125)	(0.179)	(0.134)	(0.198)	(0.283)	(0.325)	(0.381)
West TN	Daylight*Domestic	0.131	0.0655	-0.0621	-0.119	-0.0466	0.0600	-0.105	0.0670	0.208
		(0.127)	(0.182)	(0.144)	(0.176)	(0.131)	(0.221)	(0.288)	(0.311)	(0.411)
	Obs.	83076	83076	83076	83076	83076	83076	83076	83076	83076

Coefficient estimates are presented such that * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance. Standard errors are clustered on county by year in East and West Tennessee (TN) and town or patrol districts in Massachusetts (MA. Bootstrapping one-thousand random samples, we find that the p-value for a one-sided permutation test of joint significance on all nine quantiles is equal to 85.7 percent for Massachusetts, 72.3 percent for East Tennessee, and 91.1 percent for West Tennessee. The sample includes only traffic stops for speeding violations involving Non-Hispanic white motorists. Controls include time of day, day of week, and geographic location fixed-effects. The two Tennessee samples also include controls for year. Relative speed is calculated as speed relative to the speed limit and multiplied by one hundred.

Table B6: Falsification Test over Motorist Age, Vehicle Age and Vehicle Color with White Motorists

		Motorist under the Age of 30								
LHS: Rel. Speed		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		10 pct	20 pct	30 pct	40 pct	50 pct	60 pct	70 pct	80 pct	90 pct
MA	Daylight*Young Motorist	0.302	-0.113	0.626	0.539	-0.735	0.429	1.692	0.576	1.739
		(0.482)	(0.611)	(0.713)	(0.843)	(0.947)	(1.354)	(1.467)	(1.391)	(1.853)
	Obs.	8334	8334	8334	8334	8334	8334	8334	8334	8334
		Vehicle is Older than Five Years								
LHS: Rel. Speed		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		10 pct	20 pct	30 pct	40 pct	50 pct	60 pct	70 pct	80 pct	90 pct
MA	Daylight*Old Vehicle	1.467*	-0.115	0.0108	1.323*	0.454	0.423	-0.229	-0.666	-0.336
		(0.771)	(0.742)	(0.782)	(0.643)	(0.654)	(0.792)	(1.079)	(1.656)	(2.345)
	Obs.	8334	8334	8334	8334	8334	8334	8334	8334	8334
		Vehicle is Red								
LHS: Rel. Speed		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		10 pct	20 pct	30 pct	40 pct	50 pct	60 pct	70 pct	80 pct	90 pct
MA	Daylight*Red Vehicle	2.563	2.179	0.942	1.616	1.209	1.836	3.364	2.690	1.561
		(1.942)	(2.257)	(2.145)	(1.740)	(1.796)	(1.959)	(2.421)	(3.013)	(4.418)
	Obs.	8334	8334	8334	8334	8334	8334	8334	8334	8334

Notes: Coefficient estimates are presented such that * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance. Standard errors are clustered on counties (TN) and patrol districts (MA). Bootstrapping one-thousand random samples, we find that the p-value for a two-sided permutation test of joint significance on all nine quantiles is equal to 46.7 percent for MA-SP. Results estimated using absolute rather than relative results are generally robust and qualitatively similar to our primary estimates. The sample includes only traffic stops involving Non-Hispanic white motorists. Controls include time of day, day of week, and patrol location fixed-effects. The Tennessee sample also includes year indicators. Relative speed is calculated as speed above the limit relative to the limit and multiplied by one hundred

C. Calibration Appendix

C.1 Optimization Strategy

Because the surface of this function is highly non-linear and appears to contain multiple local minima and inflections points, we first use a derivative-free Simplex-based optimization algorithm, Subplex (Rowan, 1990), to identify local minima. Once we have identified a local minimum, we use a second optimization routine based on quadratic approximations to the surface, BOBYQA (Powell 2009), to precisely locate that minimum and verify that the gradients over all parameters are approximately zero in this location. Finally, after identifying a specific local minimum that fits the data well, we will identify a global minimum using a modified evolutionary-based optimization routine, ESCH as described in da Silva Santos (2010) and accessed via an open source library for non-linear optimization (NLopt). The nature of evolutionary algorithms used for global optimization requires that limits be placed on the range of each parameter, and we use the information generated from the various local optimizations to place these limits. The specific limits for each parameter are shown in Appendix Table C1.[1]

We calibrate the parameters separately for the moments from Massachusetts, East Tennessee, and West Tennessee samples in a series of stages using the results of each stage as initial values in the next stage.

1. First, we focus on matching the minority daylight speed distribution using the Simplex-based algorithm, while calibrating just distributional parameters, i.e. mean, variance, and skewness, but targeting an additional moment based on a specific positive fraction of minorities not infracting in daylight. Holding other parameters fixed at values that were found based on experimentation.
2. We next match both the daylight speed distribution and the difference between the daylight and darkness distributions for minorities additionally calibrating all motorist parameters that are common between groups plus the minority daylight stop cost, i.e. $\alpha_1, \alpha_2, b_0, \mu,$ and τ_0. At this stage, we also drop the target on the

[1] This second routine also requires that the analyst place limits on the parameter space, but this is a relatively non-restrictive process since we are simply refining an already identified local minimum. In practice, the search for the local minimum never crosses the bounds that we set on the parameters.

fraction of minorities not speeding, which was simply used to anchor the initial calibration.

3. We then target all 26 moments and calibrate all 18 parameters. We first identify the local minimum using the simplex-based algorithm, but as mentioned above, we locate the local minimum precisely using quadratic approximations to the surface.
4. We repeat the process outlined in steps 1-3 for initial fractions minority not infraction in daylight between 0.05 and 0.40 in increments of 0.05 typically identifying different local minima for each percent not infracting value (even though that moment restriction is removed starting in step 2). We then identify the local minimum arising from an initial fraction not infracting moment restriction in step 1 that results in the lowest overall Mean Squared Error in step 3. We also verify that this minimum is internal to the range of fractions considered.
5. Finally, we use an evolutionary-based optimization routine using the best local optimum identified in step 4 and imposing parameter limits that were developed by observing the optimization over many possible local minima. Again, the quadratic approximation technique is used to precisely locate the minimum once the entropy-based routine has identified the minimum.

Note that the optimization also includes a penalty function starting below 2 percent of minority motorists not infracting in daylight in order to rule out corner solution equilibria where all motorists commit infractions. The final local and global optimums always imply a percent minority motorists not infracting above 2 percent so that the penalty function has no direct impact on the final optimum identified.

C.2. Calibration Weights

Theory does not provide guidance for establishing the weights on the moments. Our simulation is matching 6 statistics: African-Americans and white daylight speed distribution, African-Americans and white daylight to darkness shift in the speed distribution, fraction stopped motorists minority in darkness and VOD test statistic. Equal weights with 6 statistics would imply a weight of 16.7 percent for each statistic. However, one might place more weight on the speed distribution statistics since they represent the sum of 6 individual moment squared deviations. On the other hand, we might limit the weight on these moments since the number of moments is arbitrary based on the number of speed percentiles considered. For our baseline calibration, we place three times the weight on the speed distribution statistics so that the weight on those four are 21.5 percent each, and the weight on the fraction stopped motorists minority and VOD test statistic are 7 percent each. We also run robustness tests where we use an equal weight of 16.7 percent, and where we place six times the weight based on the 6 moments of the speed distribution for a weight of 23.25 percent for the four speed distribution statistics and 3.5 percent for both percent minority stopped and the VOD test statistic.

We conduct a robustness test by modifying the weights. The first panel of Table C4 presents the results from Table 8. The second panel applies an equal weight of 16.7 percent to the four speed distribution components and two moments based on the percent minority stopped. The third panel assigns approximately six times the weight to the four speed distribution moments that have six components so each of those moments receive a weight of 23.25 percent and the percent minority stopped based moments receive a weight of 3.5 percent each.[2] The basic results are relatively robust with similar daylight minority stop costs across the three calibrations, and substantially larger VOD test statistics after adjusting for minority driver changes in behavior. The magnitude of the adjusted VOD test statistics is notably sensitive to the weights only for West Tennessee. The largest adjusted VOD test statistic arises for the third panel where a larger weight is placed on matching the speed distribution shift, which makes sense since the baseline calibration understated the speed distribution shift in West Tennessee. Surprisingly, placing lower weight on the speed distribution contributions also increases the West Tennessee adjusted VOD test statistic. A better match to the VOD test statistic, which now has higher weight, requires lower police stop costs for minorities in daylight, which appears to have increased the shift in the speed distribution even as the total fit of the speed distribution moments eroded due to having lower weight. The calibrated parameters based on the alternative weights are shown in Table C5.

[2] The calibrated parameters for these alternative weights are shown in Appendix Tables B4-B6 for the three sites.

Table C1: Minimum and Maximum Values for Parameters

Parameters	Min	Max
α_1	0	1
M	1	4
δ_0	0	50
A	0.8	1.5
α_2	0	3
K	100	500
H	1	1.5
b_0	0	200
τ_0	50	800
σ_m	0	3
σ_w	0	3
mean_m	-4	2
mean_w	-4	2
skew_m	-50	100
s_v	44	44
MA		
skew_w	-50	100
s_vm	0	15
s_vw	44	60
E TN		
skew_w	-50	600
s_vm	30	44
s_vw	44	50
W TN		
skew_w	-50	100
s_vm	30	44
s_vw	44	47

Notes. Table presents the bounds on parameter values used for the envolutionary based optimization selected based on the local optima identified during the initial stages of optimization. Most parameter limits are the same by site with the exception of the minority and white daylight stop costs which are influenced heavily by the empirical racial composition of stops, and for the white skewness where we observed unusually high levels of skewness in the white population in some of the initial calibrations for East Tennessee.

Table C2: Calibration Results

	Massachusetts		East Tennessee		West Tennessee	
	Data	Simulation	Data	Simulation	Data	Simulation
White Speed Distribution Daylight						
20th Percentile	12.58119726	12.8990268	13.31786436	13.3819359	11.28808471	11.0761
40th Percentile	16.42617039	16.2500592	16.22345474	15.8291645	13.56950803	13.4798
60th Percentile	20.63785929	20.3829396	18.95081273	18.8376353	15.9148927	16.184
80th Percentile	26.69713667	26.8608619	23.30887568	23.5328263	19.74395994	20.0753
90th Percentile	33.27770052	33.3347123	27.7676207	27.9992266	23.69906791	23.7206
95th Percentile	41.03735374	40.9859405	33.42494972	33.2383482	28.02024315	27.7701
Difference Daylight and Darkness						
20th Percentile	-0.49062111	-0.2660177	0.00422909	-0.0000143	-0.11309278	0
40th Percentile	-0.38312866	-0.2971691	-0.11176114	0.0008881	-0.09190034	-0.0001
60th Percentile	0.2679906	-0.3117633	-0.03097062	0.0001257	-0.02815239	-0.0001
80th Percentile	-0.57652247	-0.3265926	-0.03718293	-0.0000601	0.03660167	0
90th Percentile	0.16650752	-0.34577	-0.07980587	0.0004908	0.26197307	-0.0001
95th Percentile	-1.70325014	-0.5461246	-0.2129078	0.0002214	0.46968762	0

Notes: Empirical speed distribution in miles per hour based on regressing relative speed on day of week, time of day, geographic and for Tennessee year controls, calculating the residual, adding the means of the controls back to the sample and then calculating the miles per hour based on the mode speed limit of traffic stops for each site. The simulated moments arise from the global optimum identified by applying an evolutionary based optimization routine called ESCH and precisely located by applying a second optimization routine based on quadratic approximations to the surface BOBYQA. The calibrated parameters used to calculate these moments are shown in Appendix Table 18.

Table C3: Calibrated Parameters

Parameters	Sites		
	MA	E TN	W TN
α_1	0.522029	0.509337	0.999519
M	1.55008	1.52118	2.18566
δ_0	5.14442	35.5046	3.0628
A	1.23914	1.1562	0.987308
α_2	0.509207	0.421155	1.4297
K	320.493	331.992	235.093
H	1.00387	1.00018	1.24943
b_0	16.7978	17.7386	128.356
τ_0	139.826	122.94	495.065
σ_m	1.23344	1.16092	0.513587
σ_w	1.66537	1.47121	0.53856
mean_m	-0.157625	-0.601036	-2.04262
mean_w	-1.24202	-1.02003	-2.08983
skew_m	0.269799	0.286773	2.5971
skew_w	11.551	3.47682	9.46006
s_vm	0.0057178	30.1313	37.7525
s_vw	44.9736	44.0005	44.0004
s_v	44	44	44
MSE	0.7483	0.638	0.2591

Notes. Each column of this table contains the calibrated parameters for one of the three sites for our baseline set of weights where the speed distribution components each have a weight of 21.5 and the share stops minority in darkness and the VOT test statistics (times 100) each have a weight of 3.5%. The parameters for the Massachusetts sample are in column 1 labelled MA. Column 2 contains parameters for East Tennessee labelled E TN, and column 3 is West Tennessee labeled W TN. The last row shows the mean squared error of the moments for each site.

Table C4: Calibration Results Related to Racial Differences in Police Stop Behavior

	Massachusetts	East Tennessee	West Tennessee
Original Weights			
Minority Stop Cost Diff	43.994	13.887	6.247
Simulated VOD Test	1.379	0.997	1.090
Adjusted VOD Test	2.736	1.223	1.173
Equal Weights			
Minority Stop Cost Diff	43.994	13.9996	10.125
Simulated VOD Test	1.38	0.994	1.091
Adjusted VOD Test	2.736	1.226	1.271
Speed Moments Times Six			
Minority Stop Cost Diff	43.979	12.348	12.38
Simulated VOD Test	1.38	1	1.09
Adjusted VOD Test	2.736	1.195	1.338

Notes. The first panel repeats the results from Table 12 using the original weights. The second panel presents results where the four speed distributions receive the same weight as each of the moments associated with percent minority stopped. The third panel presents results where the speed component contribution receives six times the weight because those components contain the mean squared error for six distinct moments.

Table C5: Calibrated Parameters for Massachusetts with Alternative Weights

Parameters	Massachusetts		East Tennessee		West Tennessee	
Weights	Equal	Speed*Six	Equal	Speed*Six	Equal	Speed*Six
α_1	0.522111	0.521889	0.509832	0.509053	0.999859	0.999519
M	1.55032	1.55012	1.52139	1.52119	2.18541	2.18367
δ_0	5.15151	5.14515	35.512	35.5046	3.48442	3.28581
A	1.23914	1.23901	1.1561	0.995303	0.987312	0.987276
α_2	0.509362	0.509277	0.423291	0.421159	1.42969	1.42973
K	320.355	320.48	330.47	331.94	235.036	233.854
H	1.00383	1.00385	1.00002	1.00073	1.25016	1.2497
b_0	16.7934	16.7978	17.7361	10.4695	129.092	128.877
τ_0	139.812	139.807	122.763	122.94	506.544	506.865
σ_m	1.23477	1.23406	1.16421	1.16237	0.516049	0.516706
σ_w	1.66587	1.66551	1.46317	1.47036	0.53923	0.538645
mean_m	-0.160836	-0.157642	-0.61939	-0.601093	-2.04261	-2.04212
mean_w	-1.24327	-1.24219	-1.0126	-1.0212	-2.09014	-2.08981
skew_m	0.268804	0.26982	0.293491	0.285781	2.59473	2.59168
skew_w	11.5521	11.5507	3.4744	3.4276	9.43347	9.47268
s_vm	0.104016	0.0209493	30.0004	31.6522	33.8754	31.6203
s_vw	44.9798	44.9742	44.0514	44.0331	44.0022	44.2422
s_v	44	44	44	44	44	44
MSE	0.5781	0.8044	0.4829	0.6164	0.168	0.2335

Notes. This table presents the calibrated parameters for different weights for the State of Massachusetts sample. The first column presents parameters for the baseline weights. The second column presents parameters for equal weights of 16.7% for the four speed components and the two components based on share minority stopped (share in darkness and VOD test), and the third column presents parameters for weights where the speed distribution components that contain 6 moments each have approximately 6 times the weight or 23.25% as the weight of 3.5% for the share stops minority in darkness and the VOD test statistic.