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Abstract: Several prominent applications of the Veil of Darkness (VOD) test, where solar variation is used to identify racial profiling in traffic stops, have found reverse discrimination in cities widely purported to disproportionately target minorities. We develop a theoretical model of traffic enforcement and demonstrate that the VOD test for racial profiling cannot distinguish between discrimination and reverse discrimination. In our model, this problem arises because motorists rationally alter their driving behavior when faced with discriminatory policing. For groups that face discrimination, our model implies that motorists who previously did not speed choose to speed in darkness, when demography cannot be observed, thus creating the possibility that the share of stopped minority motorists increases in darkness. We develop a follow-up test for identifying the direction of differential treatment by examining the speed distribution of motorists across daylight and darkness. Using data on traffic stops in Massachusetts made by State and Local Police, we reject the VOD test for equal treatment and demonstrate that driving speeds of stopped African-Americans are higher in darkness consistent with discrimination.

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1 Introduction

In the United States, the possibility that police officers and departments treat minorities differently than whites has been the source of both political protest and social unrest, especially with the recent rise of the "Black Lives Matter" movement. To many advocates, the high share of minorities involved in both traffic stops and vehicle searches is a clear indication of continued discrimination on the part of law enforcement. However, the empirical evidence of discrimination in traffic stops and searches has been mixed. Although the share of minorities involved in traffic stops or searches often far exceeds the share of the local population, analysts almost never have information on the actual racial composition of motorists on the road, the behavior of those motorists, or other visible indicators of guilt (Kowalski and Lundman 2007; p. 168; Fridell et al. 2001, p. 22).[1] Some researchers address this concern by focusing on searches conditional on being stopped where the fraction of minorities among stopped motorists is observed (Knowles, Persico, and Todd 2001; Anwar and Fang 2006).[2] However, such approaches cannot address the central question of whether racial discrimination exists in police decisions to stop motorists.

Several recent papers (Grogger and Ridgeway 2006; Ridgeway 2009; Horace and Rohlin 2016) pursue an alternative approach to identifying the appropriate counterfactual or comparison basis for evaluating racial differences in police stops. These papers postulate that race is less easily observable during darkness and propose examining differences in the racial composition of traffic stops in daylight relative to darkness. This strategy, coined the "Veil of Darkness" by Grogger and Ridgeway (2006), is rapidly becoming a key tool that policymakers use to examine police departments for evidence of discrimination.

[1] See recent evidence in Rhode Island by McDevitt et al. (2014) or North Carolina by Baumgartner and Epp (2012).

[2] One can either examine the likelihood of stop or the success rate of searches. Performance based strategies using success rates arise from Becker's (1957) classic model of taste based discrimination. Such performance approaches have also been pursued in the study of mortgage lending discrimination. See Ross and Yinger (1999, 2002, chap. 8) for a review of that literature. These performance-based studies have been criticized as being biased away from finding discrimination (Ayres 2002).

In recent years, researchers have applied the VOD test in cities such as Cincinnati, OH; Oakland, CA; Minneapolis, MI; New Orleans, LA; San Diego, CA; Syracuse, NY; Portland, OR; and several in North Carolina.[3] The first statewide application by Ross et al. (2015, 2016) took place in Connecticut and has served as a model for proposed legislation and evaluations in California, Oregon, and Rhode Island. The advantage of the VOD framework is that the distribution of stopped motorists in darkness, when race is unobserved, may provide a better indication of the distribution of motorists and motorist behavior than alternative counterfactuals like the racial composition of community residents. If racial differences are larger during the daylight, then this difference-in-differences test is inferred to imply evidence of discrimination against minority motorists. This strategy is similar to strategies that compare treatment across officers of different races, such as Antonovics and Knight (2009) or Anwar and Fang (2006), in that those papers use comparisons across motorist race and officer race in order to control for the inherent racial differences in the distribution of motorists.[4]

Grogger and Ridgeway (2006), who pioneered the VOD test in Oakland, CA, and later Ridgeway (2009) in Cincinnati, OH, both find statistically insignificant daylight versus darkness differences in the racial disparities of traffic stops. In fact, for both papers, the authors note that racial disparities are higher in darkness consistent with reverse discrimination, rather than discrimination against African-American motorists, even though the police departments in both of these cities faced substantial criticism for discriminating against minority motorists. Given the importance of the VOD test for assessing racial discrimination in traffic stops in the U.S., we provide a more complete assessment of whether larger racial disparities in darkness can be interpreted as reverse

[3]Citations for these applications include Oakland, CA (Grogger and Ridgeway 2006); Cincinnati, OH (Ridgeway 2009); Minneapolis, MN (Ritter and Bael 2009; Ritter 2017); Syracuse, NY (Worden et al. 2010; Worden et al. 2012; Horace and Rohlin 2016); Portland, OR (Renauer et al. 2009); Durham, NC (Taniguchi et al. 2016a); Greensboro, NC (Taniguchi et al. 2016b); Raleigh, NC (Taniguchi et al. 2016c); Fayetteville, NC (Taniguchi et al. 2016d); New Orleans, LA (Masher 2016); and San Diego, CA (Chanin et al. 2016)

[4]An important advantage is that the VOD, as compared to strategies that exploit information on the race of police officers, can detect discrimination even when all police officers discriminate regardless of their own race.

discrimination. Specifically, we extend equilibrium models of racial profiling and police-motorist interaction by Knowles, Persico, and Todd (2001), Dharmapala and Ross (2004), Anwar and Fang (2006) and Persico (2008) to consider the effect of race blindness caused by darkness on motorist behavior.

We develop the simplest model possible that captures several key aspects of expected motorist behavior in terms of speeding:

1. Police are more likely to stop motorists traveling at higher speeds but situations exist where some motorists are stopped at speeds only modestly above the speed limit while, at other times, motorists are not stopped for significantly more severe speeding infractions;

2. at some times, some motorists choose to obey the speed limit;

3. a motorist who is on the margin between obeying the speed limit and speeding will, if they decide to speed, choose a level that is discretely over the speed limit (e.g. the choice to speed represents traveling at the speed limit versus 3 or 4 miles per hour above as opposed to choosing the speed limit versus 1/5th or 1/10th of a mile per hour above); and

4. when police stop costs rise, reducing the likelihood of being stopped at any particular speed, motorists travel at higher speeds in equilibrium but still have a reduced likelihood of being stopped (a feature critical for the validity of the VOD test).

We first document that the properties of the VOD test are unaffected by the behavioral changes of motorists in darkness under the null hypothesis of equal treatment. However, we find that higher as well as lower relative stop rates of minority groups in daylight are both potentially consistent with discrimination. Specifically, when the likelihood of a minority being stopped falls in darkness because race is unobserved (i.e. stop costs rise), two changes occur: First, all else equal, minorities are less likely to be stopped and the VOD test statistic increases above one. Second, some minorities who did not commit an infraction during daylight are now willing to commit an infraction in darkness, given the high stop costs in darkness, leading to a decrease in the VOD test statistic. These findings imply that the racial disparities identified by Grogger and Ridgeway (2006) in Oakland, CA and by Ridgeway (2009) in Cincinnati, OH could actually indicate the presence of discrimination.

Finally, we use our theoretical model to examine the impact of a change in stop costs on the speed distribution of stopped motorists. Our model is designed so that higher stop costs/lower likelihood of stop raise optimal infraction levels, i.e. increases speeding. However, the shift in the speed distribution of stopped motorists is theoretically ambiguous. We calibrate our model against speed distribution data from Massachusetts and show that changes in stop costs create a shift in the distribution of speeds for stopped motorists that is consistent with the shift in the distribution of motorists overall. Therefore, the distribution of speeds for stopped motorists can be informative as to the direction of discrimination. Admittedly, the speed distribution shifts arise based on the beliefs of motorists, rather than the behavior of police, but such beliefs would seem to be especially germane when the VOD test rejects the null hypothesis of equal treatment. In particular, our theoretical model is consistent with concerns raised by Bell et al. (2014) that minority motorists often fear that they would be pulled over and experience significant "motivation to *survive* the law enforcement encounter."

Applying the VOD test to data from Massachusetts, the same data from Antonovic and Knight (2009), we reject the null hypothesis of equal treatment.[5] Specifically, we establish an inter-twilight window where we observe both darkness and daylight at the same time of day throughout the year. Conditional on time of day, we find that the share of stopped motorists who are African-American is different during the daylight than darkness. Due to our theoretical results, however, we cannot rely on the value of the test statistic to provide an indication of whether minority motorists are racially profiled by police or favored in their treatment. To address this limitation of the VOD test,

[5] The Massachusetts data was originally reported in an article for The Boston Globe on July 20, 2003 (Dedman and Latour 2003). Anbarci and Lee (2014) also use a subset of the data to examine leniency in fines issued to motorists by Boston police.

we draw on the theoretical prediction of our model that the speed distribution of motorists will respond to changes in visibility, and our simulation results that imply that the speed distribution shift for stopped motorists appears to always be in the same direction as the shift for all motorists. In particular, we develop a supplemental test that exploits the fact that if police officers have a preference for stopping minorities over whites then the speed distribution for minority (white) motorists should shift to lower (higher) speeds in daylight. We then test our hypothesis using the same local and State Police data from Massachusetts and find a substantial negative shift in the speed distribution of African-American motorists in daylight.

Motivated by Ridgeway (2009) and as a robustness check, we re-examine both the VOD test and the speed distribution shifts utilizing the 90-day window centered on the spring and fall Daylight Savings Time (DST) changes to exploit both the relatively instantaneous change in the time associated with darkness at the DST shift and the relatively rapid change in the time of sunset during both the fall and spring. Unlike the traditional VOD estimation strategy, this framework allows us to better control for seasonal differences in driving behavior and the composition of motorists on the roadway by eliminating comparisons between driving during long summer days and early winter evenings. We provide further validation of the robustness of our findings by examining the speed distribution along several additional dimensions including gender and age as well as vehicle age and color. Notably, we do not find consistent, statistically significant shifts in the white speed distribution for other demographic subgroups or vehicle characteristics. Our findings and robustness checks are strongly consistent with African-American motorists driving slower during the daylight because they expect to face a higher probability of being stopped than whites at that time. When combined with the rejection of the null hypothesis of equal treatment, this evidence supports a conclusion of racial profiling against African-Americans in traffic stops in Massachusetts.

The paper is organized as follows: The second section begins by developing a simple model of police traffic enforcement. We examine the VOD test statistic first in a model where motorist driving behavior is exogenously determined and then in a model where we make driving behavior endogenous. After establishing that endogenous driving behavior creates a problem for the traditional VOD test statistic, we discuss a supplemental test that indicates the direction of discrimination. In section three, we provide a detailed calibration of our model for Massachusetts data and conduct a simulation of our proposed test statistic. Our simulation shows that, under reasonable conditions, the speed distribution of stopped minority motorists will uniformly shift leftward during daylight. The fourth section provides descriptive statistics and applies the VOD test to our sample of Massachusetts traffic stop data where we reject the null for no discrimination. Here, we include a series of falsification tests that show that we are unable to identify consistent shifts in the speed distribution across other demographic or vehicular characteristics. The fifth and final section concludes the paper and identifies areas in need of additional research.

2 Theoretical Model

This section explores police-motorist interaction in a model of traffic enforcement. The first two subsections begin by developing a model of traffic enforcement and examining the implications of standard statistical tests of disparate treatment. The third subsection examines the VOD test in the context of our model of traffic enforcement. The fourth subsection develops an equilibrium model of motorist behavior conditional on traffic enforcement and examines the VOD test in that context. We demonstrates that the VOD test continues to be valid under the null hypothesis of equal treatment. However, under the alternative hypothesis, interpretation of the resulting test becomes problematic when examined in the context of endogenous motorist behavior.

Our model illustrates that both minority and white motorists will rationally respond to changes in visibility by altering their driving behavior when faced with disparate treatment. Specifically, in darkness when race is unobserved, the changes in police behavior will lead to more minority motorists committing infractions and less white motorists committing infractions, and so discrimination against minorities can in principle lead to either a lower or higher minority share of stops in daylight relative to darkness. In the final subsection, we propose a theoretically motivated alternative to the VOD test for gaining insights into the direction of unequal treatment based on comparing the speed distribution of stopped minority motorists during periods of daylight and periods of darkness. The advantage of our test is that it is more robust to changes in motorist behavior than the magnitude of the VOD test for indicating the direction of differential treatment.

2.1 Developing a Simple Model of Traffic Enforcement

We begin by structuring the police officer's decision as the choice of selecting probability $\gamma(i, d, \phi)$ of making a stop. The officer's choice or decision is made after observing a non-negative infraction severity, i, e.g. miles per hour over the speed limit; a motorist's demography, d; and the circumstances surrounding the stop, ϕ, which might include both environmental factors and factors related to officers' idiosyncratic preferences and current circumstances. We assume for simplicity that $d \in \{m, w\}$ is a dichotomous random variable that indicates whether the motorist is a racial or ethnic minority, and s_d is the positive police stop cost associated with motorist race and ethnicity.

The officer's maximization problem involves trading-off the stop pay-off, u, and stop costs, which includes both race specific costs and a circumstance cost defined by the function $h(\phi)$. The maximization problem takes the following form:

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

where $\gamma \in [0, 1]$. We make the following assumptions about police pay-offs and costs:

Assumption 2.1. u is a twice differentiable, non-negative function, $\frac{du(i)}{di} > 0$

and $\frac{d^2u(i)}{di^2} > 0 \ \forall i > 0$, $\lim_{i \to 0} u(i) = u_0 > 0$ and $u(0) = 0$;

Assumption 2.2. $\phi \sim Uniform(0, 1)$;

Assumption 2.3. h is a twice differentiable, non-negative function, $\frac{dh(\phi)}{d\phi} > 0 \ \forall \ 0 \leq \phi \leq 1$, $h(0) = 0$ and $\lim_{\phi \to 1} h(\phi) = \infty$;

Assumption 2.4. $u_0 - s_d > 0 \ \forall d$

We assume u is discontinuous at zero so that the officer receives no pay-off for stopping a motorist who has a zero level of infraction, but has a pay-off bounded away from zero for any positive infraction level. This assumption is consistent with the current penalty structures in many states. We also assume that u has increasing total and marginal pay-off with respect to the severity of the infraction. The officer faces two costs for stopping a motorist: s_d, a race specific cost for stopping a motorist (henceforth, stop costs), and an additional circumstance specific cost, and $h(\phi)$ resulting from factors like the officer's idiosyncratic preferences, geographic location, discretion, and contemporaneous opportunity cost (henceforth, circumstances).

The introduction of circumstances allow for heterogeneity in whether individuals are stopped at a specific infraction level. The circumstances are drawn from a uniform (0,1) distribution without loss of generality because the monotonic function $h(\phi)$ captures possible non-linearities in the mapping between circumstances ϕ and an officer's net pay-off. We do not impose a sign restriction on the second derivative of h to allow for generality over circumstance costs. For example, if circumstance costs were distributed unimodally over R^+ such as a chi-square distribution, the curvature of h must change sign over the range of ϕ. Finally, assumption *2.4* requires a positive net pay-off for a stop under some circumstances ϕ, even for an infinitesimally small positive level of infraction i. This effectively insures that the probability of stop is bounded away from zero for any motorist with a non-zero infraction level and so allows for a situation where motorists might choose not to commit an infraction.

Conditional on circumstances ϕ, demography d and the level of infraction i, the solution to the officer's problem requires an optimal infraction threshold, above which the probability an officer makes a stop, given full information, is equal to unity and otherwise the probability is zero due to the monotonic relationship between pay-off and the severity of motorist violation. Specifically, given the officer's net utility of $u(i) - h(\phi) - s_d \; \forall \; i$, the solution to her utility maximization problem is

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

Further, solving for zero net pay-off implies that an officer will stop all motorists at any infraction level above some threshold level following a specific stop-threshold function of

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

where u^{-1} maps from (u_0, ∞) to $(0, \infty)$ and $h(\phi) + s_d$ is always greater than u_0. Finally, conditional on infraction severity and exploiting the monotonicity of $h(\cdot)$, we can solve (2) for the circumstances when the net pay-off of a stop is zero $\phi^*(i, s_d)$, and officers will stop individuals with infraction level i whenever circumstances are more favorable than $\phi^*(i, s_d)$, i.e. $\phi < \phi^*(i, s_d)$. The resulting expression for the stop threshold over circumstances is

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

where h^{-1} maps from $(0, \infty)$ to $(0, 1)$ and $u(i) - s_d$ is always greater than zero. Recall that ϕ is distributed uniform (0,1); thus (3) also represents the unconditional (i.e. circumstances have not been observed) probability that an officer stops a motorist with infraction level i.

Lemma 1. *(i) The infraction level representing the optimal stop-threshold,* $i^* = u^{-1}[h(\phi)+s_d]$*, is increasing in officer circumstances and demographic based stop costs* s_d*.*

(ii) The probability of an officer making a stop, $\phi^*(i, s_d) = h^{-1}[u(i) - s_d]$, is decreasing in stop costs s_d and increasing in the level of infraction i.

Assumption 2.1 and the Inverse Function Theorem imply that $u^{-1'}(\cdot) > 0$ over its domain (u_0, ∞). Then by inspection it is clear that the derivative of Equation (2) implies $\frac{\partial i^*}{\partial \phi} > 0$, $\frac{\partial i^*}{\partial s_d} > 0$. Assumption 2.3 and the Inverse Function Theorem imply that $h^{-1'}(\cdot) > 0$, and by inspection it is clear that the derivative of Equation (3) implies $\frac{\partial \phi *}{\partial s_d} < 0$, and $\frac{\partial \phi^*}{\partial i} > 0$. QED

If the officer's behavior is racially blind, e.g. the cost of stopping motorists is equal across race $s_m = s_w$, the stop-threshold and the stop probability would be constant across demographic groups, $i^*(\phi, s_m) = i^*(\phi, s_w)$ and $\phi^*(i, s_m) = \phi^*(i, s_w)$, respectively. In the presence of disparate treatment, however, the cost faced by an officer for stopping a minority motorist is lower than a white motorist, $s_m < s_w$, implying that the stop-threshold for stopping a minority is lower than that for a white, $i^*_m < i^*_w$. Definition 1 below presents this formally.

2.2 Standard Test for Disparate Treatment

We define the distribution $f(i, d)$ as a mixed joint density function of motorists who commit an infraction over the continuous measure of infraction severity, i, and the dichotomous random variable of motorist demography, d. The distribution represents the motorists on the roadway, in terms of their demographic characteristics and driving behavior, who are at risk of being stopped by police officers. As such, we refer to $f(i, d)$ as the risk set of motorists. We also implicitly assume that $f(i, d)$ is equivalent to the analogous distribution of motorists seen by police.

Definition 1. *A police officer is racially biased against minorities of demography $d = m$ if they incur a lower cost, $s_m < s_w$, for stopping these motorists and, as a result, has a lower threshold, $i^*(\phi, s_m) < i^*(\phi, s_w)$, for making a traffic stop.*

Given the speed distributions of white and minority motorists, and using (3), the probability that a motorist who is stopped by police is of demography d is written formally by integrating over the product of the speed distribution and the stop probability function ϕ^*. We first define the indicator *stopped* as

$$stopped = \begin{cases} 1, & \text{if } \phi < \phi^*(i, s_w) \text{ and } d = w \text{ or } \phi < \phi^*(i, s_m) \text{ and } d = m \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

Then

$$p[d \mid stopped] = \frac{\int_0^\infty f(i,d)\phi^*(i,s_d)di}{\sum\limits_{d' \in \{m,w\}} \int_0^\infty f(i,d')\phi^*(i,s'_d)di}. \tag{5}$$

The standard test for disparate treatment in police officer stops, i.e. ratio of minorities stopped relative to whites, can be written as:

$$K = \frac{p[m \mid stopped]}{p[w \mid stopped]} = \frac{\int_0^\infty f(i,m)\phi^*(i,s_m)di}{\int_0^\infty f(i,w)\phi^*(i,s_w)di}. \tag{6}$$

Based on Definition (1), the null hypothesis of no disparate treatment for the standard test in (6) equates officer costs across demographic groups, $s_m = s_w$, yielding an equal likelihood of being stopped at any i, $\phi^*(i, s_m) = \phi^*(i, s_w)$. Assuming the risk set is constant across demographic groups, $f(i, m) = f(i, w)$, under the null hypothesis the standard test will equal unity, $p[m \mid stopped]/p[w \mid stopped] = 1$. In practice, the relevant minority and white populations may differ in size, and the ratio K is compared to an estimate of the community composition testing whether the minority-white ratio of stopped motorists matches the minority-white ratio of residents or motorists in the community.

However, this test statistic may not equal the minority-white ratio in the community under the null hypothesis if the distribution of infractions or risk set of motorists differs across demographic groups. Racial differences in the distribution of infractions is referred to in the racial profiling literature as the infra-marginality problem (see Anwar and Fang 2006; and Knowles et al. 2001).

2.3 Examining the Veil of Darkness Approach in a Model of Traffic Enforcement

Grogger and Ridgeway (2006) attempt to carefully sidestep the infra-marginality problem by developing an alternative procedure for measuring racial differences in the risk set, i.e. the Veil of Darkness (VOD) approach, that relies on a variation in visibility due to solar variation. The advantage of their procedure is that it requires no external information on the relative risk set of motorists on the roadway. The identification strategy and estimation procedure rely on seasonal patterns of solar variation and discrete shifts in visibility created by Daylight Savings Time (DST) changes. Identification in the VOD comes from the assumption that police officers are better able to perceive the demography of a motorist during daylight hours, and so these shifts in visibility create circumstances where race is unobserved and circumstances where race is observed for which the risk set is stable across these circumstances because the location and the time of day are held constant.

Specifically, the test statistic assesses whether there is a higher likelihood of a minority motorist (relative to a non-minority) being stopped by police in the presence of daylight (relative to darkness). We incorporate Grogger and Ridgeway's identification strategy in our model by denoting visibility with $v \in \{\overline{v}, \underline{v}\}$, where we assume that periods of darkness occur at the lower bound of visibility $\underline{v}$ and daylight occurs at the upper bound $\overline{v}$.

Recall the officer's maximization problem from (1):

$$\max_{\gamma(i,s_{v,d},\phi)} [u(i) - h(\phi) - s_{v,d}]\gamma(i, s_{v,d}, \phi), \tag{7}$$

where $\gamma \in [0, 1]$.

We continue to make Assumptions 2.1 - 2.4 about police behavior but will now further assume:

Assumption 2.5. $s_{\underline{v}} = s_{\underline{v},m} = s_{\underline{v},w}$; and

Assumption 2.6. $s_{\underline{v}} \in (s_{\overline{v},m}, s_{\overline{v},w})$ or $s_{\underline{v}} = s_{\overline{v},m} = s_{\overline{v},w}$.

The first of these two assumptions requires that stop cost be equal across groups during low visibility, $\underline{v}$, because race is unobserved. The second assumption requires that $s_{\underline{v}}$ be between the stop costs for minority and white motorists following the logic that if race is unobserved stop costs will be an unknown weighted average of the minority and white stop costs. Accordingly, under the null of equal treatment, $s_{\underline{v}}$ is equal to the high visibility costs, $s_{\overline{v}}$, for all groups. The basic structure of the officer's problem remains unchanged between (1) and (7) as does Definition 1 and Lemma 1. As such, the solution to her utility maximization problem in low visibility can be written as:

$$\gamma(i, s_{\underline{v},d}, \phi) = \begin{cases} 1, & \text{if } i \geq i^*(\phi, s_{\underline{v}}) \\ 0, & i < i^*(\phi, s_{\underline{v}}). \end{cases}$$

As before, we use the officer's net utility to derive the equilibrium circumstances stop-threshold for a given infraction severity in low visibility, $\phi^*(i, s_{\underline{v}}) = \phi^*(i, s_{\underline{v},m}) = \phi^*(i, s_{\underline{v},w})$ for any i, which, like the officer's stop cost, is also bounded by the circumstance stop-thresholds in high visibility so that either $\phi^*(i, s_{\underline{v}}) \in (\phi^*(i, s_{\overline{v},w}), \phi^*(i, s_{\overline{v},m}))$ or under the null of equal treatment $\phi^*(i, s_{\underline{v}}) = \phi^*(i, s_{\overline{v},w}) = \phi^*(i, s_{\overline{v},m})$.

In the context of our theoretical model, a VOD test for disparate treatment can be written formally as:

$$\begin{aligned} K_{VOD} &= \frac{p[m \mid stopped, \overline{v}]p[w \mid stopped, \underline{v}]}{p[w \mid stopped, \overline{v}]p[m \mid stopped, \underline{v}]} \\ &= \frac{\int_0^\infty f(i, m)\phi^*(i, s_{\overline{v},m})di \int_0^\infty f(i, w)\phi^*(i, s_{\underline{v}})di}{\int_0^\infty f(i, w)\phi^*(i, s_{\overline{v},w})di \int_0^\infty f(i, m)\phi^*(i, s_{\underline{v}})di}. \end{aligned} \tag{8}$$

where the definition of stopped in the previous section is refined to be conditional on visibility, i.e. ϕ^* is based on $s_{v,d}$. In practice, Grogger and Ridgeway (2006) propose regressing race on visibility conditional on time of day and day of week fixed effects in order to test for differences in the likelihood that the motorist who was stopped belongs to the minority group. We verify for our data that the implications of this test statistic are always consistent with the results of an equivalent Grogger and Ridgeway (2006) style regression.

Under the null hypothesis of racially blind policing where $s_{\underline{v}} = s_{\overline{v},m} = s_{\overline{v},w}$, $\phi^*(i, s_{\underline{v}}) = \phi^*(i, s_{\overline{v},m}) = \phi^*(i, s_{\overline{v},w})$, and (8) is equal to one. Under the alternative hypothesis of disparate treatment where $s_{\overline{v},m} < s_{\underline{v}} < s_{\overline{v},w}$ and $\phi^*(i, s_{\overline{v},w}) < \phi^*(i, s_{\underline{v}}) < \phi^*(i, s_{\overline{v},m})$, (8) is greater than one. Therefore, our model of policing generates implications for this VOD test statistic that are consistent with Grogger and Ridgeway's use of the VOD test as a control for demographic differences in the distribution of motorist's driving behavior.

This identification strategy appears very reasonable when motorist behavior is exogenous, but may be problematic if motorists respond to visibility in their driving behavior. Motivated by Anwar and Fang (2006) and Knowles et al. (2001), we extend our model to a setting where the motorist's decision is an endogenous function of the stop-threshold, and as noted above, the stop threshold varies with solar visibility because officers cannot observe race. We then use this framework to consider further implications for the VOD test and the assumption of a constant relative risk set over solar visibility.

2.4 An Equilibrium Model of Motorist Driving Behavior

The simple model above ignores potential changes in the equilibrium behavior of motorists. However, we expect that motorists will adjust their infraction levels in response to changes in officer stop costs. Additionally, the definition of racial bias in a VOD context implies that changes in officer stop cost over visibility varies across demographic groups.

The motorist's utility maximization problem, over infraction level, takes the following form:

$$\max_{i(c,s_d)} b(i,c) - \tau(i) \int_0^{\phi^*(i,s_{v,d})} \Gamma(\phi) d\phi \tag{9}$$

where $b(i,c)$ is the motorist pay-off for committing an infraction of a given level

i, c is a motorist preference parameter, τ is motorist costs associated with being stopped when committing an infraction, and $\Gamma(\phi)$ is the probability density function of ϕ distributed as uniform (0,1). We make the following assumptions about motorist behavior:

Assumption 2.7. b is a twice differentiable, non-negative function, $\frac{\partial b}{\partial i} > 0$, and $\frac{\partial^2 b}{\partial i^2} < 0 \ \forall \ c$ and $i \geq 0$, and $b(0, c) = 0$ and $\lim_{i \to \infty} \frac{\partial b}{\partial i} = 0 \ \forall \ c$;

Assumption 2.8. $\frac{\partial b}{\partial c} > 0$ and $\frac{\partial^2 b}{\partial c \partial i} > 0 \ \forall \ c$ and for $i > 0$;

Assumption 2.9. τ is a 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 2.10. $\frac{\partial b}{\partial i}\Big|_{i=0} \geq \frac{d\tau}{di}\Big|_{i=0} h^{-1}[u_0 - s_{v,d}] + \tau(0) h^{-1'}[u_0 - s_{v,d}] \ \forall \ c$;

Assumption 2.11. $\frac{\frac{d^2 u}{di^2}}{\frac{du}{di}} \geq \frac{-h^{-1''}(\cdot)}{h^{-1'}(\cdot)} \frac{\partial u}{\partial i} \ \forall i \geq 0$.

Assumption 2.12. $c \sim g(c, d)$ where there exists a $c_{h,d}$ such that $g(c, d) = 0 \ \forall c > c_{h,d}$ and $g(c_{h,d}) > 0$.

The motorist maximizes the expected pay-off function in (9) with respect to infraction severity. She takes the probability of being stopped, $\gamma(i, s_{v,d}, \phi)$, from the officer's problem as given and integrates over the distribution of possible circumstances, ϕ. As such, the motorist compares the expected marginal benefits and costs when choosing an optimal i'. The term, c, captures motorist heterogeneity through context, e.g. recklessness, timing, sleep deprivation, etc. We assume that the motorist benefit or pay-off is an increasing function of infraction severity and that marginal benefit is diminishing. Additionally, both the benefit and the marginal benefit of infracting rise with recklessness, c. This assumption simply initializes the direction of the effect of this parameter on motorist benefit. We assume that the motorist's cost and marginal cost are increasing in infraction severity, and motorist's cost is bounded away from zero for infinitesimally small infraction levels, which is required to assure that some motorists choose not to commit an infraction. The cost function is assumed to be invariant to recklessness. We also assume, at low levels of infraction, the marginal benefit of increasing infraction level is higher than the marginal cost of increasing infraction level in order to assure an interior solution for motorists who choose to commit an infraction. Finally, we impose two technical assumptions. The first assumption is that the relative curvature (curvature relative to the slope) of the officer's utility function exceeds in magnitude the relative curvature of h^{-1} associated with the officer's circumstance based stop costs in order to sign the second order condition of the motorist's problem. The second assumption is that the distribution of c or recklessness is bounded above and has non-zero density at that bound. This assumption facilitates the proof of proposition 1, but in the simulations the implications of proposition 1 appear to hold for distributions with non-zero density over R, as well.

Lemma 2. *There exists a unique, non-negative optimal infraction level i' for a motorist of type $\{c, d\}$. The optimal infraction level is increasing in criminality, c, whenever infraction levels are positive.*

We first rewrite (9) using Assumption 1.2, that ϕ follows a uniform distribution, and
$\int_0^{\phi^*(i^{'},s_d)} \Gamma(\phi)\, d\phi = \phi^*\left(i^{'}\left(c, s_d\right), s_d\right)$ as

$$\max_{i'(c,s_d)} b(i,c) - \tau(i)\phi^*(i, s_d). \tag{10}$$

Thus, the motorist will solve the maximization problem in (10) by choosing an optimal infraction level that satisfies the following first-order condition:

$$FOC \equiv \frac{\partial b(i,c)}{\partial i} - \frac{d\tau(i)}{di}\phi^*(i, s_{v,d}) - \tau(i)\frac{\partial \phi^*(i, s_{v,d})}{\partial i} = 0. \tag{11}$$

By Assumption 2.7, the first term in (11) is positive, and by Assumption 2.9 and Lemma 1 the second and third terms are negative when including the subtraction signs. Assumption 2.10 implies that the left hand side of (11) is positive at $i = 0$. Assumption 2.7 requires that the first term go to zero as i limits to infinity, and Assumption 2.9 implies that the second term is non-zero. Therefore, by continuity of all functions over R^{+}, a positive solution to (11) exists. The second-order condition of the motorist's problem excludes the possibility of multiple equilibria and can be written formally as:

$$SOC \equiv \frac{\partial^2 b(i,c)}{\partial i^2} - \frac{d^2\tau(i)}{i^2}\phi^*(i,s_{v,d}) - 2\frac{d\tau(i)}{di}\frac{\partial \phi^*(i,s_{v,d})}{\partial i} \\ - \tau(i)\frac{\partial^2 \phi^*(i,s_{v,d})}{\partial i^2} < 0. \tag{12}$$

The first term in (12) is negative based on Assumption 2.7, the second term is negative based on Assumption 2.9, and the third term is negative based on Assumption 2.9 and Lemma 1. The final term is negative as well assuring uniqueness. In order to show why the final term is negative, we draw on the solution of the officer's problem and the monotonicity of $h(\cdot)$. Recall that $\phi^*(i,s_{v,d}) = h^{-1}[u(i) - s_{v,d}]$; we use this expression to expand the second derivative of ϕ^* from Equation (3):

$$\frac{\partial^2 \phi^*(i,s_{v,d})}{\partial i^2} = \left(\frac{du(i)}{di}\right)^2 h^{-1''}(u(i) - s_{v,d}) + \frac{d^2u(i)}{di^2}h^{-1'}(u(i) - s_{v,d}). \tag{13}$$

The first term is ambiguous, but the second term is positive and dominates the first term in the equation based on Assumption 2.11. Therefore, as long as the curvature of h^{-1} is not too large, there exists a unique positive value of i^{**} that maximizes motorist payoff over R^{+} conditional on c and $s_{v,d}$. If this maximum pay-off is positive, then $i' = i^{**}$; otherwise, $i' = 0$ yielding a pay-off of zero.

By total differentiation of the first order condition in (11), it is easy to show that the optimal infraction level i^{**} is increasing in criminality. Therefore,

$$\frac{di'}{dc} = \frac{di^{**}}{dc} = -\frac{\frac{\partial^2 b}{\partial c \partial i}}{SOC} > 0 \ \forall c \text{ and } s_{v,d} \text{ such that } i' > 0,$$

where SOC is the expression for the second order condition in (12) and is negative as shown above, and the sign of the numerator is established by Assumption 2.8. QED

Figure 1 provides examples of optimal infraction levels i^{**} over different values of the preference parameter c. The dashed line designates motorist expected costs by infraction level, and the solid line designates motorist pay-off. The vertical dotted line designates the optimal speed i^{**} for a specific value of c where the cost and benefit curves are parallel.

Note that the optimal infraction level may not be increasing unambiguously with $s_{v,d}$. In order to see this, we present the derivative of the first order condition with respect to $s_{v,d}$:

$$\frac{\partial(FOC)}{\partial s_{v,d}} = -\frac{\partial \tau}{\partial i}\frac{\partial \phi^*}{\partial s_{v,d}} - \tau(i)\frac{\partial^2 \phi^*}{\partial i \partial s_{v,d}}.$$

The first term is positive consistent with increases in infraction level as stop costs rise. The second term is ambiguous because it depends upon $h^{-1''}(\cdot)$. In order to assure an equilibrium where motorists behave as expected, i.e. increasing infraction level when the stop costs of police increase, we impose the following assumption:

Assumption 2.13. $\frac{\frac{\partial \tau}{\partial i}}{\tau(i)} > \frac{-h^{-1''}(\cdot)}{h^{-1'}(\cdot)}\frac{\partial u}{\partial i}$ $\forall i \geq 0$.

This again limits the curvature of the second derivative of h^{-1}, and assures that

$$\frac{di^{'}}{ds_{v,d}} > 0.$$

In practice, this assumption holds in our simulations.

Lemma 3. *For any set of functions satisfying assumptions 2.1 through 2.12, there exist parameter values such that a threshold c^* exists, above which motorists commit a traffic infraction at the optimal level $i^{'}$, and below which motorists do not commit an infraction in equilibrium. For such parameter values,* $\lim_{c \to c^*} i^{'} > 0$ *for c above c^*, and c^* is decreasing in $s_{v,d}$.*

The proof proceeds by construction. Assume a benefit function $b(i, c)$. Based on Assumption 2.8, this benefit function approaches a finite maximum value

$\overline{b}(c)$ for any c as i increases. Now pick an arbitrary value of c. Assumption 2.4 assures that $\lim_{i\to 0}\phi^*(i,s_{v,d}) = \underline{\phi^*}(s_{v,d}) > 0$. Therefore, we can set the officer and motorist cost parameters so that $\tau(0)\underline{\phi^*}(s_{v,d}) > \overline{b}(c)$. For this cost function, a motorist of type c never speeds and $\tau(i)\phi^*(i,s_{v,d})$ always lies above $b(i,c)$. Now, because τ and b are differentiable and the second order condition in the motorist problem is always negative, we can slowly and continuously reduce the function τ by multiplying by a decreasing positive scaler less than 1 (where the scaler effectively acts as a parameter of the cost function) until $\tau(i)\phi^*(i,s_{v,d})$ just touches the function $b(i,c)$ at one point. Given that the slope of the benefit function over i at $i=0$ is steeper than the slope of $\tau(i)\phi^*(i,s_d)$, the two curves will touch, yielding zero net benefits, at a positive value of i. For the selected parameters, the arbitrarily chosen c equals c^*. The benefit curves for all values of c below c^* lie below the benefits curve for c^* (and similarly, all curves lie above for c above c^*). Therefore, for c below c^*, net benefits are always negative, and for c above c^*, net benefits are positive over some range of i of R^+.

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 monotonically increasing in c. Therefore, for values of c below c^*, i^{**} is positive and must lie below the optimal infraction level for any c greater than c^*. This implies that the optimal infraction level for any c greater than c^* is bounded away from zero, or $\lim_{c\to c^*} i' > 0$ for all $c > c^*$.

An increase in $s_{v,d}$ unambiguously lowers $\phi^*(i,s_d)$ holding τ fixed. At the c^* above, the cost curve shifts down and net benefits are positive. Therefore, a new tangency between the two curves holding $b(i,c)$ and $\tau(i)$ fixed requires a decrease in c^* in order to lower the benefits curve down to just touch the now lower $\tau\phi^*(i,s_{v,d})$. QED

Figure 1 helps illustrate the implications of Lemma 3. For very low values of c, i.e. in the upper row of graphs in Figure 1, the cost of committing an infraction always lies above the pay-off, but as c rises the benefit or pay-off curve crosses the cost curve and an optimal, non-zero infraction level with positive net benefits exists. Thus, drawing from a large population of c allows us to construct a representative speed distribution. Figure 2 illustrates this for c's drawn from a skew normal distribution as in our simulations below.

We can use the distribution of motorists over race and recklessness, $g(c, d)$, to re-write (8), where we subscript to annotate that the risk set is now endogenous (ERS), such that:

$$\begin{aligned} K_{ERS} &= \frac{p[m \mid stopped, \overline{v}]p[w \mid stopped, \underline{v}]}{p[w \mid stopped, \overline{v}]p[m \mid stopped, \underline{v}]} \\ &= \frac{\int_{c^*}^{c_h} g(c,m)\phi^*(i^{'}(c, s_{\overline{v},m}), s_{\overline{v},m})dc \int_{c^*}^{c_h} g(c,w)\phi^*(i^{'}(c, s_{\underline{v}}), s_{\underline{v}})dc}{\int_{c^*}^{c_h} g(c,w)\phi^*(i^{'}(c, s_{\overline{v},w}), s_{\overline{v},w})dc \int_{c^*}^{c_h} g(c,m)\phi^*(i^{'}(c, s_{\underline{v}}), s_{\underline{v}})dc}, \end{aligned} \tag{14}$$

where c_h is the maximum value of c in the distribution.

Proposition 1. *Under the null hypothesis of racially blind policing where* $s_{\underline{v}} = s_{\overline{v},m} = s_{\overline{v},w}$ *and* $i^*_{\underline{v}} = i^*_{\overline{v},m} = i^*_{\overline{v},w}$, K_{ERS} *is equal to one. However, under the alternative hypothesis where* $s_{\overline{v},m} < s_{\underline{v}} < s_{\overline{v},w}$ *and* $i^*_{\overline{v},m} < i^*_{\underline{v}} < i^*_{\overline{v},w}$, *parameters exist for any set of functions satisfying assumptions 2.1 through 2.12 such that* $K_{ERS} < 1$ *in equilibrium.*

The first piece of *Proposition 1* is trivial by inspection. Under the null, stop behavior is unaffected by visibility and so the daylight probability of stop for each group cancels with its darkness probability.

The proof of the second half of the proposition proceeds by construction. First, based on Assumption 2.12, we impose distributions of c for whites and African-Americans that both have the same finite maximum c_h with a non-zero density at that maximum. By Assumption 2.8, the benefit function approaches a finite maximum value $\overline{b}(c_h)$ as i increases, and Assumption 2.4 assures that $\lim_{i \to 0} \phi^*(i, s_d) = \underline{\phi^*}(s_d) > 0$. Therefore, we can set the officer and motorist cost parameters so that $\tau(0)\underline{\phi^*}(s_{null}) > \overline{b}(c_{h,d})$, subject to the requirement under the null hypothesis that s_{null}=$s_{\underline{v}} = s_{\overline{v},w} = s_{\overline{v},m}$. Now, because τ and b are differentiable and the second order condition in the motorist problem is always negative, we can slowly and continuously reduce the function τ by multiplying by a decreasing positive scaler κ less than 1 until $\tau(i)\phi^*(i, s_{null})$ just touches the function $b(i, c_{h,w})$ at one point which based on Lemmas 2 and 3 will be at a positive value of i. We define the κ where this occurs as κ^*. This construction assures that no one has an incentive to commit an infraction and white and African-American motorists with $c = c_h$ are indifferent between committing an infraction and not. K_{ERS} is not defined under the current construction because the set of motorist for which $stopped = 1$ is empty or more formally contains at most a set of motorists of measure zero. However, K_{ERS} always equals 1 under the null hypothesis for non-empty sets, and so $\lim_{\kappa \to \kappa^*} K_{ERS} = 1$ for any $\kappa > \kappa^*$ because for all $\kappa > \kappa^*$ a positive measure of African-American and white motorists commit infractions under the null.

Now, for some $\kappa > \kappa^*$, we consider a marginal departure from the null hypothesis where $s_{\overline{v},w}$ increases and $s_{\overline{v},m}$ decreases while holding $s_{\underline{v}}$ fixed at s_{null}. Recall from (5) and (6) that the probability that a motorist who is stopped in high visibility by police is white has a numerator that depends only upon $s_{\overline{v},w}$, and that the denominator cancels out with the denominator for the probability that a motorist is stopped is minority in 14. The numerator can be written as

$$NUM_w \equiv \int_{c^*}^{c_h} g(c,w)\phi^*(i^{'}(c, s_{\overline{v},w}), s_{\overline{v},w})dc. \tag{15}$$

The derivative of this term with respect to $s_{\overline{v},w}$ is

$$\begin{aligned} \frac{d(NUM_w)}{ds_{\overline{v},w}} = &- \frac{\partial c^*}{\partial s_{\overline{v},w}} g(c^*, w)\phi^*(i'(c^*, s_{\overline{v},w}), s_{\overline{v},w}) \\ &+ \int_{c^*}^{c_h} g(c,w) \left(\frac{\partial \phi^*}{\partial s_{\overline{v},w}} + \frac{\partial \phi^*}{\partial i} \frac{di'}{ds_{\overline{v},w}} \right) dc. \end{aligned} \tag{16}$$

A positive derivative in (16) increases the denominator in (14) and reduces K_{ERS} to a value below 1 for a small increase in white high visibility stop costs, $s_{\overline{v},w}$, near the null hypothesis. The first term in the expression is unambiguously positive based on Lemma 3 and the non-zero density at c_h. Further, the limit of the second term as κ approaches κ^* is zero because the lower limit of integration c^* equals c_h at κ^* and the integrand is finite. Therefore,

$$\lim_{\kappa \to \kappa^*} \frac{d(NUM_w)}{ds_{\overline{v},w}} > 0 \tag{17}$$

and by continuity there exist κ' above κ^* where the derivative is positive for all $\kappa^* < \kappa < \kappa'$. For changes in minority stop costs, the same two terms arise for the derivative of the numerator of the probability that a stopped motorist is minority. As before, the integral term, which is equivalent to the second term in (16), limits to zero. The equivalent term to the first term in (16) will dominate the second term equivalent for all κ less than some κ' as long as κ' is sufficiently close to κ^*. However, an increase in disparate treatment implies a decrease in minority stop costs and so the change in the expression for κ near κ^* reduces the numerator of K_{ERS} reinforcing the effect of increasing white stop costs. Therefore, we can always find a κ close enough κ^* so that the effect of entering white motorist and exiting minority motorists during high visibility dominate any effects of changes in stop probability and driving speed yielding a K_{ERS} less than one. QED

Consider a jurisdiction where motorists face disparate treatment, $s_{\overline{v},m} < s_{\underline{v}} < s_{\overline{v},w}$. In our partial equilibrium treatment of the VOD test, we show that the relative probability that a stopped motorist is minority increases during daylight. However, this result no longer holds once we endogenize speed through the motorist's problem in the equilibrium setting. The intuition of our finding is relatively straightforward; there will be two competing effects associated with a change from high to low visibility. On the one hand, an officer will face a relatively higher cost for stopping white motorists during high visibility, thus white motorists are in all probability less likely to be stopped even if they are travelling faster. On the other hand, infra-marginal motorists, who were close to indifferent between committing an infraction and not, will respond to changes in stop costs by altering their driving behavior and committing infractions, increasing the representation of whites and reducing the representation of minorities in the pool of stopped motorists in high visibility. As is apparent in our formal model, these effects will push the VOD test statistic in opposing directions. Thus, the magnitude of (14) will depend on the size of these two competing effects, and the size of the first term in (16) will depend upon the density of motorists at c^*. If c follows a traditional unimodal distribution with very low densities at extreme values of c, the size of this first term will be positively related to the share of infra-marginal motorists or motorist who do not commit infractions, a share that is typically unobserved in empirical research on police stops.

The implication of our findings on the empirical application of VOD is of critical importance. Grogger and Ridgeway (2006) and Ridgeway (2009) apply the VOD to data collected by jurisdictions in response to repeated complaints of racial profiling. The authors concluded that the test "yields little evidence of racial profiling" in Oakland, CA (Grogger and Ridgeway 2006, p. 886) and that "African-American motorists were less likely to be stopped during daylight" in Cincinnati, OH (Ridgeway 2009, p. 14). These conclusions were made based on findings, in both jurisdictions, that minority motorists were stopped less frequently in daylight indicating potential "*reverse* racial profiling" (Grogger and Ridgeway 2006, p. 884). As shown in the preceding section, these conclusions are potentially incorrect given the possibility that the relative risk set of motorists varies in response to changes in solar visibility. The evidence in these papers is entirely consistent with either white or minority motorists being favored by police. In the next subsection, we will investigate the possibility that shifts in the speed distribution might provide insights into the direction of differential treatment when equal treatment is rejected by the VOD test.

2.5 An Alternative Test for Disparate Treatment

In our model, recall that disparate treatment occurs during daylight and is represented by lower stop costs for minority motorists, e.g. $s_{\overline{v},m} < s_{\overline{v},w}$. Since darkness makes it difficult for police to discern the race of a motorist before making a traffic stop, the VOD test proposes that officers face a common $s_{\underline{v}}$

during darkness. Further, we assume that the stop costs in darkness are bounded such that $s_{\overline{v},m} < s_{\underline{v}} < s_{\overline{v},w}$. Previously we show that under the alternative hypothesis (i.e. in the presence of disparate treatment), the magnitude of the VOD test statistic relative to 1 does not unambiguously determined the direction of discrimination. As an alternative to interpreting the magnitude or sign of the VOD test, we propose to directly examine the speed distribution of stopped motorists exploiting the same solar variation used in the VOD test. Intuitively, if the police stop cost falls for a group in daylight raising the probability of stop at all speeds, individuals in this group will decrease their optimal speed, and testing for shifts in the speed distribution will provide insights into whether stop costs are higher during high or low visibility for a given group.

However, we do not observe the speed distribution of all motorists, but rather we only observe the speed distribution of motorists who are stopped by police. Therefore, we need to examine the impact of differences in stop costs on the speed distribution conditional on being stopped. We begin by writing a function for one minus the CDF of the speed distribution for motorists whom police stop which requires integrating over both motorist preferences, c, and officer circumstances, ϕ, in order to capture the share of motorists stopped at any speed or higher for a given group relative to the total number of motorist stopped of that group. If the derivative of this expression (one minus the CDF) with respect to stop costs is positive for all speeds or infraction levels, then an increase in stop costs unambiguously shifts the speed distribution of motorists upwards or to the right. Such a result would allow us to test for the direction of discrimination, conditional on VOD based evidence of differential treatment, by examining the change in the speed distribution of stopped motorists between daylight and darkness for each race.

Our first step is to place conditions on the model so that the equilibrium probability of stop changes in the expected manner when stop costs rise. Specifically, when stop costs rise, motorists drive faster because of lower stop probabilities, but we do not expect motorists to drive so much faster that the higher speeds actually more than undue the original decline in stop probabilities that was the reason behind the faster speeds in the first place. The total derivative of ϕ^* is

$$\frac{d\phi^*}{ds_{v,d}} = \frac{\partial \phi^*}{\partial s_{v,d}} + \frac{\partial \phi^*}{\partial i}\frac{di'}{ds_{v,d}} \tag{18}$$

Notice that the first term implies a direct lower probability of being stopped from higher stop costs, but the second implies an increase in stop probability as optimal speed increases.

If we assume,

Assumption 2.14. $\frac{\partial u}{\partial i}\frac{di'}{ds_{v,d}} < 1$

and use the solution for $\phi^*(i, s_d) = h^{-1}\left(u(i) - s_{v,d}\right)$ in Equation (3), it can be shown that

$$\frac{d\phi^*}{ds_{v,d}} = \frac{\partial \phi^*}{\partial s_{v,d}} + \frac{\partial \phi^*}{\partial i}\frac{di'}{ds_{v,d}} = -h^{-1'}(u(i) - s_{v,d})\left(1 - \frac{\partial u}{\partial i}\frac{di'}{ds_{v,d}}\right) < 0 \tag{19}$$

We recognize that Assumption 2.14 is not ideal because it is based on an equilibrium function. However, the imposition of an assumption that individuals do not completely undo exogenous changes in incentives through their behavioral adjustments is relatively standard. Further, this assumption works in favor of the VOD test as a mechanism for distinguishing between disparate treatment of minorities and reverse discrimination in that it assures that at least the second term in (16) is consistent with disparate treatment against minorities yielding $K_{ERS} > 1$. Further, the assumption appears to always hold in our simulations below.

Our second step is to define the level of criminality c as a function of a motorists optimal speed i'. Specifically, we can invert the monotonic function

$i'(c, s_{v,d})$ in order to obtain a monotonic function

$$c' \equiv c'(i, s_{v,d}) \text{ such that } i = i'(c'(i, s_{v,d}), s_{v,d}) \ \forall i > 0 \tag{20}$$

Lemma 4. *The level of criminality, c', consistent with an optimal infraction level, i, can be expressed as a function $c'(i, s_{v,d})$ that is increasing in the severity of infraction and decreasing in stop cost.*

The monotonicity of $i^{'}(c, s_{v,d})$ and the Inverse Function Theorem imply that there will be a one-to-one monotonic mapping from $i'(c, s_{v,d})$ to $c'(i, s_{v,d})$ as shown in the equality in (20). We differentiate this equality with respect to i and $s_{v,d}$ yielding

$$1 = \frac{\partial i'}{\partial c}\frac{\partial c'}{\partial i} \text{ and } 0 = \frac{\partial i'}{\partial c}\frac{\partial c'}{\partial s_{v,d}} + \frac{\partial i'}{\partial s_{v,d}} \tag{21}$$

Accordingly, Lemma 2 and the above equations imply

$$\frac{\partial c'(i', s_{v,d})}{\partial i'} = \left(\frac{\partial i'}{\partial c}\right)^{-1} > 0 \text{ and } \frac{\partial c'(i', s_{v,d})}{\partial s_{v,d}} = -\frac{\partial i'}{\partial s_{v,d}}\left(\frac{\partial i'}{\partial c}\right)^{-1} < 0. \quad \text{QED}$$

Now, we define $\tilde{G}$ as one minus the CDF of the speed distribution conditional on being stopped (suppressing the visibility subscript and the minority subscript from the distribution over c for convenience) as

$$\tilde{G}(i) \equiv \frac{\int_{c'(i,s_d)}^{c_h} \int_0^{\phi^*(i'(c,s_d),s_d)} g(c)\Gamma(\phi)\, d\phi dc}{\int_{c^*(s_d)}^{c_h} \int_0^{\phi^*(i'(c,s_d),s_d)} g(c)\Gamma(\phi)\, d\phi dc}. \tag{22}$$

We utilize the equilibrium mapping from i to c in the motorist's problem to capture the portion of the distribution of motorists that travel above i, and we use the function c^* that identifies the value of c at which motorists are indifferent between committing an infraction or not in order to establish the population of stopped motorists in the denominator. Note that the density of

c can be factored out of the first integral, and recall that because ϕ follows a uniform distribution the resulting integral can rewritten as $\int_0^{\phi^*(i',s_d)} \Gamma(\phi)\, d\phi = \phi^*\left(i'\left(c, s_d\right), s_d\right)$. Equation (22) is then equivalent to:

$$\tilde{G}(i) = \frac{\int_{c'(i,s_d)}^{c_h} g(c)\phi^*\left(i'\left(c, s_d\right), s_d\right)\, dc}{\int_{c^*(s_d)}^{c_h} g(c)\phi^*\left(i'\left(c, s_d\right), s_d\right)\, dc}. \tag{23}$$

Next, we calculate the derivative of (23) with respect to s_d as

$$\begin{aligned} \frac{d\tilde{G}(i)}{ds_d} =& -\frac{\frac{dc'(i,s_d)}{ds_d} g\left(c'\left(i, s_d\right)\right) \phi^*\left(i'\left(c'\left(i, s_d\right), s_d\right), s_d\right)}{\int_{c^*(s_d)}^{c_h} g(c)\phi^*\left(i'\left(c, s_d\right), s_d\right)\, dc} \\ & + \frac{\int_{c'(i,s_d)}^{c_h} g(c)\frac{d\phi^*(i'(c,s_d),s_d)}{ds_d}\, dc}{\int_{c^*(s_d)}^{c_h} g(c)\phi^*\left(i'\left(c, s_d\right), s_d\right)\, dc} \\ & + \frac{\left(\int_{c'(i,s_d)}^{c_h} g\left(c\right)\phi^*\left(i'\left(c, s_d\right), s_d\right)\, dc\right)\frac{dc^*}{ds_d} g(c^*)\phi^*(i'(c^*, s_d), s_d)}{\left(\int_{c^*}^{c_h} g(c)\phi^*\left(i'\left(c, s_d\right), s_d\right)\, dc\right)^2} \\ & - \frac{\left(\int_{c'(i,s_d)}^{c_h} g\left(c\right)\phi^*\left(i'\left(c, s_d\right), s_d\right)\, dc\right)\int_{c^*}^{c_h} g(c)\frac{d\phi^*(i'(c,s_d),s_d)}{ds_d}\, dc}{\left(\int_{c^*}^{c_h} g(c)\phi^*\left(i'\left(c, s_d\right), s_d\right)\, dc\right)^2}. \end{aligned} \tag{24}$$

We multiply both sides by the denominator of the first two terms, which also appears squared in the denominator in the second two terms. Then, in terms three and four, we replace the ratio of the first term in the numerator to the remaining term in the denominator with $\tilde{G}(i)$ based on (23). We can then reorganize by collecting the similar terms. The first and third terms both involve the derivative of the lower limit of integration and are evaluated at c' and c^*, respectively. The second and fourth terms both involve integrals of the derivative of ϕ^* and can be converted into conditional expectations by factoring out the mass of c contained within the limits of integration. Thus we have

$$
\begin{aligned}
&\int_{c^*}^{c_h} g(c)\phi^*\left(i'\left(c, s_d\right), s_d\right) \, dc \frac{d\tilde{G}(i)}{ds_d} = \\
&\qquad -\left(\frac{dc'\left(i, s_d\right)}{ds_d} g\left(c'\left(i, s_d\right)\right) \phi^*\left(i'\left(c'\left(i, s_d\right), s_d\right), s_d\right)\right. \\
&\qquad \left. - \tilde{G}(i) \frac{dc^*\left(s_d\right)}{ds_d} g\left(c^*\left(s_d\right)\right) \phi^*\left(i'\left(c^*\left(s_d\right), s_d\right), s_d\right)\right) \\
&\qquad + H(c^*)\tilde{G}(i)\left(\int_{c'(i,s_d)}^{c_h} \frac{g\left(c\right)}{\tilde{G}(i)H(c^*)} \frac{d\phi^*}{ds_d} \, dc - \int_{c^*(s_d)}^{c_h} \frac{g\left(c\right)}{H(c^*)} \frac{d\phi^*}{ds_d} \, dc\right),
\end{aligned} \tag{25}
$$

where $H(c^*)$ is the fraction of individuals who commit infractions, i.e. who have a value of c above c^*.

The terms on the second and third line represent the direct effect of changes in stop costs on motorist behavior. The term on the second line is positive and arises because at higher stop costs the c' associated with any speed i will be lower and therefore at any c above c^* motorists will be travelling faster. The term on the third line is negative creating an ambiguity because the c where motorists are indifferent between committing an infraction or not c^* also falls with stop costs. Therefore, just like in the VOD test, one source of ambiguity in the distribution of stopped motorists arises because minority motorists who did not commit infractions during the day may commit infractions at night, and those motorists who are now at risk of being stopped slow the speed distribution of stopped motorists. If the distribution of c has a lower limit c_l and $c^* < c_l$, then all motorists commit infractions, the density at c^* is zero, and the term on the third line is zero eliminating this source of ambiguity.

Unlike the VOD test, however, several factors point to the term of the second line being larger in magnitude than the term on the third line. Given the construction of $\tilde{G}(i)$ for stopped motorists, c' is greater than or equal to c^* so that $\phi^*(i'(c', s_d), s_d)$ is greater in magnitude than $\phi^*(i'(c^*(s_d), s_d); and $\tilde{G}(i)$, which multiplies the second expression (on line 3), is less than or equal to 1. Both of these effects contribute to a positive net value of the first term (the sum of the second and third line) in $\tilde{G}(i)$ and increase in magnitude with i. If $g(c)$ is unimodal and c^* is below the mode of $g(c)$, then $g(c')$ will be greater than $g(c^*)$ for small values of i when the first two effects are not large, and for larger values of i, the first two effects may dominate anyway.

Finally, we need to compare the magnitudes of the derivatives of c' and c^* with respect to s_d. c^* is identified by the following equality (zero net benefits):

$$b(i'(c^*, s_d), c^*) - \phi^*(i'(c^*, s_d), s_d)t(i'(c^*, s_d)) = 0. \tag{26}$$

Totally differentiating this equation yields a simple expression for the derivative because the envelope theorem implies that all the terms involving derivatives of i' with respect to either c^* or s_d are multiplied by the first order condition, which is zero, and so

$$\frac{dc^*}{ds_d} = \frac{\frac{\partial \phi^*}{\partial s_d} t}{\frac{\partial b}{\partial c}} < 0. \tag{27}$$

We can also define c' based on

$$i'(c'(i, s_d), s_d) = i \tag{28}$$

Again, we can totally differentiate and use the comparative static results from Lemma 2 and Assumption 2.13 to get

$$\frac{dc'}{ds_d} = -\frac{\frac{di'}{ds_d}}{\frac{di'}{dc}} = -\frac{\frac{d}{di}\left(\frac{\partial \phi^*}{\partial s_d} t\right)}{\frac{d}{di}\left(\frac{\partial b}{\partial c}\right)} < 0. \tag{29}$$

The derivative of c' is the ratio of the slopes over infraction level of the same terms in the expression for the derivative of c^*. At present, we do not have specific intuition concerning the relative magnitude of the ratio of marginal stop costs to marginal benefits from c as compared to the ratio of the slopes of these two terms with respect to infraction severity.

Looking at the last line of (25), the second expression on the right hand side of the equation represents another second of ambiguity that does not arise for the VOD test. Specifically, the probability of being stopped at any speed ϕ^* is likely to be heterogeneous in the rate of decline of stop probability with stop costs, and so the cumulative effect of changing stop probability as stop costs change could have unexpected effects on the speed distribution of stopped motorists. Again, however, there are reasons to believe that this contribution to the derivative is also positive. In constructing (25), the density term $g(c)$ within each integral has been scaled so that it represents a conditional density within the limits of integration, and so each integral represents a conditional expectation of the derivative of ϕ^* with respect to s_d. This derivative is

$$\frac{d\phi^*}{ds_d} = h^{-1'}(u(i) - s_d)\left(\frac{\partial u}{\partial i}\frac{di'}{ds_d} - 1\right), \tag{30}$$

which is negative based on Assumption 2.13. If this derivative decreases in magnitude with c (a positive cross-partial derivative) then the second integral will be larger and the entire expression will be positive. The cross-partial of ϕ^* with respect to s_d and c is

$$\frac{d^2\phi^*}{dcds_d} = h^{-1''}\frac{\partial u}{\partial i}\frac{di'}{dc}\left(\frac{\partial u}{\partial i}\frac{di'}{ds_d} - 1\right) + h^{-1'}\left(\frac{\partial^2 u}{\partial i^2}\frac{di'}{dc}\frac{di'}{ds_d} + \frac{\partial u}{\partial i}\frac{d^2 i'}{dcds_d}\right). \tag{31}$$

The second of the two expressions involves the sum of two terms multiplied by $h^{-1'}$. The first of those two terms is positive, and it can be shown using the comparative static derivation of di'/ds_d, which is positive, that the second term is positive as well if

Assumption 2.15. $\frac{\partial}{\partial c}\frac{\partial^2 b}{\partial i^2} < 0$.

Specifically, the numerator of the comparative static expression from Lemma 2 only involves t and ϕ^*, and the only term in the denominator (the second order condition) that depends upon c is the second derivative of b with respect to i, which is signed by Assumption 2.7. The assumption on the cross-partial of b is relatively intuitive (unlike most third derivatives of preferences). Preferences for infraction level increase the positive marginal benefit of infraction level (Assumption 2.8), and Assumption 2.15 implies that preferences for the level of infraction also increase the negative slope of the marginal benefit. Therefore, when measured as a share of marginal benefit, the magnitude of the change in the marginal benefit with c can increase or decrease, but the change in the marginal benefit cannot increase in absolute terms under assumption 2.15 - a larger first derivative in infraction level (marginal benefit) will require a larger negative second derivative with respect to infraction level in order to reduce the marginal benefits sufficiently as infraction level rises. Note that this assumption is satisfied automatically based on maintained assumptions when b is multiplicative in functions of $b_1(i)$ and $b_2(c)$, so that $b(i,c) = b_1(i)b_2(c)$, and

$$\frac{\partial}{\partial c}\frac{\partial^2 b}{\partial i^2} = \frac{\partial b_2}{\partial c}\frac{\partial^2 b_1}{\partial i^2} < 0 \tag{32}$$

since Assumption 2.8 requires the derivative of b_2 to be positive and Assumption 2.7 requires the second derivative of b_1 to be negative. With the second term positive under this assumption and general restrictions on the magnitude of the second derivative of h^{-1}, which pre-multiplies the first term in (31), relative to the first derivative of h^{-1} in order to assure a well behaved equilibrium, we expect the entire second term of (25) to be positive over much of the relevant parameter space.

In the next section, we will use calibrated simulation models to provide an indication of the circumstances under which this derivative is positive under the alternative hypothesis of discrimination against African-Americans, especially relative to circumstances when the VOD statistic lies above or below 1 under the alternative hypothesis.

3 Simulation

Simulating the theoretical model allows for two key results. First, we are able to verify that there are parameter values that both match our stop and speeding data for which K_{ERS} does not have the traditionally expected magnitude under the alternative hypothesis of discrimination, but the speed distribution does shift unambiguously in the expected direction. Second, it allows us to test the flexibility of those circumstances.

To simulate the theoretical equilibrium, we use the following functional forms:

$u(i) = i^{\eta} + u_0 \;\; \eta > 1, \;\; u_0 > s_{\overline{v},w}$

$h^{-1}(h) = \frac{h^a}{h^a+k} \;\; a > 2, \;\; k > 0$

$b(i,c) = b_0 i^{\alpha_1} e^{\alpha_2 c} \;\; b_0 > 0, \;\; 0 < \alpha_1 < 1, \alpha_2 > 0$

$\tau(i) = i^{\mu} + \tau_0 \;\; \mu > 1, \;\; \tau_0 > 0$

$s_{\overline{v},w} \geq s_{\underline{v}} \geq s_{\overline{v},m}$

$c \sim \mathit{skew\ normal}(\omega), \omega > 0$

These forms satisfy most of the assumptions in the model, while retaining the necessary ambiguity, notably in h^{-1}. Specifically, the form of h^{-1} assures that the distribution of costs associated with circumstances, $h(\phi)$, follows a unimodal distribution over R^+. We relax these assumptions in two specific ways for convenience. First, b does not limit to a finite value with i, but does increase more slowly with i than τ for large values of i. Second, we select skew normal as the distribution of c, which has non-zero density over R. However, even after relaxing Assumption 20, we regularly find scenarios where K_{ERS} is less than 1. Table 1 describes the 18 parameters necessary to specify in our simulated model, delineated by whether we fix the parameter or calibrate it using moments from the data described in the following section.

[*Insert Table 1*]

Unfortunately, the data do not allow us only to recover identifying information on both motorist and officer utility simultaneously because we have no information on outcomes that are shaped separately by either officer or motorist behavior. Thus, we choose nine parameters related to motorist behavior to calibrate, and as a robustness check change the officer parameters and recalibrate motorist parameters. We calibrate these parameter values using 24 empirical moments, six speed percentiles (20th, 40th, 60th, 80th, 90th, and 95th) for each combination of daylight/darkness and minority/non-minority, and one fixed moment, the fraction of whites not infracting. The latter is unknown given data limitations, and central to the problem because a high fraction of motorists not infracting implies a greater density of motorists who are indifferent between infracting and not given our unimodal distribution of c. Therefore, we chose 10% as a reasonably conservative upper-bound, and then systematically lower the fraction while evaluating the VOD test statistic and the shifts in the speed distribution. The initial police officer parameters are selected via a manual calibration process in order to achieve a stable equilibrium, and then we calibrate the motorist problem holding those parameter fixed. Table 2 breaks down the fixed and calibrated parameter values for each run of the simulation. In total, we calibrate to 7 combinations of fixed parameters and fraction of whites not infraction. The first 3 columns in table 2 show these values for three levels of whites not infracting, 10%, 5%, and 2%. As discussed below, we then fix the fraction of whites not infracting at 5% and vary two fixed parameters: the shape parameter for the distribution of circumstances, a; and the rate of increase in officer pay-off, η. These parameter values are in columns 4 and 5, and 6 and 7, respectively, in table 2. Calibrations are conducted by selecting 1000 draws on $(0, 1)$ and then mapping those draws into c for both a population of white and minority motorists using the inverse of the CDF for the distributions of c for each race.

[*Insert Table 2*]

Figure 1 shows plots of motorist benefits and costs with a vertical line designating the optimal level of positive infractions. The figure starts with the preference parameters of 3, 2.5 and 2 standard deviations below the mean along the top row from left to right, 1 standard deviation below, zero and one standard deviation above on the middle row, and finally 2, 2.5 and 3 standard deviations above the mean on the bottom row. The plots show a clear progression of the optimal level of infraction (speed above the speed limit) across varying levels of the preference parameter or criminality. Further, for levels of 2 or more standard deviations below the mean, the cost curve always lies above the benefits curve and motorists choose not to commit an infraction. While starting near 1 standard deviation below, motorists switch to infracting at their optimal positive level.

[*Insert Figure 1*]

For a given set of parameter values, we simulate driving behavior using equivalent draws for both the white and minority populations. Again, we draw the same set of random numbers of $(0, 1)$ for white and minority motorists, which are then mapped into values of c for each population, but in order to assure precision in the reported values these calculations are conducted using 25,000 draws. Figure 2 illustrates this population behavior through a representative speed distribution for whites. Using equivalent draws for white and minority motorists implies that we do not directly recover the share of motorists who are minority. Rather, we indirectly recover this information by comparing the fraction of minority motorists stopped in the simulation (F_{SIM}) to the empirical analog (F_{DATA}) and calculating the fraction minority motorists in the population necessary to assure that the implied fraction of stopped motorists who are minority equals F_{DATA}. Noting that the simulated population is exactly 50% minority, the implicit simulated share of minority motorists is simply 0.5 times the fraction of motorists who are minority δ_T, where we find δ_T by solving $F_{DATA} = \delta_T F_{SIM}$ for T = Day and Night. We present these results along side K_{ERS} calculations for context.

[*Insert Figure 2*]

Table 3 presents the simulated speed distribution moments and the actual moments on which the calibration is based. The speed distribution is illustrated by showing the speed at which stopped motorists are driving at the 20th, 40th, 60th, 80th, 90th and 95th percentiles of the speed distribution. The columns are presented in pairs with the first column in each pair containing the speed at each percentile from the simulation and the second column presenting the speed moments on which the calibration is based. The first four columns present the speed distribution for minority motorists in daylight and darkness, and the second four columns present the distribution for white motorists. The simulation matches the speed moments from the data quite well almost always being within 1 mile per hour and often being within 1/2 mile per hour.

[*Insert Table 3*]

Table 4 presents the simulated shift of the speed distribution for both stopped white and minority motorists. The speed distribution of minority (white) motorists is clearly shifted to the right (left) in darkness, consistent with higher (lower) stop costs for minorities (whites) when visibility is limited. The unambiguous shift in the distribution of stopped motorists suggests that for our model and calibrated parameter values our proposed test for the direction of discrimination can accurately capture whether minorities believe that they are being discriminated against. As discussed above, if we reject the null of equal treatment and the magnitude of the VOD test is not informative, we argue that motorists responses to their beliefs of how they are being treated is a reasonable standard for determining the actual direction of unequal treatment. Notably, using equation (14), we also find a K_{ERS} of 0.95; well below the threshold of 1, a value that in the past might have been interpreted as reverse discrimination. This value of K_{ERS} arises in spite of the fact that in our model police have lower stop thresholds for African-Americans resulting in a clear distributional shift in speeds when police can no longer identify race. For the purpose of comparison, the similar statistic for Grogger and Ridgeway (2006) is 0.80, and for our data in Massachusetts the statistic is 1.12.[6] The table also presents

[6] See below for a description of the data. In order to be consistent with our preferred logit models that control for day or week and time of day, we use the inter-twilight sample to estimate a model of whether a stop is during daylight as a function of these controls, and predict the probability of stop for each observation. Daylight stop probabilities are based on unweighted averages from the inter-twilight sample, and darkness stop probabilities are based on weighted averages using the predictive probability divided by one minus the predicted probability of daylight as weights in order to assure that our VOD statistic is calculate holding the covariates fixed on average across the daylight and the weighted darkness motorist samples.

in the last two rows the predicted fraction of motorists who are minority for our sample, and the model predicts a larger fraction of minority motorists in daylight relative to darkness. For comparison, we calculate the average share of African-Americans as a fraction of the total number of whites and African-Americans averaged across all towns and state police barracks in our sample weighted by the number of stops during our inter-twilight window. The average share African-American for our town subsample is 22.3 percent, but the share of African-Americans as a fraction of whites in the state (potentially relevant for the state police stops) is much smaller at 6.8 percent.

[*Insert Table 4*]

Table 5 presents the speed distribution shift from daylight to darkness for all minority motorists and just those minorities who were stopped, for parameters calibrated to 10% of white motorists not infracting. The first and second columns replicate the information from Table 4, and columns 3 and 4 present the shift in the speed distribution for all motorists. These distributions are closely related because the distribution of stopped motorists is created by using all motorists weighted by the probability of being stopped at each speed. As expected, the speed distribution for all motorists are shifted in the same direction as stopped motorists, but the magnitude of the shifts in the speed distribution for stopped motorists is substantially muted relative to all motorists. Referring back to equation (25), the observed reduction in the speed distribution shift is consistent with the third line of the equation contributing to a slower speed distribution because relatively risk averse motorists who did not infract in daylight commit infractions in darkness. Regardless, unlike the VOD test statistic, we do not observe any evidence of reversals where the speed distribution shift for stopped motorists moves in the opposite direction of the distribution shift for all motorists.

[*Insert Table 5*]

Next, we examine the impact of reducing the fraction of whites who choose to not commit an infraction. In doing so, we move towards a situation where the magnitude of the VOD test statistic might provide information on the direction of discrimination because the density of motorists who are indifferent between infracting and not is much lower. We conduct three new calibrations with the fraction of white not infracting set to 5, 2 and 1 percent. While the K_{ERS} test statistic moves upwards as we lower the fraction not infracting, the statistic remains below 1 for all three simulations. The reason that the statistic never rises above 1 is because even when the fraction white not infracting is very small in daylight, discrimination under the alternative hypothesis causes a substantially larger fraction of African-Americans not to infract. These African-Americans can then choose to infract in darkness when police do not observe race. Notably, the speed distribution shifts for stopped motorists also gets larger and more closely resembles the shift for all motorists as the fraction of motorists not infracting shrinks and the density of motorists who are indifferent between committing an infraction or not during the daylight decreases. As a result, in our simulations, tests for speed distribution shifts of stopped motorists appear to have substantial power to detect shifts in the population speed distribution under circumstances involving discrimination against minorities and where the VOD test statistics would never exceed 1.

[*Insert Table 6*]

In order to assess the robustness of our findings, we modify our parameters from the officer's problem and recalibrate our model. First, we modify a, which determines the curvature of h^{-1}. The parameter must be greater than 2, and in our initial simulations the parameter is set to 2.1. In table 7, we set a to 2.05 and 2.25. Next, we modify η, which must exceed 1 and is set to 1.01 in our simulations. We now set η to 1.03 and 1.09 and recalibrate. As we can see in Table 7, our test is fairly robust to changes in both fixed parameter values with the VOD test statistic always comfortably below 1, and the speed distribution shifts for stopped motorists consistently in the right direction except at the highest percentiles where matching the skewness of the empirical speed distribution can be somewhat challenging.

[*Insert Table 7*]

4 Empirical Analysis

In this section, we examine Massachusetts traffic stop data applying the implications of our theoretical model. We begin by summarizing the overall traffic stop data and describing our construction of the analytical sample. Next, we examine the analytical sample for evidence of discrimination using the VOD approach. As established in our theoretical model, the coefficient estimate from VOD is sufficient to identify unequal treatment, but uninformative about the direction of discrimination. Thus, we apply our alternative estimation strategy that examines shifts in the speed distribution. Making use of the richness of our data, we examine racial differences in the speed distributions of stopped motorists between daylight and darkness using a quantile regression, and we also conduct a series of tests for distributional changes across additional motorist demographics and vehicle characteristics. Our findings provide strong evidence that white and African-American motorists were treated differently by Massachusetts police officers, and that African-American motorists, especially young male motorists, believed that they faced discrimination in traffic stops.

4.1 Descriptive Statistics

Our empirical analysis utilizes two distinct analytical samples and associated visibility treatments, which we describe in this section. Following Grogger and Ridgeway (2006), we focus on traffic stops made during an inter-twilight window when solar visibility varies from seasonal changes and the Daylight Savings Time (DST) change. Distinct from previous analyses, we focus explicitly on speeding stops so that we have a measure of infraction severity, e.g. relative or absolute speed above the speed limit. As noted by previous authors using the VOD approach, violations such as headlight outages or seatbelt violations could potentially be correlated with motorist race and visibility. Thus, our focus on moving violations has the added advantage of insulating the analytical sample from such confounding factors.

For our first sample, we wish to compare stops made at the same time of day and day of week where some of those stops occurred during daylight and some occurred in darkness. Therefore, we select only traffic stops made between the earliest recorded sunset and latest end to civil twilight in the state, i.e. the so-called the inter-twilight window. We select the inter-twilight window because times outside of those ranges are either always in daylight or always in darkness. We utilize data from the United States Naval Observatory to identify this window and to eliminate traffic stops that we cannot categorize as daylight or darkness, e.g. stops that occurred during the actual civil twilight period as defined by the Naval Observatory. Specifically, the inter-twilight window began at the earliest easternmost sunset occurring in Orleans, MA at 4:09 PM and the latest westernmost end to civil twilight occurring in Mount Washington, MA at 9:08 PM. Next, using the date of the traffic stop and the Navel Observatory data, we eliminate periods within the inter-twilight window that are neither exclusively dark or exclusively daylight within the state. Specifically, we eliminate stops that occur during civil twilight for that day in the state of Massachusetts. For example, on the spring equinox of 2002 (March 20th) we categorize stops as daylight if they occurred between the start of the inter-twilight period and the easternmost sunset on that day at 5:52 PM disregarding stops that occur after that time, but before the westernmost end to civil twilight at 6:34 PM, at which point the darkness period of the sample begins for that day.[7]

The Massachusetts data contained a total of 1,048,575 stops spanning from April 2001 to January 2003 of which 200,576 were made for speeding. We restrict our analytical sample to State Police, Boston, and municipal depart-

[7]The Massachusetts traffic stop data only contained the hour of the day that the stop was made and had no information related to the minute. As a result, only traffic stops that occurred during the inter-twilight window in an hour of complete daylight or darkness were included. Although this additional restriction reduced the overall sample size, we do not consider it a threat to the validity of the results.

ments with at least 100 speeding stops and with 10 percent African-American residents according to the 2010 Census.[8] These restrictions, along with limiting our sample to only stops made of African-American and white motorists, left us with 80,001 speeding stops and ensured that we had a sufficient number of observations by town to include location fixed-effects in each of our estimates. As mentioned, we focus on the 21,461 speeding stops made during the inter-twilight window for which we can clearly identify the stop as being in either complete darkness or daylight.

Table 8 presents descriptive statistics from our annual analytical sample that relate directly to controls that we include in our estimation procedure and robustness checks. The traffic stops are concentrated more heavily during the work week and during the early portion of the evening commute. African-American motorists made up 17.6 percent of the sample while 73.9 percent of the analytical sample was male and 54.5 percent were 30 years old or less. A total of 16.2 percent of the motorists from the analytical sample were stopped driving a red automobile while nearly half were in a vehicle less than 11 years old. The demographics found in our analytical sample, i.e. speeding stops within the inter-twilight window, are reasonably consistent with the overall traffic stop data.

[Insert Table 8]

For our second sample and analysis, we further restrict our analytical sample to traffic stops occurring within 45 days of the three DST shifts in the data. We restrict our sample to stops made during and after the evening commute, at 4:00 PM or later and prior to 10:00 PM. This restriction is designed to capture the entire evening inter-twilight window, which typically falls between 5:00 and 9:00 PM during these 90 day periods around the DST shifts. For this sample, our treatment variable is simply after the spring DST shift or before the fall DST shift, which represents a treatment of more daylight during and

[8] The municipal departments included in the analytical sample were Brocton, Everett, Lynn, Milton, Randolph, Springfield, and Worcester. Separate barracks fixed-effects were included for State Police.

after the evening commute.[9] This treatment exploits two sources of variation: the 1 hour time delay in sunset in the spring or 1 hour earlier sunset in the fall with the DST shift, and the relatively rapid seasonal change in sunset timing that occurs during spring and fall - a change of almost 2 hours during the 90 day period. For example, the earliest easternmost sunset (westernmost end to twilight) across the 90 day DST window of spring 2002 changed from 5:21PM (6:02PM) to 8:00PM (8:47PM) including the 1 hour DST shift. As noted above, by focusing on this period of rapid change in the timing of sunset, we avoid confounding changes in daylight with well documented, broad seasonal changes in travel patterns between summer and winter.[10] Table 9 presents the descriptive statistics from this more restrictive subsample of 7,210 traffic stops. The volume of stops across time of day and day of the week closely mirror those observed in the overall analytical sample. The demographic and vehicular characteristics in this more restrictive subsample are also comparable to the annual data.

[Insert Table 9]

4.2 Primary Estimates

In this section we examine the analytical sample for evidence of discrimination. We begin by estimating the traditional VOD test using a logistic regression and find evidence suggesting the presence of unequal treatment or discrimination. The VOD test, i.e. the odds of a stopped motorists of demography d in daylight $\overline{v}$ relative to darkness $\underline{v}$, is written such that:

$$\log\left(\frac{P\left(d|\overline{v}, t, dow, sv, b\right)}{1-P\left(d|\underline{v}, t, dow, sv, b\right)}\right) = \beta_0 + \beta_1 v + \beta_2^T t + \beta_3^T dow + \beta_4 sv + \beta_5^T b \quad (33)$$

[9] Unlike in the annual sample, we include all stops in our sample regardless of whether it is twilight or the hour of the day is completely in darkness or daylight.

[10] In principle, we could estimate a regression discontinuity analysis controlling for the calendar day as a running variable and only obtaining identification using the variation associated with the 1 hour DST shift. However, we have insufficient power to conduct such an analysis. The coefficients on both the running variable and the DST shift variable are both sizable and consistent with a higher likelihood of stopped motorists being African-American in daylight, but individually both of these sources of variation lead to statistically insignificant estimates.

In Equation 4.2, we model the relative odds ratio as a function of v denoting visibility, t for time of day, dow for day of the week, sv for overall traffic stop volume, and b for heterogeneous barracks/town effects. We estimate a weighted regression using maximum quasi-likelihood estimation where the error term takes a logistic distribution (see McCullagh and Nelder 1989).[11] Visibility is our variable of interest and is captured by a dummy variable for either daylight for our full sample or the period with more daylight in our restricted sample i.e. before (after) the fall (spring) DST shift. Time of day and day of week effects are captured using a series of binary variables. These fixed effects assure that the effect of daylight is identified by comparing stops for periods with comparable levels and composition of traffic activity. Similarly, we include a series of barrack/town fixed-effects for each of the eight municipal departments (including Boston) as well as for individual State Police troops. In an effort to better capture idiosyncratic fluctuations in driving patterns, we also include a continuous variable constructed by standardizing the overall (out of sample) daily inter-twilight traffic stop volume across the state. Note that relative to the sample described in Table 8 we drop 21 observations where gender was not recorded and restrict the sample by an additional 654 stops by only including motorists between 18 and 65 years of age.[12]

Most stops occur in daylight, and our sample varies considerably across towns and state police barracks in terms of the share of stops occurring in darkness. Towns or barracks with very few stops in darkness will provide, at best, very noisy estimates of changes in the minority share of stops between daylight and darkness. Therefore, our estimates include weights that are calculated in order to given each town a relative weight equal to the reciprocal of the variance of the individual town/barracks specific estimate of racial difference. Specifically, we estimating Equation 4.2 as a logistic regression and replace the overall visibility indicator with a full set of interactions between visibility and the barracks/town fixed-effects. Using the standard error on the estimates of

[11] We follow Grogger and Ridgeway (2006) by using reverse regression so that any measurement error, in terms of motorist race, is absorbed by the error term.

[12] These sample restrictions did not substantively impact the estimates

visibility for each barrack/town $\sigma_{\beta_{1,b}}$, we calculate a weight for each stop in each barrack/town as:

$$w_{i,b} = \left(N_{b(i)} * \sigma^2_{\beta_{1,b(i)}}\right)^{-1} / \left(\sum_j \left(N_{b(j)} * \sigma^2_{\beta_{1,b(j)}}\right)^{-1}\right)$$

where N_b is the number of stops i in any barracks or town. Similar to GLS, these weights are based on the inverse of the variance placing higher weights on locations that provide the most precise estimates of racial differences (regardless of the magnitude of the racial differences in these locations). [13]

Table 10 presents coefficient estimates from applying our estimation equation to both the main analytical sample and to the alternative subsample where we restrict traffic stops to those occurring within 45 days of the DST shift (the 90 day DST sample). Across the estimates, we sequentially introduce an increasingly comprehensive set of control variables. The leftmost panel contains estimates using the full annual inter-twilight sample where the majority of the variation comes from broad seasonal changes in the length of daylight. The coefficient estimates indicate that there is a statistically significant 0.35 to 0.48 increase in the log-odds of a stopped motorist being of minority descent during daylight. We obtain similar estimates ranging from a 0.35 to 0.37 log-odds increase using the more restrictive sample of stops where we only include stops within 45 days of the three DST shifts occurring in the data. We consistently reject the null hypothesis of equal treatment across all models and samples. While our basic findings are robust across model specifications, the very stable magnitude of the estimates for the DST window sample suggest that there is little correlation between the treatment and motorist or automobile observables, implying a balanced sample across traffic stop volume and towns/barracks.[14]

[Insert Table 10]

[13]Reweighting has only modest effects on the point estimates for the visibility indicators.

[14]Although Smith (2016) reports evidence that motor vehicle crashes increase near the spring DST shift, we expect sleep impairment to be concentrated during the morning commute (i.e. out of our sample) and to have homogeneous effects across demographic groups.

Our theoretical model has shown that, in the presence of discrimination, the share of minority motorists stopped may increase or decrease in darkness so that the VOD test statistic presented in the theory section may lie above or below 1 under the alternative hypothesis of discrimination against African-Americans. Equivalently, the regression coefficient on visibility in this context may take on either positive or negative values leaving us unable to identify the direction of the discrimination.[15] Therefore, we next directly examine the speed distribution of stopped motorists using unconditional quantile regression. In all of the proceeding estimates, we focus on absolute speed over the speed limit but Appendix 2 contains parallel estimates using relative speed.

We estimate an unconditional quantile regression following Firpo, Fortin, and Lemieux (2009) using a software package described by Borgen (2016). Put simply, our 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 speed distribution, and (3) use RIF as the outcome variable in a linear model, so-called RIF-OLS or unconditional quantile regression (Firpo, Fortin, and Lemieux 2009). As with our estimates of the VOD test statistic, we apply the weight $w_{i,b}$ that allows us to obtain a composite estimate for our sample providing more weight to the subsamples of stops from towns or barracks that provide the most information for identifying racial differences.

Our sample of observations where we observe miles per hour over the speed limit of stopped motorists (spd_i) is reduced by 902 stops because of unreported speed limits in some of the data.[16] Using this sample, we create a kernel density by smoothing spd_i so that we can observe an estimated density for any discrete point in the speed distribution:

[15] As discussed above, we verify for our data and using the information in Grogger and Ridgeway that our test statistic yields results consistent with the reverse regression methodology typically used in VOD tests. We obtain a VOD test statistic greater than 1, and positive estimates on daylight, while Grogger and Ridgeway obtain negative estimates on daylight and the estimate of the VOD test statistic using the figures from their paper is 0.80.

[16] The Boston Globe, the original data steward, eliminated information on speed traveled when the information in the record raised concerns about data quality including speeds greater than 200 mph and speed zones greater than 65 mph or less than 15 mph.

$$\widehat{f_K}\left(spd_i\right) = \frac{1}{\left(\sum_j \sqrt{w_{j,b}}\right)^h} \sum_{j=1}^{n} \sqrt{w_{j,b}} K\left(\frac{spd_i - spd_j}{h}\right) \tag{34}$$

The bandwidth parameter h is selected using a standard optimal bandwidth function where $h = \frac{9m}{10}/n^{\frac{1}{5}}$ with $m = min\left(\sqrt{var\left(spd\right)}, \frac{interquartile\ range_{spd}}{1.349}\right)$. The kernel function K is robust to a variety of alternate functional forms but is specified as Epanechnikov in our estimates. We obtain a smoothed speed and density at each numeric τ decile of the distribution since we now have a continuous representation of the distribution.

Next, we calculate the RIF for each decile τ in the kernel smoothed speeding data within the inter-twilight sample as follows:

$$\text{RIF}\left(spd_i : q_\tau, F_{\widehat{spd}}\right) = q_\tau + \frac{\tau - \mathbb{I}\left\{spd_i \leq q_\tau\right\}}{f_{spd}\left(q_\tau\right)} \tag{35}$$

where q_τ and f_{spd} are the estimated speed and density at decile τ based on the kernel smoothing estimate of the speed distribution, and $\mathbb{I}$ is an indicator function.

Using the decile RIF's for each i observation, we estimate changes in the speeding distribution by estimating linear models for the RIF at each decile τ using the following model specification:

$$\begin{aligned} \text{RIF}_{\tau,i} = \beta_{\tau,0} + \beta_{\tau,1} d_i + \beta_{\tau,2} v_i + \beta_{\tau,3}\left(d_i * v_i\right) + \beta_{\tau,3}^{T} t_i + \beta_{\tau,4}^{T} dow_i + \\ \beta_{\tau,5} sv_i + \beta_{\tau,6} l_i + \beta_{\tau,7}^{T} b_i + \varepsilon_{\tau,i} \end{aligned} \tag{36}$$

where the variable d_i is a dichotomous indicator variable equal to unity when the motorist was of African-American descent, and v_i is a binary variable indicating the presence of the daylight during the traffic stop. As with the VOD estimates, our parameter of interest $\beta_{\tau,3}$ is the coefficient on the interaction of these two variables, which captures racial heterogeneity in speed distribution shifts. As with equation Equation 4.2, we include controls for t_i time of day, dow_i day of week, sv_i daily traffic volume, and b_i barracks/town fixed-effects. In addition, we add fixed effects associated with 5 mile per hour speed limit bins.[17] Table 11 presents the results from applying equation 36 to the annual inter-twilight (panel 1) and 90 day DST sample (panel 2) of Massachusetts traffic stops for each decile of the absolute speed distribution.[18]

[Insert Table 11]

As shown in Table 11, we find strong evidence in the annual inter-twilight sample that minority motorists shift to slower speeds during daylight hours. Although we find negative coefficient estimates on the interaction between demography and visibility across the entire distribution, only those above the 30^{th} percentile were found to be statistically significant in the annual sample. Similarly, we find statistically significant negative shifts between the 30^{th} and the 50^{th} percentiles of the speed distribution for the more restrictive 45 days DST sample. Several of the estimates are significant at the 1 Percent level and this pattern is unlikely to have arisen due to type 1 error. In both samples, white motorists are not observed to adjust their behavior in response to visibility. Although our theoretical model does predict that white motorists shift towards faster speeds during daylight, we believe that this shift will be small and difficult to detect due to the fact that white motorists constitute nearly 82 percent of the overall population of traffic stops. Therefore, on average, police stop costs in darkness may be relatively close to police stop costs during daylight. Estimates using the relative speed distribution align with Table 11 and are presented in Table A.1 of the Appendix. Figure 3 plots a graphical depiction of the effect of daylight on the African-American and white speed distributions by

[17] Most speed limits are in multiples of 5 mph so we divide the bins at the one's digits of 7 and 2 so that the bins are relatively evenly spaced around the multiples of 5. Speed limits of 5 or 10 mph do not occur in Massachusetts and stops for 15 mph speed limits are placed in a bin that is 17 mph or lower, followed by a bin that is 17 mph to 22 mph. Similarly, 60 mph is a relatively rare speed limit so it is pooled with 65 mph in a top bin that is formally defined as 57 mph or higher

[18] As noted, estimates using relative speed as the dependent variable are contained in Appendix 2.

applying kernel density estimation to the more restrictive 90 day DST window.

[Insert Figure 3]

It seems plausible that specific subgroups of African-American motorists may face more discrimination than others. In particular, we postulate that the results from Table 11 and Figure 3 could be driven predominantly by discrimination against young African-American males. In an effort to investigate this hypothesis further, we apply our quantile regression model to the data but condition on age and gender subgroups where we define young as 30 years of age or less. Table 12 presents the results of this exposure analysis where we find strong evidence confirming our hypothesis that young African-American males are driving the results from Table 11. We provide estimates for relative speed in Table A.2 of the Appendix. Using both absolute and relative speed in the annual and 90 day DST samples, we find strong evidence that the downward shift of the speed distribution in daylight is largest and most significant for young African-American males. We also find consistent evidence of slower speeds for young African-American females in daylight. For older African-American males and females, the negative shift in the distribution in daylight only arises consistently for the annual sample that relies heavily on seasonal variation.

[Insert Table 12]

Our analysis of the speed distribution of stopped motorists, coupled with our finding of a non-zero coefficient estimate from the VOD test, suggests that Massachusetts police disproportionately stopped African-American motorists from 2001 to 2003. Specifically, the evidence supports the conclusion that police officers in Massachusetts treat white and African-American motorists differently, and that African-American motorists believe that they were racially profiled by those police officers, particularly young African-American males.

Of course, a natural concern is that individuals may have changed their driving behavior in darkness for reasons other than racial profiling, and motorist race is only one factor on which motorist differ in how they respond to changes in visibility. In the next section, we address this concern by examining whether motorists differ by motorist or vehicle attributes in terms of how they change their driving behavior in daylight.

4.3 Falsification Tests

The first thing to notice is that the coefficient on daylight in Table 11 is typically small and statistically insignificant, and the only sizable coefficient estimates (sixth decile in the annual sample and the sixth to tenth decile in the 90 day DST sample) are positive. Therefore, we find no evidence that white motorists drive slower in daylight (due to glare or heavier traffic volume for example) as is observed for African-American motorists. Next, we utilize the subsample of white motorists to examine whether we observe differential shifts in the speeding distribution across other motorist demographic or vehicle characteristics. As above, we estimate quantile regression models of absolute and relative speed using both the annual and 90 day DST samples and relative speed estimates are presented in Tables A.1 through A.6 of the Appendix. We examine the speed distribution for old and new vehicles in Table 13 and corresponding Table A.3 of the Appendix. We define new vehicles as those aged 10 years or less but our estimates are robust to alternative delineations. There is little evidence suggesting that the speed distribution differentially shifts in response to visibility across this particular vehicle characteristic. Out of 18 interaction coefficients only 1 is significant at the 5 percent level and 2 are significant at the 10 percent level.

[Insert Table 13]

Next, we examine the speed distribution for white motorists conditional on vehicle color. Specifically, Table 14 disaggregates white motorists reported as driving a red vehicle from those in all other color automobiles. Testing the classic notion that police target red vehicles when making traffic stops, we do not find any observable preference for stopping these automobiles. None of the estimates are statistically significant. The estimates using the relative speed distribution align with those below and are shown in Table A.4 of the Appendix.

[Insert Table 14]

In Table 15 and corresponding Table A.5 of the Appendix, we present the speed distribution for traffic stops made of white motorists by age. In particular, we examine the impact of visibility on the speed distribution for motorists 30 years of age or less versus older motorists. As above, there is very little evidence in support of a shift in the speed distribution of white motorists by age; only one rejection at the 10 percent level out of 18 tests.

[Insert Table 15]

In Table 16 and corresponding Table A.6 of the Appendix, we present the speed distribution for traffic stops made of white motorists by gender. Specifically, we examine the effect of visibility on the speed distribution for both male and female motorists. For the gender subsample estimates, we do observe a substantially larger number of rejections of the null hypothesis of no differences across the deciles, but we do not observe any consistent pattern with season variation associated with males driving slower during daylight and the variation during the DST window consistent with males driving faster in daylight. As discussed in detail in the exposure analysis from Section 4.2, we found strong evidence that age and to some extent gender have a strong impact on the speed distribution of African-American motorists. In examining the speed distribution of white motorists, however, we are unable to detect any consistent effect across these same demographic dimensions. Moreover, the 90 day DST window estimates are preferred in that they are insulated against bias from seasonality shifts in driving behavior, and for that sample young, white motorists drive faster in daylight, rather than slower like young African-American motorists.

[Insert Table 16]

In contrasting the subgroup analysis conducted in Section 4.2 with the falsification tests conducted in this section, it seems clear that white motorist driving speed is relatively unaffected by visibility, suggesting that slower driving in response to daylight is a phenomenon concentrated primarily among African-American motorists. In both the annual and 90 day DST samples, we found very little evidence that observable attributes influenced the distribution of speed. As noted throughout the text, these estimates were consistent using both absolute and relative speed above the requisite speed limit. These results are supportive of using shifts in the speed distribution of minority motorists for identifying the direction of discrimination.

5 Conclusion

In this paper, we develop a model of police and motorist behavior concerning speeding and speeding stops. Using this model, we examine the behavior of minority motorists in darkness when race cannot be observed under the alternative hypothesis of discrimination against minority motorists for speeding stops in daylight. Not surprisingly, our model predicts that the speed distribution of minority motorists is shifted to slower speeds during daylight relative to darkness. Using our model, we consider the recently developed "Veil of Darkness" approach to testing for racial profiling, which uses racial differences in stops in darkness as a benchmark to assess whether discrimination exists in police stops made in daylight. Our model implies that the VOD test for differential treatment of white and minority motorists is still consistent under the null hypothesis, but when the null of equal treatment is rejected, the value of the test statistic is not informative as to whether a given group is being favored or disfavored in police stop decisions. While the speed distribution is affected by the same source of ambiguity as the VOD test, our model and simulations suggest that tests based on shifts in the distribution of the driving speeds of stopped motorists are likely to be much more powerful for identifying evidence of disparate treatment against minority motorists, at least from the perspective of the motorists themselves.

We apply the VOD test to data from Massachusetts and consistently reject the null of equal treatment using a variety of models. We then examine the speed distribution and again find statistically significant evidence of slower speeds in daylight by minority motorists. These findings are consistent with racial discrimination in speeding stops against minority motorists. Further, we assess daylight/darkness differences in the speed distribution along a number of other dimensions including age and gender, and we do not find consistent evidence of a shift in the speed distribution for any subgroups other than minority motorists.

These findings call into question reliance on solely VOD tests for identifying racial differences in the rate of police stops. Such tests, which have become ubiquitous in recent years, can only identify differential treatment. Unless we are willing to rely on information revealed by motorist behavior, as done in this paper, it is impossible to identify whether police are discriminating against minority motorists with tests of this type. As such, our results points to the need for the development of additional methods for calculating counterfactuals for the purpose of assessing the racial distribution of police stops, especially methods that are not sensitive to the behavioral adjustments of motorists.

References

Anbarci, Nejat and Jungmin Lee. 2014. Detecting Racial Bias in Speed Discounting: Evidence from Speeding Tickets in Boston. International Review of Law and Economics.

Anwar, Shamena and Hanming Fang. 2006. An Alternative Test for Racial Bias in Law Enforcement: Vehicle Searches: Theory and Evidence. American Economic Review.

Antonovics, Kate Brian G. Knight. 2009. "A New Look at Racial Profiling: Evidence from the Boston Police Department." The Review of Economics and Statistics. MIT Press, vol. 91(1), pages 163-177, February.

Borgen, Nicolai T. 2016. Fixed Effects in Unconditional Quantile Regression. Stata Journal, 16. issue 2, p. 403-415

Castle Bell, Gina and Mark C. Hopson and Richard Craig and Nicholas W. Robinson. 2014. Exploring Black and White Accounts of 21st Century Racial Profiling: Riding and Driving While Black. Quantitative Research Reports in Communications. Eastern Communication Association, Vol. 15 (1)

Chanin, Joshua and Megan Welsh and Dana Nurge and Stuart Henry. 2016. Traffic enforcement in San Diego, California: An analysis of SDPD vehicle stops in 2014 and 2015. Report. Public Affairs, San Diego State University.

Dedman, Bill and Francie Latour. 2003. Speed Trap: Who Gets a Ticket and Who Gets a Break? The Boston Globe.

Dharmapala, Dhammika and Stephen L. Ross. 2003. Racial Bias in Motor Vehicle Searches: Additional Theory and Evidence. The B.E. Journal of

Economic Analysis and Policy.

Firpo, Sergio and Nicole M. Fortin and Thomas Lemieux. 2009. Unconditional Quantile Regression. Econometrica.

Fridell, Lorie and Robert Lunney and Drew Diamond and Bruce Kubu. 2001. Racially Biased Policing: A Principled Response. Police Executive Research Forum. Washington, DC

Grogger, Jeffrey and Greg Ridgeway. 2006. Testing for Racial Profiling in Traffic Stops from Behind a Veil of Darkness. Journal of American Statistical Association.

Horrace, William C., and Shawn M. Rohlin. 2016. "How Dark Is Dark? Bright Lights, Big City, Racial Profiling." Review of Economics and Statistics 98, no. 2

Knowles, John and Nicola Persico and Petra Todd. 2001. Racial Bias in motor Vehicle Searches: Theory and Evidence. Journal of Political Economy.

Kowalski, Brian R. & Richard J. Lundman. 2007. Vehicle Stops by Police for Driving While Black: Common Problems and Some Tentative Solutions. Journal of Criminal Justice. Elsevier, Vol. 35 (2)

Masher, Jeff. 2016. "What The Veil of Darkness Says About New Orleans Traffic Stops." NOLA Crime News. Accessed February 22, 2017. https://nolacrimenews.com/2016/09/08/wh the-veil-of-darkness-says-about-new-orleans-traffic-stops.

McCullagh, P., and J.A Nelder. 2000. *Generalized Linear Models.* London,: Champman and Hall/CRC.

Persico, Nicola and Petra E. Todd. 2006. Generalizing the Hit Rates Test for Racial Bias in Law Enforcement, With an Application to Vehicle Searches in Wichita. University of Pennsylvania: Penn Institute for Economic Research Working Paper Archive 05-004.

Renauer, Brian C. and Kris Henning and Emily Covelli. 2009. Prepared for Portland Police Bureau. Report. Criminal Justice Policy Research Institute.

Ridgeway, Greg and Terry Schell and K. Jack Riley and Susan Turner and Travis L. Dixon. 2006. Police-community Relations in Cincinnati: Year Two Evaluation Report. Rand Corporation: Safety and Justice Program.

Ridgeway, Greg. 2009. Cincinnati Police Department Traffic Stops: Applying RANDs framework to Analyze Racial Disparities. Rand Corporation: Safety and Justice Program.

Ritter, Joseph A. 2017 forthcoming. "How do police use race in traffic stops and searches? Tests based on observability of race." Journal of Economic Behavior & Organization

Ritter, Joseph A. and David Bael. 2009. Detecting Racial Profiling in Minneapolis Traffic Stops: A New Approach. Center for Urban and Regional Affairs: Reporter. University of Minnesota.

Ross, Stephen L. and John Yinger. 1999. The Default Approach to Studying Mortgage Discrimination: A Rebuttal. Mortgage lending discrimination: A Review of Existing Evidence. Washington, DC. Urban Institute, Chapter 5.

Ross, Matthew B. and James Fazzalaro and Ken Barone and Jesse Kalinowski. 2015. State of Connecticut Traffic Stop Data Analysis and Findings, 2013-14. Racial Profiling Prohibition Project. Connecticut State Legislature.

Ross, Matthew B. and James Fazzalaro and Ken Barone and Jesse Kalinowski.

2016. State of Connecticut Traffic Stop Data Analysis and Findings, 2014-15. Racial Profiling Prohibition Project. Connecticut State Legislature.

Schell, Terry and Greg Ridgeway and Travis L. Dixon and Susan Turner and K. Jack Riley. 2007. Police-community Relations in Cincinnati: Year Three Evaluation Report. Rand Corporation: Safety and Justice Program. 2007.

Smith, Austin C. "Spring Forward at Your Own Risk: Daylight Saving Time and Fatal Vehicle Crashes." American Economic Journal: Applied Economics 8, no. 2 (2016): 65-91. doi:10.1257/app.20140100.

Taniguchi, T. and Hendrix, J. and Aagaard, B. and Strom, K., Levin-Rector, A. and Zimmer, S. 2016a. Exploring racial disproportionality in traffic stops conducted by the Durham Police Department . Research Triangle Park, NC: RTI International.

Taniguchi, T. and Hendrix, J. and Aagaard, B. and Strom, K., Levin-Rector, A. and Zimmer, S. 2016b. A test of racial disproportionality in traffic stops conducted by the Greensboro Police Department . Research Triangle Park, NC: RTI International.

Taniguchi, T. and Hendrix, J. and Aagaard, B. and Strom, K., Levin-Rector, A. and Zimmer, S. 2016c. A test of racial disproportionality in traffic stops conducted by the Raleigh Police Department . Research Triangle Park, NC: RTI International.

Taniguchi, T. and Hendrix, J. and Aagaard, B. and Strom, K., Levin-Rector, A. and Zimmer, S. 2016d. A test of racial disproportionality in traffic stops conducted by the Fayetteville Police Department. Research Triangle Park, NC: RTI International.

Worden, Robert E. and Sarah J. McLean and Andrew P. Wheeler. 2012.

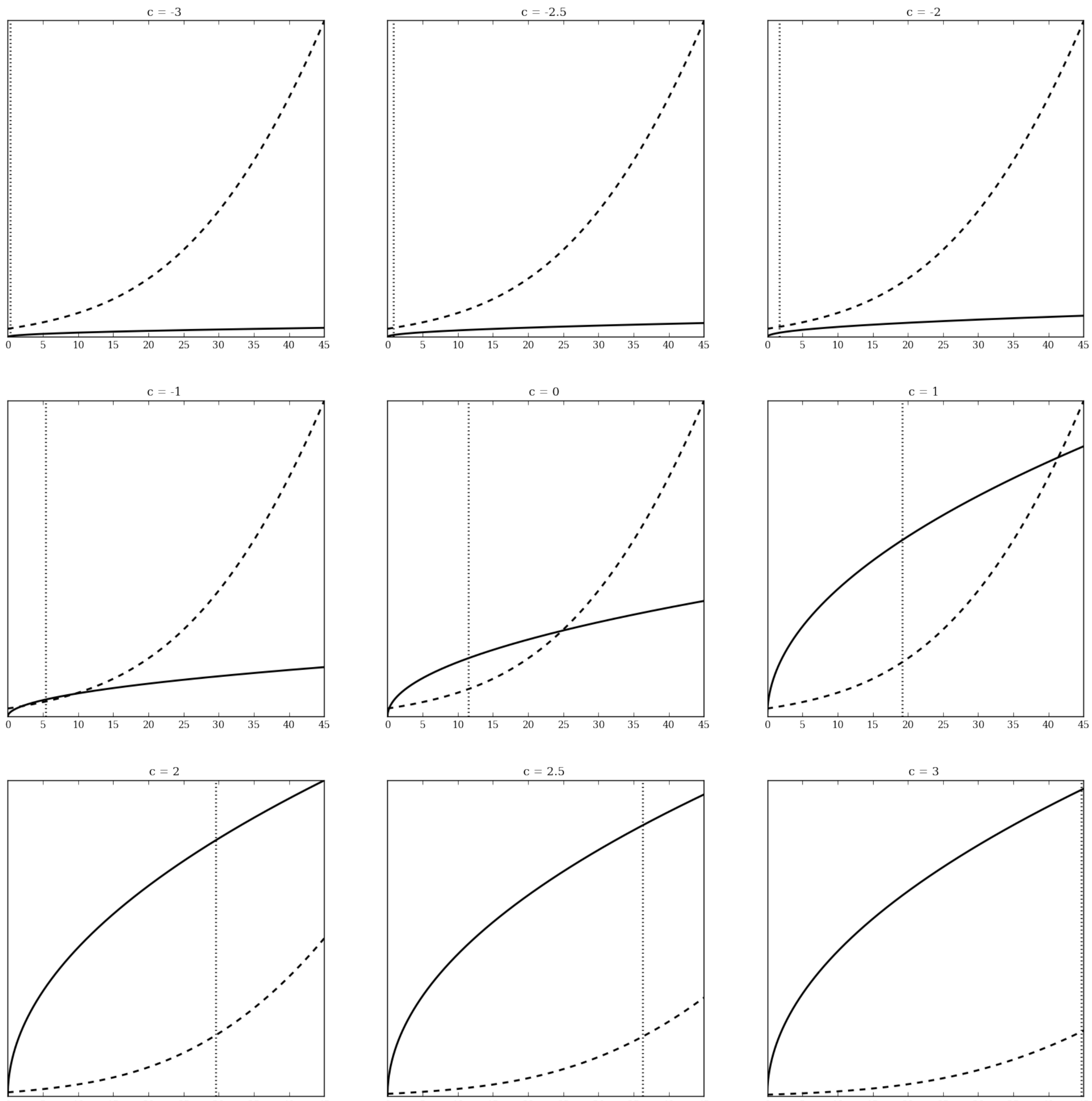
Testing for Racial Profiling with the Veil-of-Darkness Method. Police Quarterly.

Worden, Robert E. and Sarah J. McLean and Andrew P. Wheeler. 2012. Testing for Racial Profiling with the Veil-of-Darkness Method. Police Quarterly.

Worden, Robert E. and Sarah J. McLean and Andrew P. Wheeler. 2010. Stops by Syracuse Police, 2006-2009. The John F. Finn Institute for Public Safety, Inc. Report.

Tables and Figures

Figure 1: Equilibrium for Select Levels of Criminality



Note: The horizontal axis is level of infraction (i.e. 'speed above the speed limit'). The solid line, dashed line, and dotted line are motorist benefit, motorist cost, and optimal solution, respectively.

Figure 2: Density of Infracting White Motorists

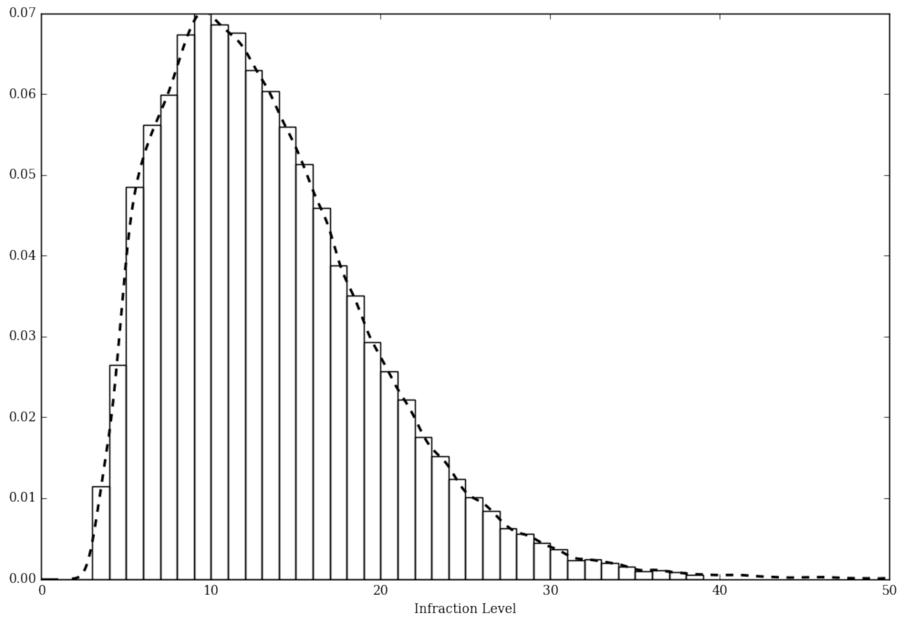


Table 1: Simulation Parameter Names and Symbols

Parameter Name	Symbol
Fixed	
Mean of white infraction preference distribution	m_w
Std. Dev. of white infraction preference distribution	σ_w
Initial level of officer pay-off	u_0
Shape parameter for distribution of circumstances	a
Shift parameter for distribution of circumstances	k
Rate of increase in officer pay-off	η
Stop cost for minorities in light	$s_{\overline{v},m}$
Motorist payoff level parameter	b_0
Calibrated	
Skewness of white infraction preference distribution	$skew_w$
Mean of minority infraction preference distribution	m_m
Std. Dev. of minority infraction preference distribution	σ_m
Skewness of minority infraction preference distribution	$skew_m$
Rate of increase with infraction in motorist payoff	α_1
Rate of increase with preferences in motorist payoff	α_2
Initial level of infraction costs if stopped	τ_0
Rate of increase in infraction costs if stopped	μ
Stop cost for whites in light	$s_{\overline{v},w}$
Stop cost in darkness	$s_{\underline{v}}$

Table 2: Fixed and Calibrated Parameters Values
for each Simulation Run

		10%	5%	2%	5%		5%	
Fixed	m_w		0		0		0	
	σ_w		1		1		1	
	k		700		700		700	
	u_0		8.39		8.39		8.39	
	$s_{\overline{v},m}$		1		1		1	
	a		2.1		**2.05**	**2.25**	2.1	
	η		1.01		1.01		**1.03**	**1.09**
Calibrated	m_m	0.0012	0.0012	0.0012	0.0008	0.0013	0.0012	0.0013
	σ_m	0.8969	0.8940	0.9018	0.9018	0.8921	0.8916	0.8886
	$skew_m$	-0.0006	-0.0006	-0.0006	-0.0005	-0.0006	-0.0006	-0.0007
	$skew_w$	0.0049	0.0049	0.0048	0.0064	0.0047	0.0050	0.0051
	α_1	0.5006	0.5006	0.5006	0.5004	0.5006	0.5006	0.5006
	α_2	0.8542	0.8489	0.8460	0.8032	0.8342	0.8459	0.8446
	τ_0	93.799	73.796	62.4401	62.557	35.578	73.092	44.678
	μ	2.2766	2.2857	2.2951	2.3134	2.2128	2.2479	2.2226
	$s_{\overline{v},w}$	2.7512	3.1044	3.2314	2.7444	3.7692	3.1209	3.3177
	s_v	2.1549	2.0025	1.9764	1.9086	2.0151	2.1400	1.9502

Note: Bolded values indicate manual changes for robustness. All non-fixed parameters are re-calibrated to those changes.

Table 3: Comparison of Simulation Moments to the Data
10% of Whites Not Infracting

	Minority				White			
	Day		Night		Day		Night	
Percentile	Simulated	Data	Simulated	Data	Simulated	Data	Simulated	Data
20	10.8665	11.9966	10.9793	12.1858	11.4538	11.1008	11.3374	10.7167
40	13.8992	14.6590	14.0329	15.1177	14.7386	14.8668	14.6336	14.5273
60	16.7758	17.1187	16.8954	17.6369	17.9037	18.2523	17.8081	17.9000
80	20.7347	20.4836	20.8470	20.8977	22.3612	22.5142	22.2756	22.0989
90	24.0900	23.6711	24.2139	23.9983	26.2626	26.4992	26.1923	25.7294
95	27.3353	27.0675	27.4117	26.9751	30.0364	30.3582	29.9703	29.4817

Table 4: Simulation Percentile Moments
10% of Whites Not Infracting

		Minority			White	
Percentile	Day	Night	Difference	Day	Night	Difference
20	10.8665	10.9793	-0.1128	11.4538	11.3374	0.1164
40	13.8992	14.0329	-0.1337	14.7386	14.6336	0.1050
60	16.7758	16.8954	-0.1195	17.9037	17.8081	0.0956
80	20.7347	20.8470	-0.1123	22.3612	22.2756	0.0856
90	24.0900	24.2139	-0.1239	26.2626	26.1923	0.0703
95	27.3353	27.4117	-0.0764	30.0364	29.9703	0.0661
$\overline{M}_{Day}$			0.1675			
K_{ERS}			0.9524			
$0.5\delta_{Day}$			0.2307			
$0.5\delta_{Night}$			0.1744			

Note: The calibrations are always within 0.05% of the target fraction of whites not infracting. $\overline{M}_{Day}$ is the fraction of minorities not infracting during daylight. 0.5δ is the fraction of African-Americans in the simulation population in daylight and darkness respectively.

Table 5: Simulation Day and Night Speed Differences
10% of Whites Not Infracting

	Stopped Drivers		All Drivers	
Percentile	Minority	White	Minority	White
20	-0.1128	0.1164	-0.4696	0.2890
40	-0.1337	0.1050	-0.4490	0.2735
60	-0.1195	0.0956	-0.4024	0.2391
80	-0.1123	0.0856	-0.3461	0.1982
90	-0.1239	0.0703	-0.3052	0.1691
95	-0.0764	0.0661	-0.2714	0.1453

Table 6: Simulation Day and Night Speed Differences

	5%		2%		1%	
Percentile	Minority	White	Minority	White	Minority	White
20	-0.2286	0.3496	-0.3116	0.4958	-0.3495	0.5567
40	-0.2290	0.3228	-0.2888	0.4526	-0.3306	0.5055
60	-0.2384	0.3062	-0.2811	0.4083	-0.3119	0.4680
80	-0.2104	0.2712	-0.2489	0.3577	-0.2801	0.4200
90	-0.1884	0.2199	-0.2131	0.3234	-0.2646	0.3784
95	-0.1421	0.2122	-0.2001	0.2816	-0.2378	0.3334
$\overline{M}_{Day}$	0.0994		0.0672		0.0400	
K_{ERS}	0.9600		0.9788		0.9971	
$0.5\delta_{Day}$	0.2165		0.2000		0.1882	
$0.5\delta_{Night}$	0.1658		0.1548		0.1471	

Note: The calibrations are always within 0.05% of the target fraction of whites not infracting. $\overline{M}_{Day}$ is the fraction of minorities not infracting during daylight. 0.5δ is the fraction of African-Americans in the simulation population daylight and darkness respectively.

Table 7: Robustness Simulation Percentile Moments
for 5% White not Infracting

	$a = 2.05$		$a = 2.25$		$\eta = 1.03$		$\eta = 1.09$	
Percentile	Minority	White	Minority	White	Minority	White	Minority	White
20	-0.3226	0.3298	-0.1064	0.1837	-0.1956	0.3245	-0.1831	0.1224
40	-0.3263	0.3257	-0.1125	0.1457	-0.2044	0.2974	-0.1373	0.1016
60	-0.3105	0.2780	-0.0525	0.0993	-0.2131	0.2724	-0.1056	0.0777
80	-0.2917	0.2648	-0.0741	0.0661	-0.1807	0.2354	-0.0526	0.0529
90	-0.2692	0.2110	-0.0101	-0.0171	-0.1494	0.1783	-0.0219	0.0202
95	-0.2325	0.2052	-0.0080	0.0201	-0.1333	0.1579	0.0287	-0.0153
$\overline{M}_{Day}$	0.0870		0.1020		0.1047		0.0912	
K_{ERS}	0.9755		0.9692		0.9646		0.9665	
$0.5\delta_{Day}$	0.2169		0.1866		0.1946		0.1945	
$0.5\delta_{Night}$	0.1673		0.1431		0.1490		0.1489	

Note: The calibrations are always within 0.05% of the target fraction of whites not infracting. $\overline{M}_{Day}$ is the fraction of minorities not infracting during daylight. 0.5δ is the fraction of African-Americans in the simulation population daylight and darkness respectively.

Table 8: Descriptive Statistics for Massachusetts Traffic Stop Data within the Annual Inter-twilight Sample

Sample Size	All Times			Intertwilight Window		
	All Stops	Speeding Stops		All Stops	Speeding Stops	
	376,912	80,001		111,386	16,208	
Speeding Stops within the Intertwilight Window						
Season	Winter	Spring		Summer	Fall	
	15.1%	28.8%		34.4%	21.7%	
Day of the Week	Monday	Tuesday	Wednesday	Thursday	Friday	Sat & Sun
	14.4%	14.8%	15.2%	14.2%	14.3%	27.2%
Time of Day	4:00 PM	5:00 PM	6:00 PM	7:00 PM	8:00 PM	8:00 PM
	23.4%	23.9%	19.7%	9.9%	7.8%	15.3%
Motorist	African-American		Male		Age < 30	
	17.3%		73.6%		54.4%	
Vehicle	Red Vehicle			Vehicle Age < 11		
	16.4%			49.2%		
Absolute Speed Over Limit	25th	50th		Mean	75th	
	10mph	15mph		17mph	20mph	
Relative Speed Over Limit	25th	50th		Mean	75th	
	24%	35%		39%	50%	

Table 9: Descriptive Statistics for Massachusetts Traffic Stop Data within the DST Inter-twilight Sample

<table>
<tr><td rowspan="3">Sample Size</td><td colspan="3">All Times</td><td colspan="3">Intertwilight Window</td></tr>
<tr><td>All Stops</td><td colspan="2">Speeding Stops</td><td>All Stops</td><td colspan="2">Speeding Stops</td></tr>
<tr><td>143,157</td><td colspan="2">29,617</td><td>40,125</td><td colspan="2">7,210</td></tr>
<tr><td colspan="7">Speeding Stops within the Intertwilight Window</td></tr>
<tr><td rowspan="2">DST Window</td><td colspan="2">Fall 2001</td><td colspan="2">Spring 2002</td><td colspan="2">Fall 2002</td></tr>
<tr><td colspan="2">30.8%</td><td colspan="2">36.6%</td><td colspan="2">32.7%</td></tr>
<tr><td rowspan="2">Day of the Week</td><td>Monday</td><td>Tuesday</td><td>Wednesday</td><td>Thursday</td><td>Friday</td><td>Sat & Sun</td></tr>
<tr><td>15.3%</td><td>15.5%</td><td>14.6%</td><td>15.0%</td><td>13.6%</td><td>26.1%</td></tr>
<tr><td rowspan="2">Time of Day</td><td>4:00 PM</td><td>5:00 PM</td><td>6:00 PM</td><td>7:00 PM</td><td>8:00 PM</td><td>8:00 PM</td></tr>
<tr><td>23.7%</td><td>22.3%</td><td>16.5%</td><td>11.3%</td><td>11.4%</td><td>14.8%</td></tr>
<tr><td rowspan="2">Motorist</td><td colspan="2">African-American</td><td colspan="2">Male</td><td colspan="2">Age < 30</td></tr>
<tr><td colspan="2">17.8%</td><td colspan="2">74.6%</td><td colspan="2">54.4%</td></tr>
<tr><td rowspan="2">Vehicle</td><td colspan="3">Red Vehicle</td><td colspan="3">Vehicle Age < 11</td></tr>
<tr><td colspan="3">15.8%</td><td colspan="3">52.0%</td></tr>
<tr><td rowspan="2">Absolute Speed Over Limit</td><td>25th</td><td colspan="2">50th</td><td>Mean</td><td colspan="2">75th</td></tr>
<tr><td>12mph</td><td colspan="2">16mph</td><td>17mph</td><td colspan="2">20mph</td></tr>
<tr><td rowspan="2">Relative Speed Over Limit</td><td>25th</td><td colspan="2">50th</td><td>Mean</td><td colspan="2">75th</td></tr>
<tr><td>25%</td><td colspan="2">36%</td><td>40%</td><td colspan="2">50%</td></tr>
</table>

Table 10: Logistic Regression Estimates of Demography on Visibility in Traffic Stops Made for Speeding within the Annual and DST Inter-twilight Sample

	(1)	(2)	(3)	(1)	(2)	(3)
	Annual Sample			45 Day DST Sample		
Daylight	0.350***	0.439***	0.483***	0.369**	0.372**	0.348*
	(0.0678)	(0.0722)	(0.0853)	(0.170)	(0.168)	(0.194)
Day of Week	X	X	X	X	X	X
Time of Day	X	X	X	X	X	X
Daily Volume		X	X			
DST Window					X	X
Troop FE			X			X

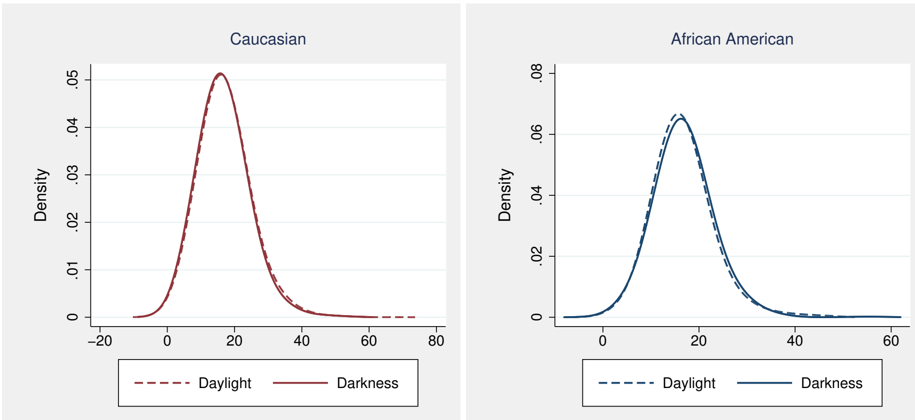
Note 1: A coefficient estimate concatenated with a * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance.
Note 2: Standard errors are clustered at the barracks level.

Table 11: Unconditional Quantile Regression Estimates of Absolute Speed on Visibility and Demography within the Annual and DST Inter-twilight Sample

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	Annual Sample								
African-American	-0.015	-0.015	0.407	0.384	0.384	0.817	0.284	0.511	-0.348
	(0.129)	(0.129)	(0.809)	(0.300)	(0.300)	(0.628)	(0.552)	(0.951)	(0.553)
Daylight	0.021	0.021	-0.294	-0.363	-0.363	0.683	0.073	0.503	-0.437
	(0.165)	(0.165)	(0.791)	(0.446)	(0.446)	(1.085)	(0.580)	(1.178)	(0.657)
Daylight x African-American	-0.164	-0.164	-4.179***	-1.716***	-1.716***	-2.291**	-0.824*	-0.712	0.280
	(0.164)	(0.164)	(1.353)	(0.473)	(0.473)	(1.062)	(0.466)	(0.726)	(0.488)
	45 Day DST Sample								
African-American	0.053	0.053	-0.194	0.087	0.087	0.799	-0.009	1.011	0.424
	(0.092)	(0.092)	(1.024)	(0.350)	(0.350)	(0.802)	(0.500)	(0.813)	(0.483)
DST	0.031	0.031	0.121	-0.060	-0.060	0.818	0.403	1.465	0.601
	(0.112)	(0.112)	(0.643)	(0.338)	(0.338)	(0.715)	(0.423)	(0.941)	(0.364)
DST x African-American	0.137	0.137	-2.555***	-0.904***	-0.904***	-2.124	-0.567	-1.237	-0.596
	(0.137)	(0.137)	(0.724)	(0.284)	(0.284)	(1.372)	(0.432)	(1.097)	(0.607)

Note 1: A coefficient estimate concatenated with a * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance.
Note 2: The estimates include a daily traffic volume control, six binary indicator variables for time of day, seven for day of week, speed limit fixed-effects, and barracks fixed-effects.
Note 3: Standard errors are clustered at the barracks level.

Figure 3: Kernel Density Estimates of the Absolute Speed Distribution by Demography within the DST Inter-twilight Sample



Note 1: The bandwidth of the kernel density estimates has been set to half a standard deviation.

Table 12: Unconditional Quantile Regression Estimates of Absolute Speed on Visibility and Demography by Age and Gender Subgroup within the Annual and DST Inter-twilight Sample

Annual Sample											
Daylight x	Male	Young	-0.134 (0.257)	-0.134 (0.257)	-4.293*** (0.823)	-2.471*** (0.418)	-2.096*** (0.582)	-1.313** (0.488)	-1.313** (0.488)	-0.288 (0.787)	0.423 (0.924)
		Old	-0.259 (0.325)	-0.259 (0.325)	-1.316* (0.654)	-1.842** (0.782)	-1.842** (0.782)	-2.202 (1.516)	-0.605 (0.775)	-0.676 (0.764)	1.302 (0.785)
African-American	Female	Young	-0.235 (0.191)	-0.235 (0.191)	-2.990* (1.439)	-1.152 (0.911)	-1.152 (0.911)	-1.030 (2.599)	-0.151 (1.501)	0.220 (1.635)	-0.654 (1.773)
		Old	-0.389 (0.255)	-0.389 (0.255)	-1.070** (0.484)	-2.632* (1.350)	-1.214 (0.699)	-0.689 (0.795)	-1.511 (1.050)	-1.059 (1.110)	-0.494 (2.149)
45 Day DST Sample											
DST x	Male	Young	-0.077 (0.364)	-0.077 (0.364)	-2.630*** (0.686)	-2.048*** (0.475)	-1.985* (1.025)	-1.911** (0.887)	-1.911** (0.887)	-1.863* (1.047)	-2.296 (2.559)
		Old	0.478 (0.345)	0.478 (0.345)	-0.497 (0.863)	-0.418 (0.652)	-0.418 (0.652)	-0.461 (1.126)	-0.110 (1.070)	-0.839 (1.113)	0.518 (1.309)
African-American	Female	Young	-0.880*** (0.252)	-0.880*** (0.252)	-2.756 (2.029)	-0.831 (1.734)	-0.831 (1.734)	-3.167 (2.849)	-0.066 (2.268)	-0.213 (2.145)	-1.133 (2.652)
		Old	0.957** (0.333)	0.957** (0.333)	-0.070 (0.902)	1.339 (1.190)	0.231 (1.105)	0.231 (1.105)	0.049 (0.601)	1.249 (0.729)	-0.296 (1.460)

Note 1: A coefficient estimate concatenated with a * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance.
Note 2: The estimates include a daily traffic volume control, six binary indicator variables for time of day, seven for day of week, speed limit fixed-effects, and barracks fixed-effects.
Note 3: Standard errors are clustered at the barracks level.

Table 13: Unconditional Quantile Regression Estimates of Absolute Speed on Visibility and Vehicle Age for White Motorists within the Annual and DST Inter-twilight Sample

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	Annual Sample								
Vehicle Age < 11	-0.072	-0.072	-0.068	-0.035	-0.036	-0.135	-0.270*	0.149	0.292
	(0.082)	(0.082)	(0.397)	(0.165)	(0.145)	(0.217)	(0.143)	(0.561)	(0.401)
Daylight	-0.061	-0.061	-0.508	-0.478	0.435	0.362	0.107	0.613	1.013
	(0.195)	(0.195)	(1.131)	(0.615)	(0.830)	(0.733)	(0.652)	(1.250)	(0.778)
Daylight x Vehicle Age < 11	0.035	0.035	-0.175	-0.086	-0.214	-0.368	-0.190	-0.899	-0.902*
	(0.063)	(0.063)	(0.422)	(0.206)	(0.227)	(0.240)	(0.252)	(0.656)	(0.502)
	45 Day DST Sample								
Vehicle Age < 11	-0.053	-0.053	-0.328**	-0.277*	0.177	-0.174	-0.114	0.326	-0.141
	(0.068)	(0.068)	(0.134)	(0.154)	(0.247)	(0.248)	(0.231)	(0.372)	(0.477)
DST	0.060	0.060	-0.105	-0.111	0.502	0.620	0.520	2.035**	1.731***
	(0.115)	(0.115)	(0.422)	(0.413)	(0.452)	(0.497)	(0.405)	(0.780)	(0.264)
DST x Vehicle Age < 11	-0.028	-0.028	0.160	0.018	-0.654*	-0.371	-0.317	-1.842**	-0.718
	(0.160)	(0.160)	(0.299)	(0.351)	(0.372)	(0.364)	(0.397)	(0.661)	(0.660)

Note 1: A coefficient estimate concatenated with a * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance.
Note 2: The estimates include a daily traffic volume control, six binary indicator variables for time of day, seven for day of week, speed limit fixed-effects, and barracks fixed-effects.
Note 3: Standard errors are clustered at the barracks level.

Table 14: Unconditional Quantile Regression Estimates of Absolute Speed on Visibility and Vehicle Color for White Motorists within the Annual and DST Inter-twilight Sample

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	Annual Sample								
Red Auto.	-0.153	-0.153	-0.053	-0.141	-0.141	0.133	0.212	-0.048	-0.400
	(0.149)	(0.149)	(0.654)	(0.318)	(0.318)	(0.453)	(0.341)	(0.996)	(0.750)
Daylight	-0.044	-0.044	-0.547	-0.519	-0.519	0.269	0.181	0.178	0.039
	(0.190)	(0.190)	(0.962)	(0.537)	(0.537)	(0.728)	(0.675)	(1.149)	(0.604)
Daylight x Red Auto.	0.271	0.271	0.395	0.279	0.279	-0.009	0.233	0.434	1.064
	(0.223)	(0.223)	(1.225)	(0.501)	(0.501)	(0.414)	(0.389)	(1.130)	(0.888)
	45 Day DST Sample								
Red Auto.	-0.086	-0.086	0.691	0.617	0.846	0.908	0.927	0.347	-0.125
	(0.140)	(0.140)	(0.851)	(0.721)	(0.731)	(0.858)	(0.849)	(1.299)	(0.902)
DST	0.066	0.066	0.071	0.016	0.111	0.504	0.420	0.727	0.723**
	(0.199)	(0.199)	(0.497)	(0.468)	(0.548)	(0.513)	(0.495)	(0.737)	(0.323)
DST x Red Auto.	0.055	0.055	-0.834	-0.801	-1.152	-1.413	-1.437	-1.501	-0.222
	(0.122)	(0.122)	(0.887)	(0.824)	(0.805)	(0.984)	(0.980)	(1.118)	(0.983)

Note 1: A coefficient estimate concatenated with a * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance.
Note 2: The estimates include a daily traffic volume control, six binary indicator variables for time of day, seven for day of week, speed limit fixed-effects, and barracks fixed-effects.
Note 3: Standard errors are clustered at the barracks level.

Table 15: Unconditional Quantile Regression Estimates of Absolute Speed on Visibility and Age for White Motorists within the Annual and DST Inter-twilight Sample

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	Annual Sample								
Age < 31	0.183**	0.183**	1.388***	0.615***	1.063***	1.140***	1.274***	2.277***	1.684***
	(0.082)	(0.082)	(0.385)	(0.185)	(0.218)	(0.205)	(0.236)	(0.238)	(0.154)
Daylight	-0.081	-0.081	-0.866	-0.675	0.158	-0.001	-0.129	-0.451	0.317
	(0.227)	(0.227)	(1.029)	(0.556)	(0.851)	(0.666)	(0.543)	(0.932)	(0.451)
Daylight x Age < 31	0.062	0.062	0.398	0.239	0.236	0.252	0.188	0.932	0.293
	(0.110)	(0.110)	(0.450)	(0.226)	(0.270)	(0.276)	(0.304)	(0.598)	(0.405)
	45 Day DST Sample								
Age < 31	0.203	0.203	0.524***	0.477***	0.647**	0.852***	0.871***	1.354**	2.030***
	(0.167)	(0.167)	(0.145)	(0.120)	(0.303)	(0.276)	(0.232)	(0.634)	(0.504)
DST	-0.097	-0.097	-0.295	-0.276	-0.211	0.031	-0.052	0.390	0.396
	(0.123)	(0.123)	(0.422)	(0.369)	(0.413)	(0.277)	(0.252)	(0.328)	(0.606)
DST x Age < 31	0.260	0.260	0.507*	0.327	0.666*	0.724	0.737	1.236	1.731
	(0.227)	(0.227)	(0.282)	(0.258)	(0.379)	(0.561)	(0.456)	(1.384)	(1.454)

Note 1: A coefficient estimate concatenated with a * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance.
Note 2: The estimates include a daily traffic volume control, six binary indicator variables for time of day, seven for day of week, speed limit fixed-effects, and barracks fixed-effects.
Note 3: Standard errors are clustered at the barracks level.

Table 16: Unconditional Quantile Regression Estimates of Absolute Speed on Visibility and Gender for White Motorists within the Annual and DST Inter-twilight Sample

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	Annual Sample								
Male	-0.075	-0.075	1.010**	0.362	0.485**	1.252***	1.216***	3.273***	1.885***
	(0.057)	(0.057)	(0.434)	(0.243)	(0.170)	(0.212)	(0.238)	(0.572)	(0.314)
Daylight	-0.116	-0.116	-0.027	-0.394	0.456	0.695	0.544	1.512	1.233*
	(0.123)	(0.123)	(1.275)	(0.723)	(0.900)	(0.562)	(0.495)	(1.027)	(0.687)
Daylight x Male	0.102	0.102	-0.741	-0.159	-0.157	-0.659*	-0.672*	-1.750***	-0.880**
	(0.107)	(0.107)	(0.448)	(0.229)	(0.189)	(0.309)	(0.324)	(0.550)	(0.409)
	45 Day DST Sample								
Male	0.016	0.016	0.103	-0.023	-0.040	0.445	0.470*	1.293*	1.856*
	(0.076)	(0.076)	(0.184)	(0.227)	(0.208)	(0.354)	(0.256)	(0.672)	(0.898)
DST	0.126	0.126	-0.101	-0.166	-0.249	-0.036	-0.104	0.224	0.824
	(0.132)	(0.132)	(0.479)	(0.461)	(0.472)	(0.500)	(0.452)	(1.008)	(0.951)
DST x Male	-0.103	-0.103	0.119	0.100	0.550**	0.627*	0.617**	1.133	0.706
	(0.197)	(0.197)	(0.438)	(0.397)	(0.247)	(0.305)	(0.258)	(0.776)	(1.244)

Note 1: A coefficient estimate concatenated with a * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance.
Note 2: The estimates include a daily traffic volume control, six binary indicator variables for time of day, seven for day of week, speed limit fixed-effects, and barracks fixed-effects.
Note 3: Standard errors are clustered at the barracks level.

Appendices (Online Publication Only)

Empirical Appendix

Table A.1: Unconditional Quantile Regression Estimates of Relative Speed on Visibility and Demography within the Annual and DST Inter-twilight Sample

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	Annual Sample								
African-American	0.450	0.493	0.668	1.431**	1.059**	1.480*	1.928	4.420**	7.288**
	(0.719)	(0.569)	(0.527)	(0.524)	(0.457)	(0.795)	(1.219)	(1.521)	(2.729)
Daylight	0.490	0.888	1.458	1.119	-0.516	-0.516	-0.888	-2.428	-2.164
	(1.004)	(0.867)	(1.059)	(0.851)	(1.055)	(1.370)	(1.661)	(3.127)	(3.946)
Daylight x African-American	-0.056	-0.312	-0.215	-1.570*	-4.324**	-6.461**	-8.132**	-11.170***	-14.262***
	(0.810)	(0.665)	(0.893)	(0.752)	(1.780)	(2.240)	(2.822)	(3.194)	(4.651)
	45 Day DST Sample								
African-American	0.970	0.781	2.177*	2.258**	1.451	0.035	0.474	4.206**	2.081
	(0.721)	(0.748)	(1.167)	(0.985)	(1.058)	(0.970)	(1.341)	(1.832)	(1.463)
DST	0.890	0.781	1.460	1.105*	0.878	-0.257	-0.415	-0.851	1.076
	(0.957)	(0.669)	(0.936)	(0.567)	(0.572)	(0.543)	(0.844)	(1.123)	(1.403)
DST x African-American	0.363	0.811	0.434	0.235	-1.948	-3.291**	-3.395*	-6.511*	-7.641***
	(1.011)	(0.759)	(1.421)	(0.941)	(1.816)	(1.384)	(1.733)	(3.535)	(1.902)

Note 1: A coefficient estimate concatenated with a * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance.
Note 2: The estimates include a daily traffic volume control, six binary indicator variables for time of day, seven for day of week, speed limit fixed-effects, and barracks fixed-effects.
Note 3: Standard errors are clustered at the barracks level.

Table A.2: Unconditional Quantile Regression Estimates of Relative Speed on Visibility and Demography by Age and Gender Subgroup within the Annual and DST Inter-twilight Sample

			0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Annual Sample											
Daylight x	Male	Young	0.042	-0.675	-0.507	-0.763	-4.493**	-6.942**	-11.129***	-12.167***	-15.331***
			(1.034)	(1.202)	(1.116)	(1.227)	(2.066)	(2.356)	(2.688)	(2.799)	(2.717)
		Old	-0.306	0.322	-0.146	-1.951**	-1.906***	-5.451*	-8.114*	-12.848**	-18.508**
			(0.932)	(0.579)	(0.719)	(0.827)	(0.471)	(2.606)	(3.987)	(5.142)	(6.499)
African-American	Female	Young	-0.906	-0.600	0.893	-1.862	-5.876*	-6.993***	-5.508	-4.707	-5.900
			(1.684)	(1.527)	(1.358)	(1.223)	(2.960)	(2.017)	(3.654)	(4.344)	(11.360)
		Old	-1.417	-1.713	-1.431	-1.091	-1.708	-3.646*	-5.761*	-5.809*	-13.192**
			(1.277)	(1.154)	(1.324)	(1.128)	(1.235)	(1.715)	(3.002)	(2.846)	(5.406)
45 Day DST Sample											
DST x	Male	Young	-0.588	-0.462	-2.631**	-0.973	-5.635*	-6.335***	-8.947***	-13.636**	-12.697***
			(0.947)	(1.157)	(1.131)	(1.359)	(3.097)	(1.827)	(2.570)	(4.685)	(4.140)
		Old	2.950	2.374	2.850	1.723	0.293	-0.838	-2.165	-5.769	-7.211***
			(2.289)	(1.861)	(2.018)	(1.882)	(2.296)	(1.736)	(2.761)	(4.206)	(2.355)
African-American	Female	Young	-4.061*	-1.786*	-2.409	-4.226**	-5.310	-5.864	-1.163	-0.213	-4.039
			(1.766)	(0.863)	(1.895)	(1.820)	(3.825)	(4.279)	(9.358)	(13.954)	(16.386)
		Old	-0.923	3.984**	4.609*	3.108	4.609**	3.881	7.698**	6.482**	2.407
			(2.669)	(1.668)	(2.016)	(2.344)	(1.807)	(2.496)	(2.919)	(2.215)	(4.494)

Note 1: A coefficient estimate concatenated with a * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance.
Note 2: The estimates include a daily traffic volume control, six binary indicator variables for time of day, seven for day of week, speed limit fixed-effects, and barracks fixed-effects.
Note 3: Standard errors are clustered at the barracks level.

Table A.3: Unconditional Quantile Regression Estimates of Relative Speed on Visibility and Vehicle Age for White Motorists within the Annual and DST Inter-twilight Sample

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	Annual Sample								
Vehicle Age < 11	0.024	0.146	0.412	-0.284	0.085	0.229	1.519*	0.791	1.466
	(0.293)	(0.665)	(0.570)	(0.489)	(0.565)	(0.735)	(0.733)	(0.895)	(1.185)
Daylight	0.144	0.728	1.489	1.293	0.225	-0.716	-0.679	-2.186	-1.852
	(0.601)	(1.214)	(1.148)	(0.999)	(1.056)	(1.697)	(2.162)	(3.655)	(5.329)
Daylight x Vehicle Age < 11	-0.221	0.223	0.484	0.758	0.495	-0.098	-1.063	-0.251	-0.391
	(0.282)	(0.870)	(0.558)	(0.486)	(0.346)	(0.562)	(0.810)	(0.972)	(1.557)
	45 Day DST Sample								
Vehicle Age < 11	0.015	0.077	0.587	0.159	0.330	1.323*	1.845**	2.524**	1.231
	(0.467)	(0.474)	(0.643)	(0.522)	(0.682)	(0.735)	(0.798)	(1.111)	(1.707)
DST	0.628	0.632	0.835	1.436	1.062	0.912	-0.176	0.698	2.201
	(1.056)	(0.695)	(0.764)	(0.920)	(0.817)	(0.547)	(1.052)	(1.123)	(1.876)
DST x Vehicle Age < 11	0.073	0.116	-0.080	-0.217	0.242	-1.238	-1.897	-4.262*	-2.934
	(0.578)	(0.524)	(0.663)	(0.846)	(1.057)	(1.018)	(1.228)	(2.048)	(2.923)

Note 1: A coefficient estimate concatenated with a * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance.
Note 2: The estimates include a daily traffic volume control, six binary indicator variables for time of day, seven for day of week, speed limit fixed-effects, and barracks fixed-effects.
Note 3: Standard errors are clustered at the barracks level.

Table A.4: Unconditional Quantile Regression Estimates of Relative Speed on Visibility and Vehicle Color for White Motorists within the Annual and DST Inter-twilight Sample

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	Annual Sample								
Red Auto.	-0.600	-0.225	-0.252	0.035	0.096	0.094	-0.191	-0.888	2.173
	(0.930)	(1.049)	(0.833)	(0.690)	(0.963)	(1.190)	(1.167)	(1.749)	(2.277)
Daylight	0.495	0.775	1.870*	2.649**	-0.202	-0.940	-1.662	-3.188	-1.919
	(0.913)	(0.825)	(1.040)	(1.145)	(1.751)	(1.849)	(2.343)	(4.077)	(5.417)
Daylight x Red Auto.	0.496	0.157	-0.378	-0.076	-0.116	0.762	2.277	3.551**	1.103
	(1.770)	(1.680)	(1.261)	(1.293)	(1.408)	(1.309)	(1.511)	(1.462)	(2.349)
	45 Day DST Sample								
Red Auto.	-0.631	0.096	0.936	1.364	-0.172	0.119	0.073	1.635	3.605
	(1.272)	(1.678)	(1.774)	(2.273)	(1.807)	(1.646)	(2.115)	(3.360)	(6.433)
DST	0.624	0.769	0.885	1.457	0.759	0.050	-1.639*	-2.240	1.045
	(1.163)	(0.646)	(0.778)	(0.910)	(0.597)	(0.725)	(0.931)	(1.931)	(1.958)
DST x Red Auto.	1.775	-0.034	0.117	0.207	1.816	-0.126	0.791	-2.905	-5.899
	(1.560)	(2.208)	(2.004)	(2.623)	(1.815)	(1.350)	(2.112)	(2.031)	(6.674)

Note 1: A coefficient estimate concatenated with a * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance.
Note 2: The estimates include a daily traffic volume control, six binary indicator variables for time of day, seven for day of week, speed limit fixed-effects, and barracks fixed-effects.
Note 3: Standard errors are clustered at the barracks level.

Table A.5: Unconditional Quantile Regression Estimates of Relative Speed on Visibility and Age for White Motorists within the Annual and DST Inter-twilight Sample

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	Annual Sample								
Age < 31	0.445*	1.653***	1.461***	1.987***	1.993***	2.521***	1.649*	3.453***	3.441***
	(0.234)	(0.374)	(0.395)	(0.424)	(0.455)	(0.456)	(0.935)	(1.096)	(1.128)
Daylight	-0.037	0.992	1.489	1.473	0.468	-1.137	-2.282	-2.592	-2.119
	(0.611)	(0.798)	(1.042)	(0.908)	(1.027)	(1.649)	(2.294)	(3.711)	(5.741)
Daylight x Age < 31	0.092	-0.401	0.304	0.254	-0.133	0.477	1.680	0.195	-0.241
	(0.334)	(0.484)	(0.456)	(0.673)	(0.599)	(0.591)	(1.128)	(1.056)	(1.762)
	45 Day DST Sample								
Age < 31	0.944*	1.004**	0.804*	1.602**	0.807	0.813	1.240	3.000*	2.897*
	(0.474)	(0.351)	(0.391)	(0.583)	(1.076)	(1.461)	(1.285)	(1.463)	(1.451)
DST	-0.019	0.084	-0.246	0.134	-0.060	-0.777	-1.828	-1.841	1.465
	(0.985)	(0.555)	(0.763)	(0.582)	(1.063)	(1.276)	(1.393)	(1.979)	(2.056)
DST x Age < 31	1.215	1.069	1.821**	2.111*	2.212	1.804	1.079	0.417	-1.535
	(0.801)	(0.676)	(0.801)	(1.143)	(1.849)	(1.980)	(1.924)	(2.611)	(2.252)

Note 1: A coefficient estimate concatenated with a * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance.
Note 2: The estimates include a daily traffic volume control, six binary indicator variables for time of day, seven for day of week, speed limit fixed-effects, and barracks fixed-effects.
Note 3: Standard errors are clustered at the barracks level.

Table A.6: Unconditional Quantile Regression Estimates of Relative Speed on Visibility and Gender for White Motorists within the Annual and DST Inter-twilight Sample

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	Annual Sample								
Male	0.044	1.789*	2.165***	1.786**	2.070**	2.406*	2.049	4.076***	7.558**
	(0.269)	(1.013)	(0.617)	(0.764)	(0.954)	(1.336)	(1.333)	(0.793)	(3.219)
Daylight	0.434	2.514	4.037**	2.816	1.945	0.363	-1.626	-2.779	-3.157
	(0.316)	(1.456)	(1.509)	(1.740)	(1.913)	(3.375)	(4.076)	(5.054)	(4.046)
Daylight x Male	0.054	-1.474	-1.809**	-1.344	-1.341	-1.564	-0.397	-2.071	-2.495
	(0.464)	(1.059)	(0.630)	(1.036)	(1.154)	(1.314)	(1.709)	(1.196)	(3.693)
	45 Day DST Sample								
Male	1.038*	0.601	0.583	0.535	0.333	1.132	0.376	1.642	2.802
	(0.589)	(0.422)	(0.490)	(0.688)	(0.962)	(1.034)	(0.823)	(1.306)	(2.170)
DST	1.542**	0.943**	0.683	0.538	-0.228	0.006	-3.535***	-3.673**	-2.185
	(0.675)	(0.361)	(0.942)	(1.180)	(0.988)	(0.999)	(1.156)	(1.372)	(2.480)
DST x Male	-1.182	-0.348	0.105	1.035	1.857	0.282	3.087***	2.791	3.766
	(1.177)	(0.806)	(0.707)	(0.899)	(1.099)	(0.999)	(0.962)	(1.880)	(2.996)

Note 1: A coefficient estimate concatenated with a * represents a p-value .1, ** represents a p-value .05, and *** represents a p-value .01 level of significance.
Note 2: The estimates include a daily traffic volume control, six binary indicator variables for time of day, seven for day of week, speed limit fixed-effects, and barracks fixed-effects.
Note 3: Standard errors are clustered at the barracks level.