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by

Jesse J. Kalinowski
Quinnipiac University

Matthew B. Ross
New York University

Stephen L.Ross
University of Connecticut

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365 Fairfield Way, Unit 1063
Storrs, CT 06269-1063
Phone: (860) 486-3022
Fax: (860) 486-4463
http://www.econ.uconn.edu/

Addressing Seasonality in Veil of Darkness Tests for Discrimination: An Instrumental Variables Approach

Jesse J. Kalinowski	Matthew B. Ross	Stephen L. Ross
Quinnipiac University	New York University	University of Connecticut

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Abstract: Veil of Darkness tests identify discrimination by exploiting seasonal variation in the timing of sunset to compare the rate that minorities are stopped by police at the same hour of the day in daylight versus darkness. Such tests operate under the presumption that race is more easily observed by police prior to traffic stops during daylight relative to darkness. This paper addresses concerns that seasonal variation in traffic patterns could bias Veil of Darkness tests. The conventional approach to addressing seasonality is to restrict the sample to a window around Daylight Savings Time (DST) changes when the time of sunset is abruptly changed by one hour twice a year. However, this restriction reduces the variation in the timing of sunset potentially exacerbating measurement error in daylight and may still fail to address seasonality. The latter point is due to the fact that a substantial fraction of the seasonal change in daylight hours occur in the fall and spring (near DST) because of the elliptical nature of earth's orbit. Therefore, we consider an alternative to simply restricting the sample to fall and spring where we instead apply an instrumental variables and fuzzy regression discontinuity approach. Our approach allows us to isolate the treatment effect associated with one hour of additional daylight on the share of police stops that are of African-American motorists. We find larger racial differences in Texas highway patrol stops using the regression discontinuity approach as compared to the annual sample, even though traditional approaches using the DST sample yield smaller estimates than the annual sample. The larger estimates are robust to the fall DST change sample, addressing concerns that motorists are tired and more accident prone immediately after the spring DST change.

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1. Introduction

Identifying whether police discriminate in the decision to stop minority motorists is challenging because it is difficult to observe or measure the share of minority motorists at risk of being stopped. A solution to this counterfactual problem in traffic stops, deemed the Veil of Darkness (VOD) test, was proposed by Grogger and Ridgeway (2006) and more recently applied by Ridgeway (2009), Horace and Rohlin (2016) and Ross et al. (2017). The authors argue that race is more easily observed by police during daylight relative to darkness. Thus, the racial composition of stops in darkness provides a counterfactual distribution for stops that are made in daylight at the same time of day and day of week. To control for differences in traffic patterns by time of day, the test is implemented by regressing motorist race on whether the stop is in daylight or darkness and controlling for time of day and day of week, and so exploiting seasonal variation in the timing of sunset occurring within the "inter-twilight window". Over the last decade, an increasing number of states have mandated the collection of motorist race in traffic stop records, and the VOD approach has quickly become the gold standard for evaluating such data for evidence of discrimination.[1]

The maintained assumption behind the VOD test is that the composition of drivers on a given roadway at a given time of day and day of week is unaffected by changes in the timing of sunset, an assumption that appears especially reasonable within the evening commute. This assumption, however, will be violated if the composition of motorists changes with the seasons. For example, summer traffic patterns may differ because schools are not in session, tourism at recreational areas, or seasonal construction; while winter traffic patterns may be affected by inclement weather. Further, many large-scale federally funded enforcement campaigns are concentrated during the summer months and focus on different types of enforcement like cellphone, seatbelt, and impaired driving. Ridgeway (2009) suggests addressing the concern about seasonality by exploiting only the variation in sunset occurring around Daylight Savings Time (DST) changes. Following this approach, the convention in the literature has been to conduct a robustness check where the standard VOD model is estimated using a sample that is restricted to stops that are close to a DST change. Two key concerns with such an approach are that 1. this restriction eliminates much of the systematic variation in daylight conditional on time of day, and 2. the remaining sample still contains two sources of variation: the hour change from DST and the rapid pace of seasonality occurring in the fall and spring.

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[1] Applications of the VOD approach include Grogger and Ridgeway (2006) in Oakland, CA; Ridgeway (2009) Cincinnati, OH; Ritter and Bael (2009) and Ritter (2017) in Minneapolis, MN; Worden et al. (2010; 2012) as well as Horace and Rohlin (2016) in Syracuse, NY; Renauer et al. (2009) in Portland, OR; Taniguchi et al. (2016a, 2016b, 2016c, 2016d) in Durham Greensboro, Raleigh, and Fayetteville, North Carolina; Masher (2016) in New Orleans, LA; Chanin et al. (2016) in San Diego, CA; Ross et al. (2015; 2016; 2017a; 2017b) in Connecticut and Rhode Island; Criminal Justice Policy Research Institute (2017) in Corvallis PD, OR; Milyo (2017) in Columbia, MO; Smith et al. (2017) in San Jose, CA; and Wallace et al. (2017) in Maricopa, AZ.

To our knowledge, daylight in VOD studies is always based entirely on the time of day, the day of the year and the physical location of the stop, but the actual time at which visibility becomes a barrier to identifying the race of motorists is unknown and likely varies with the weather and other visibility conditions, creating measurement error in the VOD daylight variable. Figure 1A shows the timing of sunset over the entire year and documents a three-hour change in sunset timing between summer and winter. Figure 1B shows the timing of sunset within 42-days of the spring DST change. This window contains only a two-hour change in sunset timing, which falls to one and a half hours for a 21-day window. Therefore, sample restrictions around DST are likely to reduce signal and exacerbate bias from measurement error. Further, VOD analyses typically drop stops during actual twilight, which tends to last 25 to 35 minutes in the northern hemisphere, because the level of light is uncertain. Given this additional sample restriction, daylight/darkness comparisons at the same time of day can only occur after a substantial change in sunset timing, further limiting the systematic variation in daylight for DST samples.

On the other hand, the elliptical nature of the earth's orbit is such that even within tight windows surrounding the fall/spring DST change, the seasonal component approaches or even exceeds that of the discrete change in the timing of sunset. Figure 1A illustrates the higher rate of change outside of summer and winter, and Figure 1B illustrates the point that the seasonal change in sunset is substantial relative to the direct effects of the DST change. In fact, this seasonal changes accounts for about half of the variation in sunset using a 42-day window on either side of the DST change.

In order to address these concerns, we propose examining the effects of DST on the racial composition of stops using an Instrumental Variables (IV) approach. Rather than controlling for daylight and simply restricting the time period of data included in the sample, we consider the DST change to be a treatment that treats stops on one side of the change at the same time of day with more daylight. Then, we use the date of the DST change as an instrument for Daylight when estimating models for the race of the stopped motorist. Second, in order to address the second concern of seasonal variation, we extend the IV analysis by adding a running variable over the day of the stop effectively converting our model to a fuzzy Regression Discontinuity (RD) analysis. This RD analysis identifies the effect of a one hour change in daylight exactly on the day of the time change, and so should eliminate bias from seasonality. It is important to note that seasonal changes in weather could create measurement error that correlates with whether a stop is made before or after DST leading to bias that would not be eliminated by the simple IV strategy. However, the exact day of the DST change is almost certainly uncorrelated with idiosyncratic variation in visibility across days and so the fuzzy RD analysis should eliminate all bias from measurement error in daylight.

We apply these techniques in the context of stops made by the Texas Highway Patrol from 2010 to 2015. Starting with traditional VOD techniques, we show that in Texas daylight leads to a 1.5 percent increase in the fraction of speeding stops by Texas Highway Patrol officers that involve African-American motorists. This effect is relative to a 13 percent fraction of African-American motorists among all speeding stops during the inter-twilight window and is consistent with the relative magnitude of estimates found in other studies. Following Ridgeway (2009), we initially address seasonality by restricting the sample to either 42 or 21-days before and after each DST change. This restriction reduces the effect of daylight by about half, to 0.7 percentage points, for the 42-day window and to near zero for the 21-day window, suggesting that seasonality is a significant concern. We then estimate IV models of the effect of daylight on the race of stopped motorists using the DST change as an instrument, but not including a running variable. The resulting estimates are similar regardless of the window size and range between 0.9 to 1.1 percentage points falling in between the VOD estimates for the annual and 42-day DST samples. These results, particularly those within the 21-day window, suggest the presence of measurement error in the conventional VOD method which is alleviated by our proposed IV approach. As discussed above, VOD methods rely on the expected time of sunset without consideration of each day's weather and visibility conditions. With annual data, the larger changes in seasonality outweigh the day to day measurement error in the control for daylight, but the signal in the daylight measure falls with the smaller variation in the DST windows exacerbating the effects of measurement error and attenuating estimates.

We then estimate the effect of daylight on the racial composition of stopped motorists using the fuzzy RD approach. Our estimates of the effect of daylight on the race of stopped motorists using the RD framework are significantly larger ranging primarily between 2.5 and 3.3 percentage points. These estimates imply that a stop is at least two and one-half percentage points more likely to be an African-American motorist relative to the 13 percent share of African-Americans out of all stopped motorists, which is nearly four times as large as the VOD estimates using the 42-day DST sample and substantially larger than the initial annual estimates. The RD framework estimates suggest that a simple restriction to stops near the DST might be misleading even in terms of the direction of bias from seasonality. The effects of both classic measurement error and seasonality, which might contain correlated measurement error, appear to bias traditional VOD estimates downwards in both the annual and restricted DST samples. In light of both the widespread adoption of such methods and the frequent failure of VOD studies to find evidence of discrimination, these findings are particularly important.[2]

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[2] Specifically, 11 of 21 studies fail to reject the null hypothesis of equal treatment while seven of the remaining studies had statistically weak and inconsistent results. Grogger and Ridgeway (2006) fail to reject the null of equal treatment in Oakland, CA; Ridgeway (2009) fails to reject the null in Cincinnati, OH; Ritter and Bael (2009) and Ritter (2017) reject the null in Minneapolis, MN; Worden et al. (2010; 2012) fail to reject the null in Syracuse, NY while Horace and Rohlin (2016) reject the null in the same location; Renauer et al. (2009) fail to reject the null in Portland, OR; Taniguchi et al. (2016a, 2016b, 2016c, 2016d) focus on North Caroline and find mixed results in Durham but fail to reject the null in Greensboro, Raleigh, and Fayetteville; Masher (2016) fails to reject the null in New Orleans, LA; Chanin et al. (2016) find mixed results in San Diego, CA; Ross et al. (2015; 2016; 2017a; 2017b) report mixed results across Connecticut and Rhode Island but reject the null in several individual police departments; Criminal Justice Policy Research Institute

2. Texas Highway Patrol Traffic Stop Data

The paper uses data collected as part of the Stanford Open Policing Project which contains 13.5 million stops made by 3,606 Texas Highway Patrol officers from 2010 to 2015. These officers are assigned to one of nineteen highway patrol districts, where each district contains between 3 and 30 counties, with an average of approximately 13 counties per district. The data identifies the location of the stop, date and time of the stop, all violations associated with the stop, the resulting disposition for each violation (warning or citation), the race and ethnicity of the motorist stopped, and an identifier for the police officer making the stop.

Following Grogger and Ridgeway (2006) and based on findings in Kalinowski, Ross and Ross (In Press), we select a sample of all speeding stops because the composition of stops over citation type may change between daylight and darkness for the same time of day. We also restrict the sample to just stops of non-Hispanic whites and African-Americans. For the VOD test, we establish an inter-twilight window using data from the United States Naval Observatory such that the lower bound is the earliest time of day that sunset begins during the year in the county in which the stop is made. Likewise, the upper bound is the latest end to the evening civil twilight in the county. We select only stops that fall within the inter-twilight window and do not fall during actual twilight for the date of the stop, again using the earliest start and latest end of twilight in the county for this date. For the DST analyses, we further restrict the inter-twilight window sample to within 42 or 21-days of the fall or spring DST changes.

For the IV analyses, we use the same sample of all stops during the inter-twilight window. However, unlike the VOD samples described above, we do not exclude stops during actual twilight since we are treating all stops on one side of the DST change as treated with one additional or one less hour of daylight. In fact, during and near twilight is likely when the extra hour of daylight has the largest effect on the ability of officers to identify motorist race. For the 42-day window, we consider multiple order polynomials for the running variable specification in the RD model. We also restrict the window further to 21-days on either side of the DST change and use a linear specification for the running variable in the RD model. For the daylight variable, we code daylight to zero, representing darkness, during actual twilight, and so only consider stops made before the onset of sunset as being in daylight. However, very similar IV and RD results arise if actual twilight is coded as daylight rather than darkness.

The descriptive statistics for each of these four samples are shown in Table 1. The first column summarizes the inter-twilight window sample, and columns 2 and 3 show the statistics after restricting the sample to be near the date of a DST change. The DST samples include stops made during twilight since those stops are included in the IV and RD analyses, even though they are excluded from the traditional DST

(2017) fail to reject the null in Corvallis PD, OR; Milyo (2017) fails to reject the null in Columbia, MO; Smith et al. (2017) fail to reject the null in San Jose, CA; and Wallace et al. (2017) find mixed results in Maricopa, AZ.

approach. Approximately, 13 percent of speeding stops are of African-American motorists. About half of stops are in daylight, but this falls to 25% of stops (about one-third of stops excluding twilight) when looking near the DST time change. This is an indication that driving or stop patterns may change significantly across the seasons. About 28% of stops are on interstate highways; half of these are on state highways and the rest are divided between rural, county and city roads. Almost 40% of speeding stops are issued as warnings. We also observe more stops on Friday and Saturday than on other days of the week. All variable means are relatively stable across the samples with the exception of fewer stops in daylight near DST time changes.

3. Traditional Veil of Darkness Tests

First, we estimate traditional VOD tests by regressing whether the motorist stopped is Black (R_i) on whether the stop was made in daylight (D_i) and controlling for time of day and day of week (X_i) using a linear probability model.

$$R_i = \beta_1 D_i + \gamma_1 X_i + \varepsilon_{1i} \tag{1}$$

For the baseline model, X_i contains a fixed-effect for each hour, day of the week, and year in the sample. Additional high-dimensional models are presented that include county, or year by county, and officer fixed-effects. In this particular model as well as those discussed below and in subsequent sections, our estimates are robust to these less parsimonious modeling specifications. Across all models, standard errors are clustered at the county by year level.

The topmost panel in Table 2 presents the estimates from applying (1) to our sample of traffic stops. Column 1 shows the baseline model with time of day, day of week, and year fixed-effects. Column 2 presents results including county fixed-effects, column 3 results are based on county by year fixed-effects, and column 4 adds a separate set of individual officer fixed-effects to the specification with county by year controls. Regardless of controls, a speeding stop made in daylight at the same time of day and day of week is associated with the stop being approximately 1.4 to 1.5 percentage points more likely to involve a black motorist relative to the total black share of stops in the state of 13 percent.

We next follow Ridgeway (2009) in restricting the sample to stops made near the DST change. The bottom two panels of Table 2 present results estimated using a 42 and 21-day window surrounding the combined spring and fall DST changes where the specifications including year or year by county fixed-effects are replaced with year by season controls, as noted by # in the Table. The estimated effects are again stable across model specifications, but smaller in the DST samples with daylight raising the likelihood that a stop is of a black motorist by between 0.6 to 0.7 percentage points in the 42-day sample and falling to nearly zero in the more restrictive 21-day sample. Without the further insights provided in the subsequent sections of this paper, we might conclude that much of the evidence of adverse treatment in the annual estimates is due to bias from seasonal changes in driving or police stop patterns. As we will demonstrate using our new approach, it appears to be more likely the case that both the annual and DST samples estimates are biased *downward* by measurement error and seasonality.

4. Instrumental Variable Tests

In order to develop the Instrumental Variable (IV) tests, we modify the model specification to allow daylight (D_i) to be explained by the DST change (C_i) where the time change treats the inter-twilight window with more daylight.

$$D_i = \beta_2 C_i + \gamma_2 X_i + \varepsilon_{2i} \tag{2}$$

Then, we estimate a second model for motorist race (R_i) using two-stage least squares for daylight based on equation (2)

$$R_i = \beta_3 D_i + \gamma_3 X_i + \varepsilon_{3i} \tag{3}$$

Given the intent-to-treat/treatment-on-the-treated framework, the model does not require the detailed time of day and day of week fixed-effects. As noted above, the year by county fixed-effects are replaced by year by season (fall/spring) by county fixed-effects.

Then, to estimate a fuzzy Regression Discontinuity (RD) model, we add additional controls for the number of days before or after the DST change (V_i), where the running variable is reversed in fall relative to spring so that it always represents an increase in daylight. Following the standard RD structure, the model specification also includes the interaction of V_i and C_i and can be extended to allow V_i to be a vector of polynomial terms of the running variable. Specifically, we first estimate

$$D_i = \beta_4 C_i + \gamma_4 X_i + \delta_{a1} V_i + \delta_{b1} V_i C_i + \varepsilon_{4i} \tag{4}$$

and then estimate a model for motorist race (R_i) using two stage least squares for daylight based on equation (4)

$$R_i = \beta_5 D_i + \gamma_5 X_i + \delta_{a2} V_i + \delta_{b2} V_i C_i + \varepsilon_i \tag{5}$$

Then, the models presented are allowed to vary by the size of the window, or bandwidth, and in the case of equations (4) and (5) the functional form for the running variable.

Table 3 shows the IV results with the left set of columns (1-4) presenting results for the 42-day window while the right set of columns (5-8) presents results within a 21-day window surrounding DST. The top panel presents the second stage of the 2SLS estimator outlined by (2) and (3). As before, estimates are stable across the model specification in terms of the controls ranging from 0.9 to 1.1 percentage points. While smaller than the annual sample VOD estimates, these estimates are somewhat larger than the VOD estimates based on the 42-day DST sample in Table 2, and further unlike in Table 2 we observe little evidence of attenuation as the window size is restricted. These results are consistent with measurement error in the daylight variable that is addressed by the use of the DST change as an instrument.. The bottom panel presents the first-stage estimates implying that the more daylight side of a DST change is associated with stops that are about 50 percent more likely to be in daylight with almost no variation over window size and fixed-effect structure.

Table 4 shows similar results for daylight on stopped motorist race using our fuzzy RD model where county by year by season and officer fixed-effects are included across all specifications. The first four columns present estimates for the 42-day bandwidth using a linear running variable with constant slope, a linear running variable where the slope varies on either side of the DST cutoff, a quadratic running variable, and a cubic. The last two columns present estimates for the 21-day bandwidth using the linear running with either constant slope or slope that varies on either side of the threshold. For both the 21-day and the 42-day window, with one exception, we find that the likelihood that a motorist is black increases by between 2.4 and 3.3 percentage points on the more daylight side of the DST boundary. For the cubic specification, we observe a larger estimate of 4.7 percentage points. These estimates are well above the annual sample estimates. In addition, the RD estimates imply a seasonality bias in the opposite direction of the simple correction proposed of restricting the sample to observations near DST changes. Again, it is important to note that one possible source of seasonality bias is measurement error in daylight based on changing weather patterns that correlate with the changing seasons. Figure 2 depicts the traditional RD design using the 42 and 21-day windows, illustrating a clear discontinuity at the DST change. Table 5 shows the first-stage estimates of the effect of the DST change on daylight which imply that the more daylight side of the DST change is associated with between a 26 and 33 percentage point increase in daylight stops. Figure 3 also presents the first-stage effects on daylight. Reduced form estimates for the IV and RD models of stopped motorist race are shown in Appendix Tables 1 and 2, respectively.

A final concern is that the RD estimate of the effect of daylight could be biased by some change that is occurring right at the DST change that affects the likelihood of a stopped motorist being black independently of the change in daylight hours. Specifically, Smith (2016) documents that accident rates rise after spring DST, possibly due to drivers being tired. Thus, the higher rates of accidents may lead to a change in patrolling patterns and stop activity. However, in general, there is no reason to believe that moving clocks an hour ahead should have the exact opposite effect of moving clocks an hour back, and more we should not expect drivers to be equally or less accident prone during the fall DST change. In fact, Smith (2016) does not find any effect of the fall DST change on accident rates. Therefore, we split our sample to separately analyze the effects of the fall and spring DST changes. These estimates are shown in Table 6a and 6b. While the estimated effects of daylight in the spring (Table 6a) are smaller and noisy, the clear pattern that emerges is that the estimates for fall and spring are similar, and whenever there are differences the larger estimates arise in the fall, not the spring when motorist driving and accident rates are likely to be affected. The first-stage estimates are shown in Appendix Tables 3a and 3b, and the reduced form estimated are contained in Appendix Tables 4a and 4b. Again, the estimates are relatively stable across the fixed-effect specifications.

5. Sample Balance

One reason that a test relying on a clever natural experiment, like the timing of sunset, has been so widely adopted in the literature is largely due to the dearth of representative data on driving populations. Although the VOD presents a reasonable set of identifying assumptions, those pertaining to the invariance of motorist composition and police enforcement behavior remain difficult to validate in practice, particularly with respect to seasonal variation. We cannot use our stop data to conduct a true balancing test because we do not observe the attributes of a representative sample of motorists who are on the road at any point in time, nor their driving behavior.[3] Indeed, we are only able to observe the attributes of a select sample of motorists who are stopped by police. Nonetheless, it might be useful to know whether introducing the attributes of stopped motorists or their vehicles as control variables has an impact on our main estimates. Recent work by Taniguchi et al. (2017) suggests that including such covariates might be important to accurately estimating discrimination. On the other hand, such controls might mask discrimination if the changes in the composition of stopped motorists arise from changes in the rate at which black motorists are stopped.

In Table 7, we re-estimate our models adding available motorist and vehicle controls in order to test if our estimates of the effect of daylight on race are sensitive to the addition of these motorist and vehicle controls. The first column presents the traditional VOD estimates for the annual sample, the next four columns present the 42-day window estimates for the VOD, the IV, and the fuzzy RD with linear and quadratic running variable specifications. The final three columns present the 21-day window estimates for VOD, IV and RD with linear running variable controls. The changes arising from motorist and vehicle controls are modest at most with the annual VOD estimates falling from about 1.5 to 1.3, the DST sample VOD and IV estimates remaining unchanged, and the RD estimates falling between 2.1 and 2.8 relative to between 2.5 and 3.3 without controls. The first stage estimates for the IV and RD specifications are shown in Appendix Table 5.

6. Discussion

This paper investigates the sensitivity of the VOD test for discrimination in traffic stops to measurement error and seasonal variation in traffic patterns. The VOD test compares stops at the same time of day that are in darkness at one time of year and in daylight at another due to seasonal variation in the timing of sunset. The estimated impact of daylight on the racial composition of stops attenuates substantially when restricting the sample of stops from an annual sample where much of the variation arises from comparing summer and winter stops to a sample of stops made near DST changes. In fact, the estimated effects fall to zero for a 21-day window around DST changes. We use an IV approach to mitigate measurement error and a fuzzy RD analysis to focus on the effects right at the DST time change. Applying this strategy to the Texas traffic stop data, we find that the racial differences in stops between daylight and darkness increase to magnitudes substantially larger

[3] If we had access to such data, there would be no need for applying VOD-style tests in the first place.

than in the annual sample and much larger than VOD estimates using a DST sample. These results are robust to focusing on fall DST, which should not lead to tired drivers and more accidents.

The results suggest that VOD tests for discrimination may be biased by seasonality, but that this bias may not be corrected by simply restricting the sample to stops made near the DST change. Further, simply restricting the sample of stops to those surrounding DST, but not applying our prescribed IV approach, may actually exacerbate measurement error and increase the downward bias on the estimates. In fact, for our data, this DST sample restriction appears to imply that seasonal variation has biased VOD tests upwards, in favor of more discrimination, when in fact the RD analysis implies that the VOD test is biased downwards by seasonality. The techniques developed in this paper may be especially valuable to state policymakers as they continue, or begin, to analyze the police stop data that is increasingly being collected for the purpose of monitoring the racial patterns of police stops.

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Worden, R. 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.
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Figures and Tables

Figure 1a: Timing of Sunset for Dallas in 2015

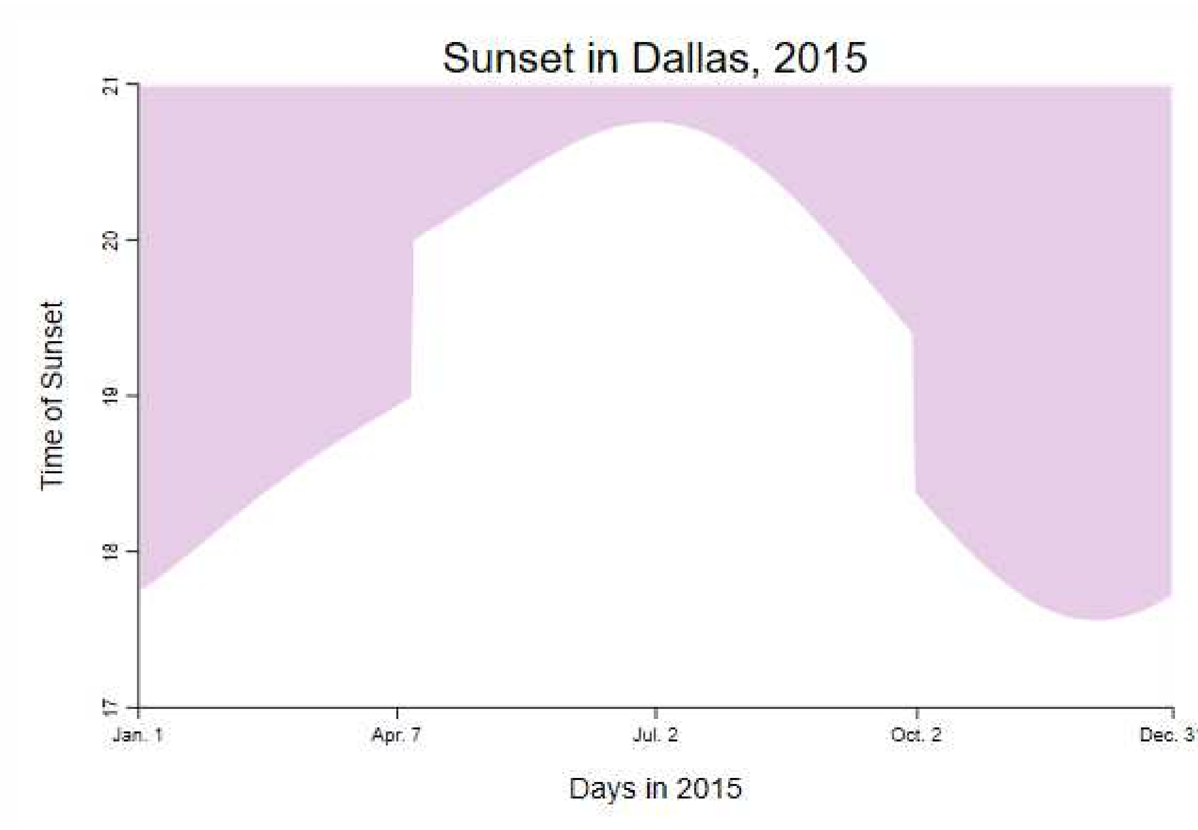


Figure 1b: Timing of Sunset for Dallas in the 42-Day DST Window for spring 2015

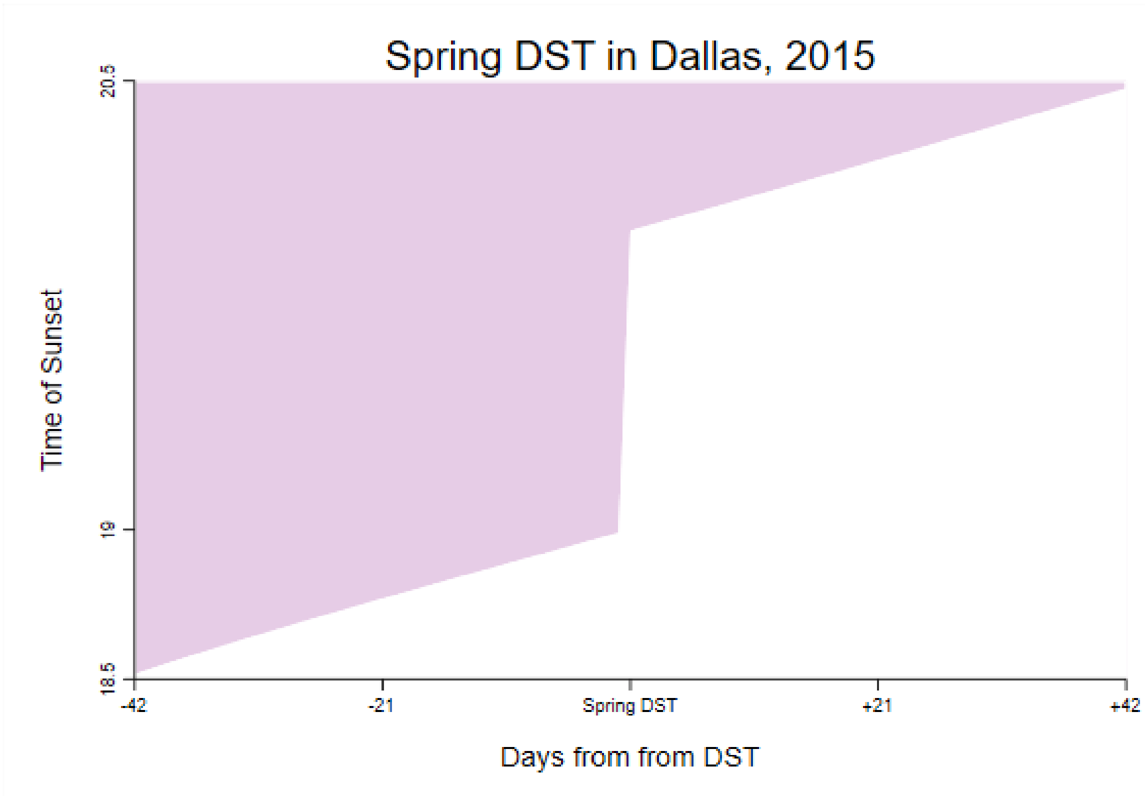
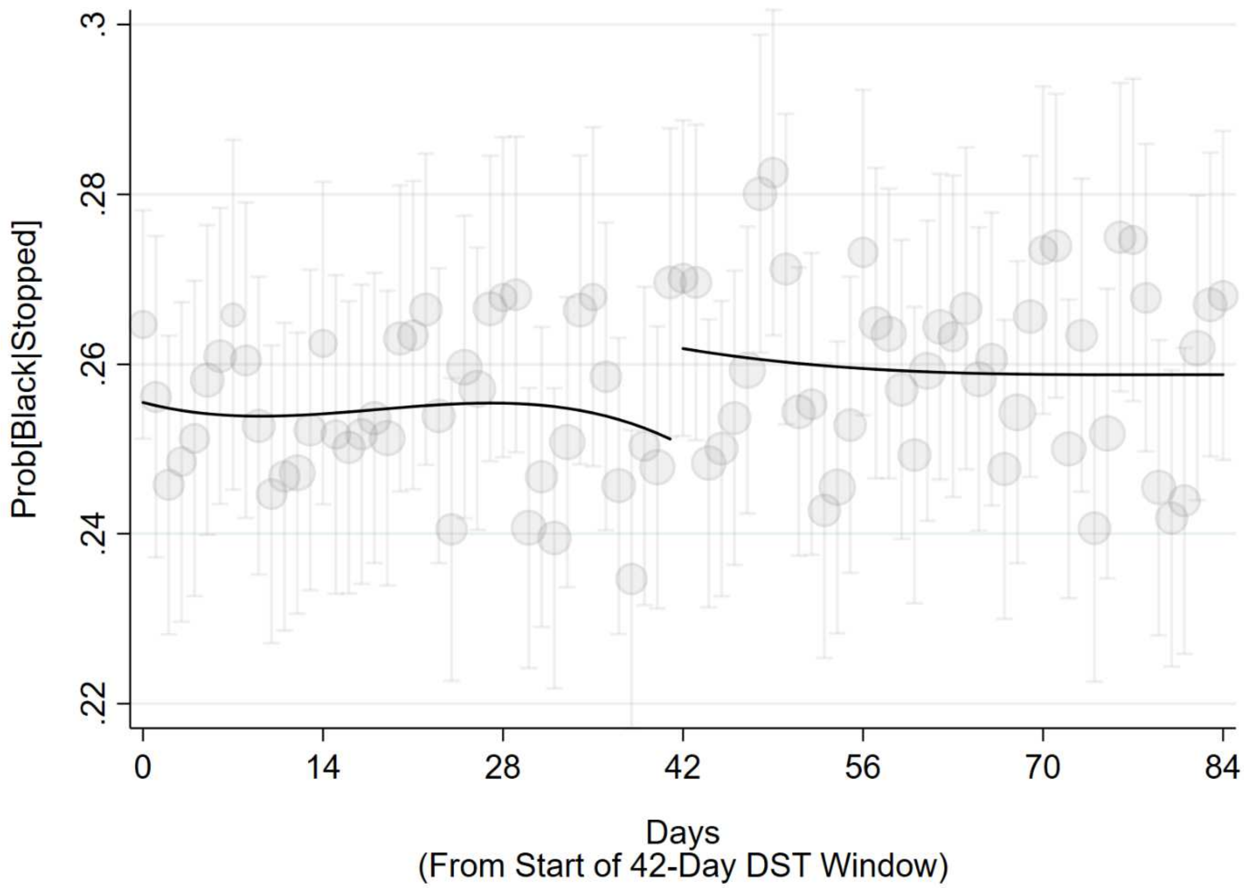
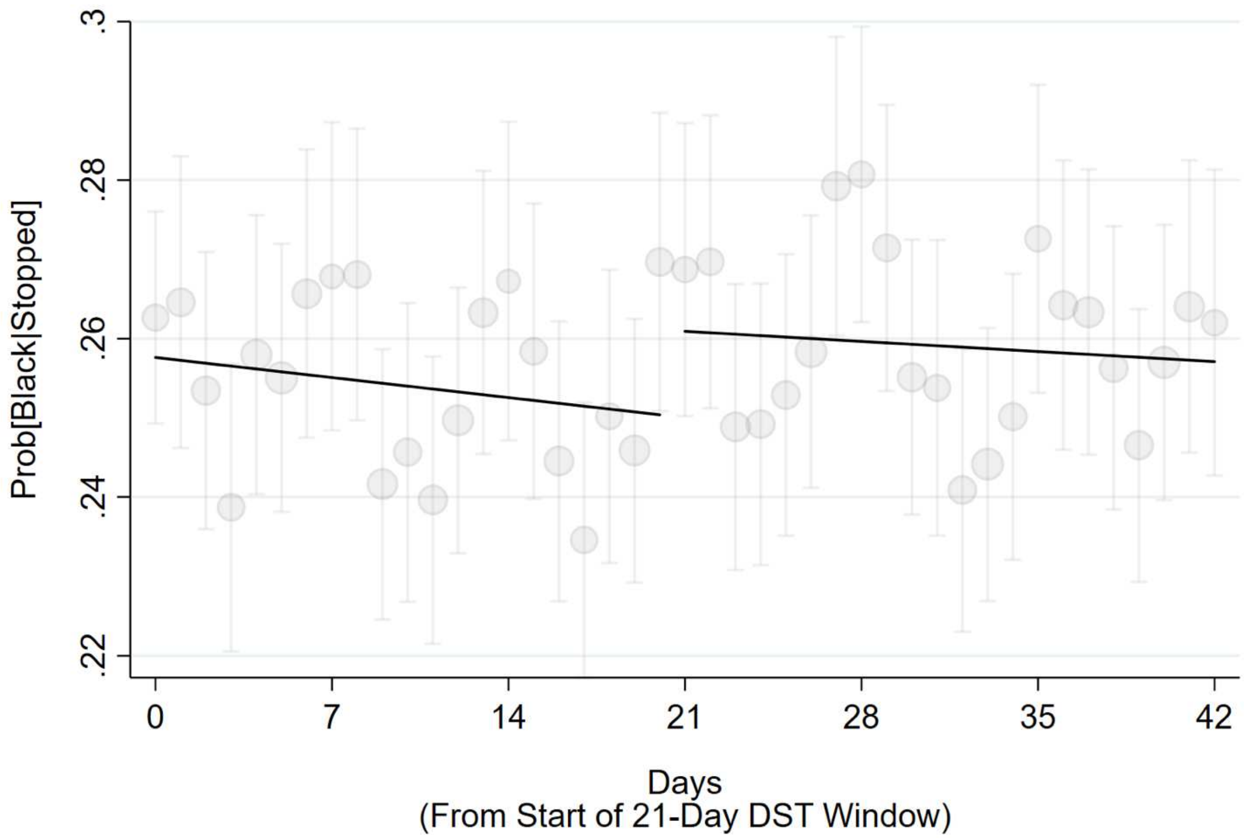


Figure 2a: Regression Discontinuity Plot for the 42-Day DST Window



Notes. The running variable is shown on the horizontal axis running from less to more daylight with DST occurring at day 42. The vertical axis shows the fraction of stops that were of African-American motorists during the inter-twilight window. Each circle represents a single day. The solid line represents a third-order polynomial fit to the day on either side of the DST boundary

Figure 2b: Regression Discontinuity Plot for the 21-Day DST Window



Notes. The running variable is shown on the horizontal axis running from less to more daylight with DST occurring at day 21. The vertical axis shows the fraction of stops that were of African-American motorists during the inter-twilight window. Each circle represents a single day. The solid line represents a linear fit to the day on either side of the DST boundary.

Figure 3a: First Stage Estimates for Regression Discontinuity Plot for the 42-Day DST Window

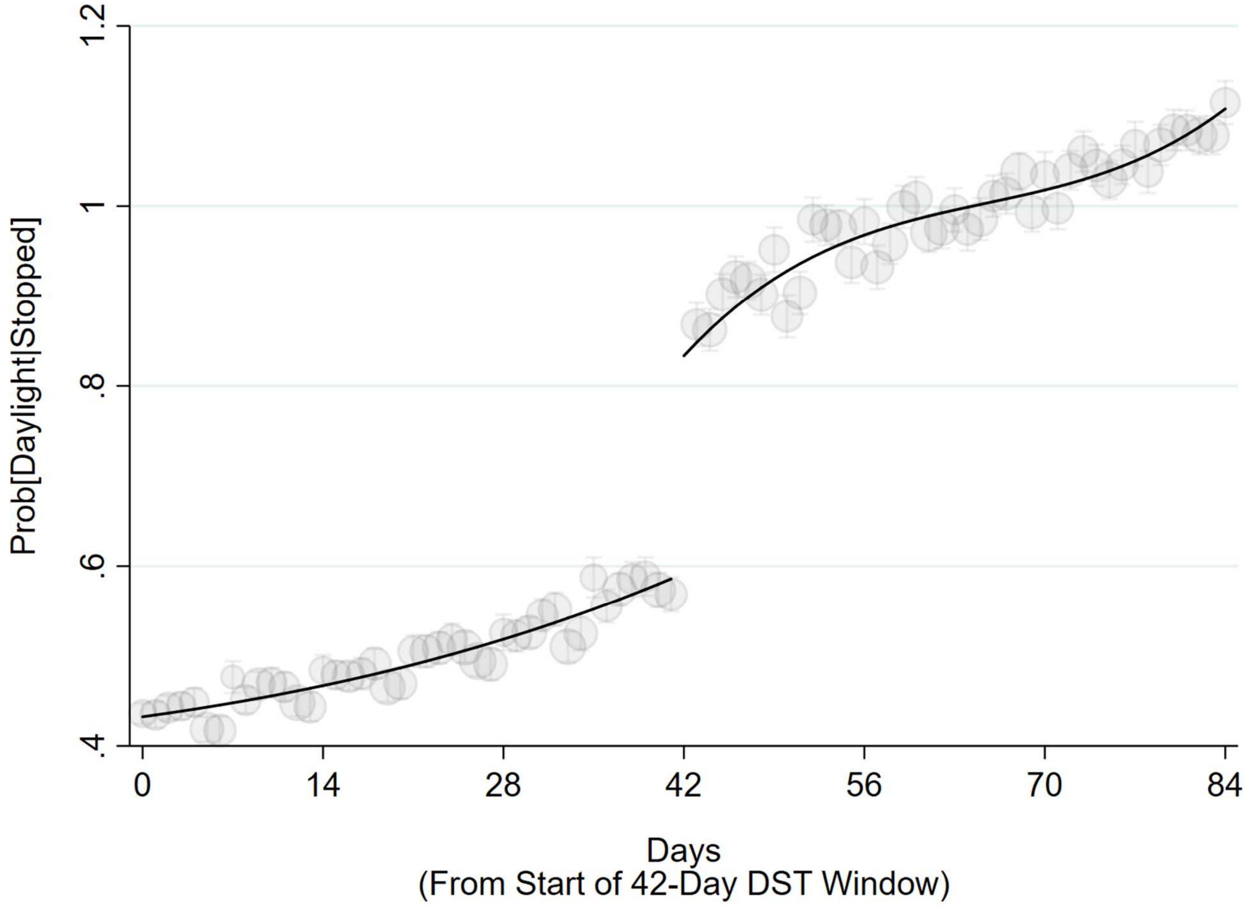


Figure 3b: First Stage Estimates for Regression Discontinuity Plot for the 21-Day DST Window

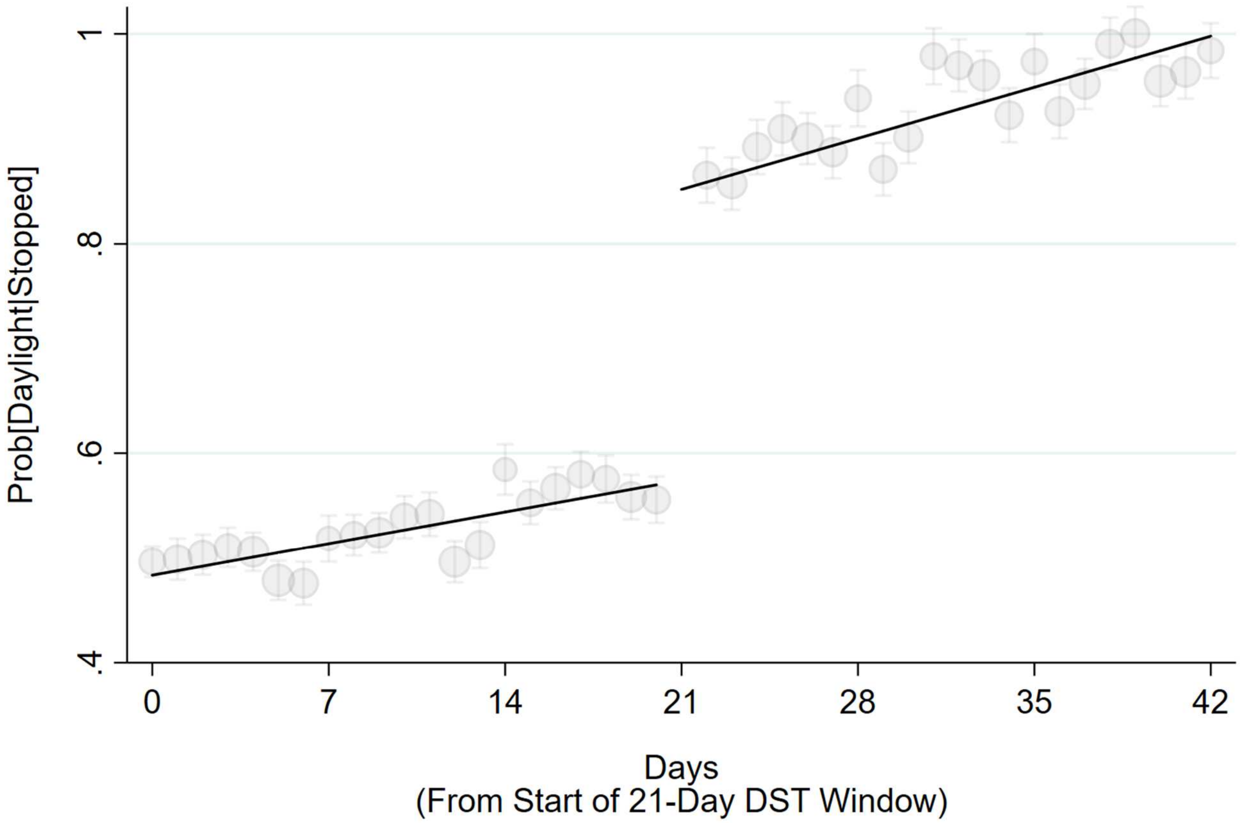


Table 1: Descriptive Statistics for Texas Highway Patrol Speeding Stops

		Inter-Twilight Window					
		Annual Sample		42-Day DST Sample		21-Day DST Sample	
		Mean	SD	Mean	SD	Mean	SD
Black		0.13	0.34	0.13	0.34	0.13	0.34
Visibility	Daylight	0.68	0.47	0.53	0.50	0.52	0.50
	Darkness	0.32	0.47	0.47	0.50	0.48	0.50
	Twilight	N/A	N/A	0.00	0.00	0.00	0.00
	DST (Lighter)	N/A	N/A	0.56	0.50	0.55	0.50
Motorist and Vehicle	Vehicle Age	6.64	5.32	6.73	5.37	6.73	5.37
	Car	0.54	0.50	0.54	0.50	0.54	0.50
	Bright Color	0.09	0.29	0.10	0.29	0.10	0.30
	Resident	0.91	0.29	0.91	0.28	0.91	0.28
	Male	0.65	0.48	0.65	0.48	0.65	0.48
Time of Day	4:00 PM	0.01	0.08	0.01	0.08	0.01	0.08
	5:00 PM	0.30	0.46	0.31	0.46	0.32	0.47
	6:00 PM	0.23	0.42	0.18	0.39	0.17	0.38
	7:00 PM	0.21	0.41	0.16	0.37	0.14	0.35
	8:00 PM	0.16	0.36	0.21	0.40	0.22	0.41
	9:00 PM	0.10	0.30	0.13	0.34	0.14	0.34
Day of Week	Mon.	0.11	0.32	0.11	0.31	0.11	0.31
	Tues.	0.12	0.32	0.12	0.33	0.12	0.33
	Weds.	0.13	0.33	0.13	0.34	0.13	0.34
	Thurs.	0.14	0.35	0.14	0.35	0.14	0.35
	Fri.	0.21	0.40	0.20	0.40	0.20	0.40
	Sat.	0.18	0.38	0.17	0.37	0.17	0.37
	Sun.	0.12	0.32	0.12	0.32	0.13	0.34
Sample	Counties	252		252		252	
	Officers	3299		3297		3293	
	Years	2010-15		2010-15		2010-15	
	Observations	534528		248506		110720	

Notes: Descriptive statistics for the regression samples. Columns 1 and 2 present means and standard deviations for the annual inter-twilight sample omitting stops made in actual twilight. Columns 3 and 4 present statistics for the DST inter-twilight window sample with the 42-day window on either side of the change (twilight stops not omitted). The 21-day window sample statistics are shown in Columns 5 and 6.

Table 2: VOD Analysis for Annual and DST Samples

LHS: Black		(1)	(2)	(3)	(4)
		Annual Inter-Twilight Sample			
Daylight		0.01526***	0.01427***	0.01417***	0.01392***
		(0.00220)	(0.00181)	(0.00182)	(0.00175)
Observations		534528	534528	534528	534528
		+/- 42-Day DST Inter-Twilight Sample			
Daylight		0.00669*	0.00623*	0.00715**	0.00748**
		(0.00377)	(0.00352)	(0.00355)	(0.00355)
Observations		149103	149103	149103	149103
		+/- 21-Day DST Inter-Twilight Sample			
Daylight		0.00098	0.00061	0.00174	0.00522
		(0.00592)	(0.00556)	(0.00568)	(0.00585)
Observations		58697	58697	58697	58697
Controls	Officer				X
	County x Year#			X	X
	County		X		
	Year#	X	X		
	Day of Week	X	X	X	X
	Hour	X	X	X	X

Notes: Linear probability model of an indicator for motorist race on daylight plus controls. Sample includes all speeding stops made in daylight or darkness within the inter-twilight window. Panels 1 through 3 present estimates for the annual, the 42-day window and the 21-day window, respectively. Column 1 presents results including fixed-effects for time of day using hour time segments, day of week, and year. Columns 2 and 3 present results after including county fixed-effects and county by year fixed-effects, respectively. Column 4 includes a set of high-dimensional fixed-effects for individual officers. Standard errors clustered by county by year in panel 1 and by county by year by season in panels 2 and 3 with *** 1% significance level, ** 5% significance level, * 10% significance level.
For Panels 2 and 3, the year or county by year fixed-effects are replaced by year by season or county by year by season fixed-effects.

Table 3: VOD Analysis using the DST Change as an Instrument

LHS: Black	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Second Stage Estimates							
	+/- 42-Day DST Inter-Twilight Sample				+/- 21-Day DST Inter-Twilight Sample			
Daylight	0.01058***	0.00988***	0.01078***	0.01090***	0.00940**	0.00958**	0.00991**	0.01131***
	(0.00299)	(0.00253)	(0.00257)	(0.00255)	(0.00444)	(0.00395)	(0.00400)	(0.00412)
Observations	248506	248506	248506	248506	110720	110720	110720	110720
	First Stage Estimates							
	+/- 42-Day DST Inter-Twilight Sample				+/- 21-Day DST Inter-Twilight Sample			
Daylight	0.54200***	0.54097***	0.53939***	0.53767***	0.51761***	0.51650***	0.51467***	0.51384***
	(0.00230)	(0.00231)	(0.00234)	(0.00235)	(0.00311)	(0.00311)	(0.00320)	(0.00320)
Observations	248506	248506	248506	248506	110720	110720	110720	110720
Controls: Officer				X				X
Controls: County x Season x Year			X	X			X	X
Controls: County		X				X		
Controls: Season x Year	X	X			X	X		
Controls: Day of Week	X	X	X	X	X	X	X	X
Controls: Hour	X	X	X	X	X	X	X	X

Notes: Linear probability model of an indicator for motorist race on daylight plus controls where daylight has been instrumented with the period of more light before/after a DST change. Sample includes all speeding stops made in daylight, twilight, or darkness within the 42 (Panel 1) or 21-day (Panel 2) inter-twilight window. Daylight is coded to zero for twilight stops. Columns 1 and 5 present results including fixed-effects for time of day using hour time segments, day of week, and year. Column 2 and 6 present results after including county fixed-effects while column 3 and 7 include county by year fixed-effects. Column 4 and 8 include a set of high-dimensional fixed-effects for individual officers. Standard errors clustered by county by year by season with *** 1% significance level, ** 5% significance level, * 10% significance level.

Table 4: Fuzzy Regression Discontinuity Analysis of Race as a Function of Daylight over the DST Boundary

LHS: Black	42-Day Window				21-Day Window	
	Linear	Interaction	Quadratic	Cubic	Linear	Interaction
Daylight	0.02487***	0.02453***	0.03308**	0.04676**	0.03207***	0.03216***
	(0.00827)	(0.00824)	(0.01336)	(0.02101)	(0.01204)	(0.01198)
Running	-0.00018*	-0.00014	0.00001	-0.00072	-0.00049*	-0.00050*
	(0.00010)	(0.00011)	(0.00031)	(0.00078)	(0.00025)	(0.00030)
Running*DST		-0.00008	-0.00013	0.00021		0.00003
		(0.00012)	(0.00044)	(0.00110)		(0.00033)
Running^2			-0.00000	0.00004		
			(0.00001)	(0.00004)		
Running^2*DST			0.00001	0.00008		
			(0.00001)	(0.00008)		
Running^3				-0.00000		
				(0.00000)		
Running^3*DST				0.00000		
				(0.00000)		
Observations	248506	248506	248506	248506	110720	110720

Notes: Linear probability model of an indicator for motorist race on daylight plus controls where daylight has been instrumented with the period of more light before/after a DST change. Sample includes all speeding stops made in daylight, twilight, or darkness within the inter-twilight window. Daylight is coded to zero for twilight stops. The first four columns present results for the 42-day window with different specifications of the running variable, and the last two columns present results for the 21-day window. All specifications include county by year by season fixed-effects as well as a set of high-dimensional fixed-effects for individual officers. Standard errors clustered by county by year by season with *** 1% significance level, ** 5% significance level, * 10% significance level.

Table 5: First Stage Estimates for Noisy Regression Discontinuity Analysis of Daylight as a Function of the DST Boundary

LHS: Daylight	42-Day Window				21-Day Window	
	Linear	Interaction	Quadratic	Cubic	Linear	Interaction
DST	0.32826***	0.33067***	0.29536***	0.26230***	0.34963***	0.35278***
	(0.00412)	(0.00402)	(0.00604)	(0.00821)	(0.00645)	(0.00617)
Running	0.00502***	0.00413***	0.00174***	0.00257***	0.00753***	0.00600***
	(0.00008)	(0.00010)	(0.00032)	(0.00062)	(0.00025)	(0.00023)
Running*DST		0.00168***	0.00175***	0.00978***		0.00283***
		(0.00019)	(0.00064)	(0.00158)		(0.00049)
Running^2			0.00006***	0.00001		
			(0.00001)	(0.00004)		
Running^2*DST			-0.00012***	-0.00070***		
			(0.00001)	(0.00008)		
Running^3				0.00000		
				(0.00000)		
Running^3*DST				0.00001***		
				(0.00000)		
Observations	248506	248506	248506	248506	110720	110720

Notes: Linear probability model of an indicator for daylight on the period of more light before/after a DST change plus controls. Sample includes all speeding stops made in daylight, twilight, or darkness within the 42 or 21-day inter-twilight window. Daylight is coded to zero for twilight stops. All specifications include county by year by season fixed-effects as well as a set of high-dimensional fixed-effects for individual officers. Standard errors clustered by county by year by season with *** 1% significance level, ** 5% significance level, * 10% significance level.

Table 6a: Noisy RD Analysis of Race as a Function of Daylight over DST Boundary, Spring

LHS: Black	42-Day Window				21-Day Window	
	Linear	Interaction	Quadratic	Cubic	Linear	Interaction
Daylight	0.01934	0.01835	0.02365	0.01339	0.02358	0.02257
	(0.01238)	(0.01248)	(0.01756)	(0.02514)	(0.01603)	(0.01609)
Running	-0.00005	0.00010	-0.00006	0.00093	-0.00013	0.00019
	(0.00014)	(0.00018)	(0.00043)	(0.00116)	(0.00035)	(0.00047)
Running*DST		-0.00027	-0.00075	-0.00170		-0.00059
		(0.00017)	(0.00062)	(0.00156)		(0.00051)
Running^2			0.00000	-0.00005		
			(0.00001)	(0.00006)		
Running^2*DST			0.00001	-0.00005		
			(0.00002)	(0.00009)		
Running^3				0.00000		
				(0.00000)		
Running^3*DST				-0.00000		
				(0.00000)		
Observations	125635	125635	125635	125635	53382	53382

Notes: Linear probability model of an indicator for motorist race on daylight plus controls where daylight has been instrumented with the period of more light after a spring DST change. Sample includes all speeding stops made in daylight, twilight, or darkness within the 42 or 21-day inter-twilight window. Daylight is coded to zero for twilight stops. All specifications include county by year by season fixed-effects as well as a set of high-dimensional fixed-effects for individual officers. Standard errors clustered by county by year by season with *** 1% significance level, ** 5% significance level, * 10% significance level.

Table 6b: Noisy RD Analysis of Race as a Function of Daylight over DST Boundary, Spring

LHS: Black	42-Day Window				21-Day Window	
	Linear	Interaction	Quadratic	Cubic	Linear	Interaction
Daylight	0.02928***	0.02967***	0.04191**	0.09766***	0.03954**	0.04089**
	(0.01133)	(0.01112)	(0.01973)	(0.03438)	(0.01876)	(0.01843)
Running	-0.00031**	-0.00036***	0.00011	-0.00233**	-0.00076**	-0.00093**
	(0.00013)	(0.00014)	(0.00047)	(0.00109)	(0.00038)	(0.00043)
Running*DST		0.00008	0.00049	0.00169		0.00029
		(0.00017)	(0.00064)	(0.00163)		(0.00048)
Running^2			-0.00001	0.00014**		
			(0.00001)	(0.00006)		
Running^2*DST			0.00001	0.00028**		
			(0.00002)	(0.00012)		
Running^3				-0.00000**		
				(0.00000)		
Running^3*DST				0.00000		
				(0.00000)		
Observations	122745	122745	122745	122745	57095	57095

Notes: Linear probability model of an indicator for motorist race on daylight plus controls where daylight has been instrumented with the period of more light before a fall DST change. Sample includes all speeding stops made in daylight, twilight, or darkness within the 42 or 21-day inter-twilight window. Daylight is coded to zero for twilight stops. All specifications include county by year by season fixed-effects as well as a set of high-dimensional fixed-effects for individual officers. Standard errors clustered by county by year by season with *** 1% significance level, ** 5% significance level, * 10% significance level.

Table 7: Various VOD Estimators with Motorist and Vehicle Controls

LHS: Black	Annual	42-Day Window				21-Day Window		
		DST	Fuzzy RDD			DST	Fuzzy RDD	
			IV Only	Interaction	Quadratic		IV Only	Interaction
Daylight	0.01287***	0.00690**	0.01041***	0.02131***	0.02871**	0.00489	0.00968**	0.02666**
	(0.00171)	(0.00350)	(0.00252)	(0.00819)	(0.01332)	(0.00581)	(0.00410)	(0.01185)
Vehicle Age	0.00136***	0.00161***	0.00174***	0.00175***	0.00176***	0.00172***	0.00196***	0.00198***
	(0.00013)	(0.00018)	(0.00015)	(0.00015)	(0.00015)	(0.00028)	(0.00021)	(0.00021)
Resident	-0.05447***	-0.05444***	-0.05076***	-0.05077***	-0.05079***	-0.05582***	-0.04491***	-0.04501***
	(0.00277)	(0.00425)	(0.00324)	(0.00324)	(0.00324)	(0.00649)	(0.00451)	(0.00451)
Car	-0.09236***	-0.09306***	-0.08877***	-0.08882***	-0.08885***	-0.08892***	-0.08644***	-0.08651***
	(0.00263)	(0.00257)	(0.00225)	(0.00225)	(0.00225)	(0.00350)	(0.00274)	(0.00274)
Male	0.00688***	0.00693***	0.00627***	0.00642***	0.00651***	0.00370	0.00380*	0.00397*
	(0.00127)	(0.00193)	(0.00146)	(0.00147)	(0.00148)	(0.00301)	(0.00218)	(0.00218)
Bright Color	-0.01431***	-0.01304***	-0.01247***	-0.01244***	-0.01242***	-0.01141**	-0.01218***	-0.01219***
	(0.00171)	(0.00313)	(0.00246)	(0.00246)	(0.00246)	(0.00512)	(0.00369)	(0.00369)
Observations	534528	149103	248506	248506	248506	58697	110720	110720

Notes: Linear probability model of an indicator for motorist race on daylight plus controls where daylight has been instrumented with the period of more light before/after a DST change. Sample includes all speeding stops made in daylight, twilight, or darkness within the 42 or 21-day inter-twilight window. Daylight is coded to zero for twilight stops. The first column presents the annual sample VOD results, the next four present results for the 42-day window including the VOD, the IV and the RD analyses, and the last four columns present results for the 21-day window. All specifications include county by year by season fixed-effects as well as a set of high-dimensional fixed-effects for individual officers. Standard errors clustered by county by year by season with *** 1% significance level, ** 5% significance level, * 10% significance level.

Appendix Tables and Figures

Appendix Table 1: Reduced Form Estimates of Race as a Function of DST Change

LHS: Black		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		42-Day Window				21-Day Window			
DST		0.00573***	0.00534***	0.00582***	0.00586***	0.00487**	0.00495**	0.00510**	0.00581***
		(0.00162)	(0.00137)	(0.00138)	(0.00137)	(0.00230)	(0.00204)	(0.00206)	(0.00212)
Controls	Officer				X				X
	County x Year x Season			X	X			X	X
	County		X				X		
	Year x Season	X	X			X	X		
Observations		248506	248506	248506	248506	110720	110720	110720	110720

Notes: Linear probability model of an indicator for motorist race on daylight plus controls where daylight has been instrumented with the period of more light before/after a DST change. Sample includes all speeding stops made in daylight, twilight, or darkness within the 42 or 21-day Inter-Twilight window. Columns 1 and 5 presents results including fixed-effects for time of day using hour time segments, day of week, and year. Column 2 and 6 present results after including county fixed-effects while column 3 and 7 include county by year fixed-effects. Column 4 and 8 includes a set of high-dimensional fixed-effects for individual officers. Standard errors clustered by county by year by season with *** 1% significance level, ** 5% significance level, * 10% significance level.

Appendix Table 2: Reduced Form Regression Discontinuity Estimates of Race as a Function of DST Change

LHS: Black	42-Day Window				21-Day Window	
	Linear	Interaction	Quadratic	Cubic	Linear	Interaction
DST	0.00816***	0.00811***	0.00977**	0.01226**	0.01121***	0.01135***
	(0.00271)	(0.00272)	(0.00394)	(0.00549)	(0.00420)	(0.00421)
Running	-0.00006	-0.00004	0.00006	-0.00059	-0.00025	-0.00031
	(0.00006)	(0.00009)	(0.00032)	(0.00076)	(0.00017)	(0.00025)
Running*DST		-0.00004	-0.00007	0.00067		0.00012
		(0.00012)	(0.00044)	(0.00111)		(0.00034)
Running^2			-0.00000	0.00004		
			(0.00001)	(0.00004)		
Running^2*DST			0.00001	0.00004		
			(0.00001)	(0.00006)		
Running^3				-0.00000		
				(0.00000)		
Running^3*DST				0.00000		
				(0.00000)		
Observations	248506	248506	248506	248506	110720	110720

Notes: Linear probability model of an indicator for motorist race on the period of more light before/after a DST change plus controls. Sample includes all speeding stops made in daylight, twilight, or darkness within the 42 or 21-day inter-twilight window. All specifications include county by year by season fixed-effects as well as a set of high-dimensional fixed-effects for individual officers. Standard errors clustered by county by year by season with *** 1% significance level, ** 5% significance level, * 10% significance level.

Appendix Table 3a: First Stage Estimates for Noisy Regression Discontinuity Analysis of Daylight as a Function of the DST Boundary, Spring

LHS: Daylight	42-Day Window				21-Day Window	
	Linear	Interaction	Quadratic	Cubic	Linear	Interaction
DST	0.31992***	0.31734***	0.31155***	0.30379***	0.39110***	0.38974***
	(0.00581)	(0.00574)	(0.00887)	(0.01201)	(0.00894)	(0.00874)
Running	0.00501***	0.00618***	0.00697***	0.00667***	0.00644***	0.00753***
	(0.00011)	(0.00013)	(0.00049)	(0.00107)	(0.00036)	(0.00037)
Running*DST		-0.00219***	0.00020	0.00311		-0.00203***
		(0.00023)	(0.00094)	(0.00236)		(0.00073)
Running^2			-0.00002	-0.00000		
			(0.00001)	(0.00007)		
Running^2*DST			-0.00002	-0.00016		
			(0.00002)	(0.00013)		
Running^3				-0.00000		
				(0.00000)		
Running^3*DST				0.00000		
				(0.00000)		
Observations	125635	125635	125635	125635	53382	53382

Notes: Linear probability model of an indicator for daylight on the period of more light after a spring DST change plus controls. Sample includes all speeding stops made in daylight, twilight, or darkness within the 42 or 21-day inter-twilight window. Daylight is coded to zero for twilight stops. All specifications include county by year by season fixed-effects as well as a set of high-dimensional fixed-effects for individual officers. Standard errors clustered by county by year by season with *** 1% significance level, ** 5% significance level, * 10% significance level.

Appendix Table 3b: First Stage Estimates for Noisy Regression Discontinuity Analysis of Daylight as a Function of the DST Boundary, Fall

LHS: Daylight	42-Day Window				21-Day Window	
	Linear	Interaction	Quadratic	Cubic	Linear	Interaction
DST	0.33711***	0.34614***	0.29305***	0.23805***	0.31290***	0.32300***
	(0.00588)	(0.00559)	(0.00799)	(0.01042)	(0.00908)	(0.00863)
Running	0.00501***	0.00203***	-0.00218***	-0.00054	0.00848***	0.00464***
	(0.00011)	(0.00009)	(0.00032)	(0.00071)	(0.00035)	(0.00034)
Running*DST		0.00561***	0.00395***	0.01667***		0.00705***
		(0.00022)	(0.00085)	(0.00207)		(0.00066)
Running^2			0.00010***	0.00000		
			(0.00001)	(0.00004)		
Running^2*DST			-0.00017***	-0.00116***		
			(0.00002)	(0.00011)		
Running^3				0.00000**		
				(0.00000)		
Running^3*DST				0.00001***		
				(0.00000)		
Observations	122745	122745	122745	122745	57095	57095

Notes: Linear probability model of an indicator for daylight on the period of more light before a fall DST change plus controls. Sample includes all speeding stops made in daylight, twilight, or darkness within the 42 or 21-day inter-twilight window. Daylight is coded to zero for twilight stops. All specifications include county by year by season fixed-effects as well as a set of high-dimensional fixed-effects for individual officers. Standard errors clustered by county by year by season with *** 1% significance level, ** 5% significance level, * 10% significance level.

Appendix Table 4a: Reduced Form Regression Discontinuity Estimates of Race as a Function of DST Change, Spring

LHS: Black	42-Day Window				21-Day Window	
	Linear	Interaction	Quadratic	Cubic	Linear	Interaction
DST	0.00619	0.00582	0.00737	0.00407	0.00922	0.00880
	(0.00395)	(0.00395)	(0.00547)	(0.00764)	(0.00626)	(0.00626)
Running	0.00005	0.00021*	0.00010	0.00102	0.00002	0.00036
	(0.00009)	(0.00012)	(0.00047)	(0.00109)	(0.00026)	(0.00038)
Running*DST		-0.00031*	-0.00074	-0.00165		-0.00064
		(0.00017)	(0.00062)	(0.00156)		(0.00051)
Running^2			0.00000	-0.00005		
			(0.00001)	(0.00006)		
Running^2*DST			0.00001	-0.00005		
			(0.00001)	(0.00009)		
Running^3				0.00000		
				(0.00000)		
Running^3*DST				-0.00000		
				(0.00000)		
Observations	125635	125635	125635	125635	53382	53382

Notes: Linear probability model of an indicator for motorist race on the period of more light after a spring DST change plus controls. Sample includes all speeding stops made in daylight, twilight, or darkness within the 42 or 21-day inter-twilight window. All specifications include county by year by season fixed-effects as well as a set of high-dimensional fixed-effects for individual officers. Standard errors clustered by county by year by season with *** 1% significance level, ** 5% significance level, * 10% significance level.

Appendix Table 4b: Reduced Form Regression Discontinuity Estimates of Race as a Function of DST Change, Fall

LHS: Black	42-Day Window				21-Day Window	
	Linear	Interaction	Quadratic	Cubic	Linear	Interaction
DST	0.00987***	0.01027***	0.01228**	0.02325***	0.01237**	0.01321**
	(0.00382)	(0.00385)	(0.00576)	(0.00809)	(0.00585)	(0.00593)
Running	-0.00016**	-0.00030**	0.00002	-0.00238**	-0.00042*	-0.00074**
	(0.00008)	(0.00012)	(0.00045)	(0.00110)	(0.00023)	(0.00036)
Running*DST		0.00025	0.00066	0.00332**		0.00058
		(0.00017)	(0.00064)	(0.00165)		(0.00048)
Running^2			-0.00001	0.00014**		
			(0.00001)	(0.00006)		
Running^2*DST			0.00001	0.00017*		
			(0.00001)	(0.00009)		
Running^3				-0.00000**		
				(0.00000)		
Running^3*DST				0.00000*		
				(0.00000)		
Observations	122745	122745	122745	122745	57095	57095

Notes: Linear probability model of an indicator for motorist race on the period of more light before a fall DST change plus controls. Sample includes all speeding stops made in daylight, twilight, or darkness within the 42 or 21-day inter-twilight window. All specifications include county by year by season fixed-effects as well as a set of high-dimensional fixed-effects for individual officers. Standard errors clustered by county by year by season *** 1% significance level, ** 5% significance level, * 10% significance level.

Appendix Table 5: First Stage Estimates for Various VOD Estimators with Motorist and Vehicle Controls

LHS: Daylight	42-Day Window			21-Day Window	
	Noisy RDD			Noisy RDD	
	IV Only	Interaction	Quadratic	IV Only	Interaction
DST	0.53582***	0.32880***	0.29297***	0.51209***	0.35073***
	(0.00234)	(0.00400)	(0.00600)	(0.00319)	(0.00616)
Vehicle Age	-0.00084***	-0.00085***	-0.00085***	-0.00105***	-0.00108***
	(0.00016)	(0.00015)	(0.00015)	(0.00022)	(0.00022)
Resident	0.00189	0.00130	0.00144	0.00321	0.00428
	(0.00311)	(0.00307)	(0.00307)	(0.00473)	(0.00469)
Car	0.00603***	0.00543***	0.00538***	0.00625**	0.00556**
	(0.00167)	(0.00165)	(0.00165)	(0.00248)	(0.00246)
Male	-0.01391***	-0.01362***	-0.01357***	-0.01157***	-0.01093***
	(0.00175)	(0.00173)	(0.00173)	(0.00253)	(0.00253)
Bright Color	-0.00285	-0.00264	-0.00262	0.00054	0.00049
	(0.00308)	(0.00305)	(0.00304)	(0.00460)	(0.00457)
Observations	248506	248506	248506	110720	110720

Notes: Linear probability model of an indicator for daylight on the period of more light before/after a DST change plus controls. Sample includes all speeding stops made in daylight, twilight, or darkness within the 42 or 21-day inter-twilight window. All specifications include motorist and vehicle attributes, county by year by season fixed-effects as well as a set of high-dimensional fixed-effects for individual officers. Standard errors clustered by county by year by season with *** 1% significance level, ** 5% significance level, * 10% significance level.