Does Ambient Light Influence Criminal Activity in Rural and Urban areas?

Ridhika Agrawal[1*]

December 2019

Abstract:

Driven by the fact that crime incurs major costs to the economy, studying the determinants of crime is of special importance. This paper studies the effect of ambient light on criminal activity in general, and in urban and rural areas in particular. I use a sharp regression discontinuity design, with daylight savings time as the exogenous shift in light. The model measures crime rates at two levels: daily and hourly. The overall effect on crime is ambiguous, with a decrease in robberies in rural areas, but an increase in aggravated assault. As expected, the effect is felt most in the hours directly affected by the shift in daylight and in rural areas in particular.

Keywords: Crime, Daylight Savings, Robberies

JEL A22, J11, O33

[1]I would like to thank Dr. Eric Ohrn and Yuejun Chen for their assistance and helpful comments.
[*] Micro-econometrics, Economics Department, Grinnell College, IA 50112. Email: agrawalr@grinnell.edu.

I. Introduction

Crime yields substantial social, economic and financial costs, in both the short run and long run, and in both direct and indirect ways. This burden comes in the form of costs of policy implementation and correction, costs to victims and cost of lost productivity (Anderson 1999). In 2018 there was an estimated 368.9 criminal offenses per 100,000 inhabitants. Victims' families suffered losses of approximately $16.4 billion (FBI 2019). Annually, the total cost of crime is estimated to exceed $1 trillion (Anderson 1999C). To that end, there are many crime prevention and criminal control policies, which, if successfully implemented, can greatly reduce crime-induced losses (McCollister, French and Fang 2010).

The effect of ambient light and general environment is an interesting determinant of crime. A potential mechanism of crime is that an increase in light would decrease criminal activity since it decreases the likelihood of getting detected, thereby making it harder to engage in crime. On the other hand, an increase in light makes people feel more comfortable staying out, which increases the demand for crime. To that end, the goal of this paper is to study the effect of ambient light on criminal activity, specifically felony robbery.

Further, crime differs in different geographical areas, especially between urban and rural locations. The Office for Victims of Crime noted that in 2014, metropolitan counties had 115.2 robberies per 100,000 inhabitants while non-metropolitan counties had 11.1 robberies per 100,000 inhabitants. The uneven distribution of crime is accompanied by unequal levels of impact of light on crime. It is expected that in metropolitan locations, where there is artificial ambient light present, a change in natural ambient light would not make a significant difference. Inspired by this difference, the paper also seeks to understand the difference in impact of ambient light on rural and urban areas.

In order to identify the causal effect of ambient light on criminal activity, I used a sharp regression discontinuity design (RD) where I used daylight savings time (DST) as the exogenous shock to light. Thus, I add to literature on varying determinants of crime in urban and rural areas. I also contribute to economic literature that uses DST as an exogenous shift. And finally, DST is an active decision by the government which has been contended by certain people. I also add to the body of literature that debates the usefulness of the DST in the 21st century. The results from this paper indicate that overall, ambient light has an effect of decreasing robberies significantly in the hours most affected by DST. However, the effect of DST on crime in general is ambiguous. As expected, ambient light has no significant impact in urban counties but does so in rural counties.

The paper is organized in the following manner. Section II is a review of existing literature regarding factors affecting crime in the long and short run. I explain the data collection and creation in Section III along with some summary statistics. Section IV defines the model specifications followed by the results in section V. Section VI includes robustness checks. Finally, Section VII contains the conclusion and lays out the limitations.

II. Literature Review

Many papers have evaluated the various determinants of crime with the goal of creating policies aimed at these identified causes of crime. There is a causal relationship between crime rates and income inequalities as established by Fainzylber, Lederman and Loayza (1998). Several papers have identified the importance of ambient population in violent crime calculations, crime prevention and crime mapping (Andresen 2011). Buonanno and Montolio (2008) identify several of the socio-economic and demographic determinants of crime across

Spanish provinces. They recognized lagged crime rate, clearance rate, urbanization rate and fraction of foreigners as positively correlated with crime rates. Male youth unemployment and real male average weekly earnings are also correlated with fraud, homicide and motor vehicle theft (Narayan and Smyth 2004). However, there is sparse research on the short-run dynamics of crime. Weather shocks are identified as correlational to crime rates in the short run by Jacob, Lefgren and Moretti (2007). Ambient light is also one of the determinants of crime in the short and long run (Calandrillo and Buehler 2008). Nonetheless, very few papers evaluate the effect of variations in crime specifically explained by ambient light as a causal variable. Koppen and Jansen (1999) are one of the first to explain volatilities in number of robberies during the day, week and year. They conclude that the variations are due to the availability of suitable targets and the presence of adequate guardianship. Thus, 'adequate guardianship', or perceived safety, including presence of ambient light, is an important causal variable of crime.

Doleac and Sanders (2015) provide the first empirical evidence of the effect of ambient light on crime rates in the United States. They use Daylight Saving Time (DST) as an exogenous shock to daylight and use both, regression discontinuity and difference-in-differences, to establish a causal relationship. They conclude that there is a 7% decrease in robberies after the shift to DST. The analysis is done using National Incident Based Reporting System (NIBRS) data from 2005 to 2008. One of the methodological innovations of Doleac and Sanders (2015) is the use of DST as an exogenous shock for measuring ambient light. DST, as a measure of time, has been previously investigated as the causal variable for fatal accidents (Varughese and Allen 2001) and academic performance (Maghakian and West 2011) and as measured by SAT scores (Gaski and Sagarin 2011). However, the use of DST as an exogenous shock to identify causality of ambient light on crime as done by Doleac and Sanders is unique and calls for a more nuanced analysis.

A limitation of Doleac and Sanders (2015) is that the data is disproportionally from smaller population centers. Criminal decision-making process differs between urban and rural areas. In this paper I replicate the sharp regression discontinuity design used by Doleac and Sanders (2015) with data from 2007-2016. In addition to specifying a general model with more data across a longer time period, I also specify models separately for high population density and low population density jurisdictions. Thus, this paper covers 10 years, a more extensive length of time and extends the RD to include an urban/rural subgroup analysis.

III. Data

The crime data was compiled using the National Incident Based Reporting System (NIBRS) from the year 2007 to 2016. NIBRS has incident level data and is used by law enforcement agencies in the United States. The primary crime statistics of interest are robbery, rape, murder and aggravated assault. I am particularly interested in robbery; however, rape, murder and aggravated assault have been included since they represent robberies gone wrong.

Data about the geographical location of each record is obtained from ICPSR. I got data that mapped each jurisdiction to a time zone from the National Weather Service. Sunrise and sunset times for each latitude-longitude in the United States across the ten years was created using a python script, which was based on a formula by the National Oceanic and Atmospheric Administration. The sunset times were used to measure the direct timing of the effect of DST. The frequency of the sunset times the day before DST that is used in the analysis is displayed in Figure 1. Finally, all these data sets were then merged with the NIBRS data using latitude-longitude information and FIPS code (five-digit Federal Information Processing Standards code, which uniquely identifies US counties).

Figure 1: Distribution of Sunset Times in the Day before DST for Total Population

Note: The vertical axis represents the number of different sunset times used, where jurisdiction sunset time is determined by latitude and longitude. The horizontal axis shows the time of day using 24-hour time.

In order to make the urban-specific and rural-specific models, population density data at the county level was downloaded from the Inter-university Consortium for Political and Social Research (ICPSR). The United States Census Bureau defines an urban area as any block having a population density of at least 1000 people per square mile. Using this conditional, I created urban and rural dummies and split the data set into a dataset containing observations for only crimes in urban areas, and another for rural areas. There were 82,278 observations for urban data and 433,566 for rural data.

Table 1: Summary Statistics

Crime Rate per Million		Total	All Day		Sunset Hour	
			Pre-DST	Post-DST	Pre-DST	Post-DST
Robbery	All	2.167 (7.413)	2.034 (7.214)	2.300 (7.605)	0.283 (2.481)	0.232 (2.258)
	Urban	3.375 (7.057)	3.133 (6.683)	3.617 (7.404)	0.427 (2.028)	0.378 (1.972)
	Rural	1.695 (7.495)	1.605 (7.367)	1.785 (7.620)	0.227 (2.635)	0.175 (2.358)
Rape	All	0.817 (5.315)	0.806 (5.283)	0.828 (5.347)	0.073 (1.607)	0.068 (1.542)
	Urban	0.672 (3.265)	0.647 (3.20)	0.697 (3.323)	0.063 (0.967)	0.065 (0.970)
	Rural	0.874 (5.925)	0.868 (5.898)	0.879 (5.952)	0.078 (1.796)	0.069 (1.714)
Aggravated Assault	All	5.749 (14.185)	5.395 (13.605)	6.103 (14.735)	0.595 (4.245)	0.709 (4.650)
	Urban	6.127 (10.642)	5.679 (10.049)	6.574 (11.186)	0.606 (2.741)	0.737 (2.982)
	Rural	5.602 (15.346)	5.284 (14.761)	5.920 (15.904)	0.591 (4.704)	0.698 (5.157)
Murder	All	0.103 (1.633)	0.096 (1.496)	0.111 (1.760)	0.010 (0.371)	0.012 (0.532)
	Urban	0.142 (1.054)	0.129 (1.044)	0.155 (1.064)	0.015 (0.337)	0.016 (0.305)
	Rural	0.088 (1.810)	0.083 (1.639)	0.093 (1.965)	0.008 (0.384)	0.010 (0.597)

Note: Crime rates at the daily and hourly level for each geographical unit, before and after DST.

Table 1 shows summary statistics of the average crime rate per million people. Column 1 shows the daily total of the entire data set. Column 2 and 3 shows the daily total of pre-DST and post-DST. All the raw numbers show an increase in the number of crimes. Columns 4 and 5 show pre and post crime rates per million in the hours only around sunset time.

IV. Empirical Strategy

The causal inference design used here is a sharp Regression Discontinuity (RD). The discontinuity was on the day DST was imposed. The reason this is expected to work is because criminal activity is expected to change in response to the fact that hours that used to be dark, now are lighter. The treatment variable is binary- 1 if it is during DST, 0 otherwise. For example, in 2007, the treatment was 0 up to March 11, 2007, after which it became 1, until November 4, 2007. The running variable for the RD is number of days before and number of days after DST. The model specification controls for the running variable with a linear model that has varied slopes on both the sides. I use a linear specification, since I am following the specification used by Doleac and Sanders (2015).

The identifying assumption for a sharp RD is that nothing else happens at the time of the exogenous shock, the DST in this case, except the exogenous shock itself. The model does not meet this assumption due to the use of time as the running variable. For example, DST always falls on a Sunday, which might be inherently different in terms of crime than any other day. In order to account for this, day of week fixed effects are added to the model.

Further, jurisdiction-by-year fixed effects were also added to allow for difference in absolute values of crime rates between jurisdictions. I also was unable to find sufficient data on daily weather conditions, however in order to make my specification robust to weather fluctuations, I include jurisdiction-by-week fixed effects. As is done by Doleac and Sanders (2015), the time frame used was 21 days bandwidth with the analysis being robust to changes in the bandwidth. Finally, in order to estimate the effect of ambient light on each crime (robbery, rape, aggravated assault and murder) I used the following specification:

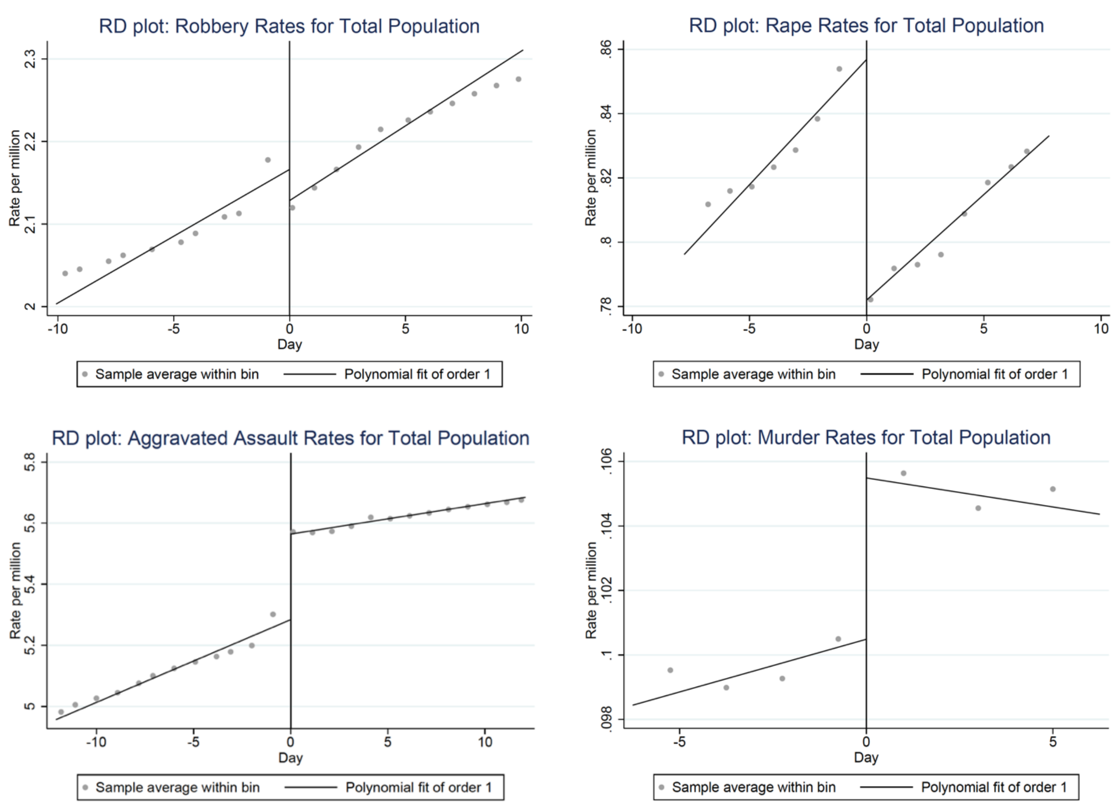
$$crime = \alpha + \beta_1 day + \beta_2 DST + \beta_3 DST * day + \sigma_{jusrisdiction*year} + \delta_{jusrisdiction*week} + \gamma_{day-of-week} + \varepsilon$$

Here, *day* is the running variable, days before and after DST, *DST* is a binary variable which measures if DST is in effect, as described above. $\sigma_{jusrisdiction*year}$ represents jurisdiction by year fixed effects, $\delta_{jusrisdiction*week}$ represents jurisdiction by week fixed effects and $\gamma_{day-of-week}$ is day of week fixed effects. ε is the error term. *Crime* (robbery, rape, aggravated assault and murder) represents crimes per million population. I use this specification to construct two models which measure crime at the daily and the hourly levels each. The model measures crime at the daily level, which focuses on daily averages of crime in the days before and after DST occurs. The other specification measures crime at the hourly level, which focuses at the hours most affected by DST, which is the hour at which sunset occurs and the hour right after sunset. The reason I zoomed in to the hourly level is because the effect of DST in relation to ambient light is almost not permanent. If sunset occurs at 7pm, then 2pm on a day not affected by DST and 2pm on a day affected by DST would have similar, almost indistinguishable levels of ambient light. However, the light levels at 7pm with DST would be different from the amount of light at 7pm on a day without DST. This perceived light level is what matters, since one mechanism through which light affects crime rates is through a change in perceived safety.

Next, since crime levels inherently differ between Urban and Rural populations, I run the same specifications (with daily and hourly level measures of crime) on just urban data and just rural population data. I expect that the impact of ambient light on crime that is observed in the total population will be mirrored by the rural population rates in terms of direction and magnitude. However, I think the urban subgroup might have varying results: both the magnitude and direction of the effect of ambient light on crime rate might be different from total population or at least the magnitude. I would expect there to be a significant effect of ambient light in rural areas, but perhaps not as strongly in urban areas. The reason is based on the intuition that urban areas have a significant amount of artificial ambient light already present, so changes in natural ambient light would not make too much of a difference. It could also be because urban populations are denser, have more ambient population, therefore a change in light does not have a significant impact on changing perceived safety.

Figures 2.a-d provides an illustration of the daily estimates of an RD for each of the crimes across the days before and after DST for total population. The points in the graphs are averages of true observed crime at the daily level. In the following graph weekends are excluded to make the axis more readable since weekends usually have higher crime rates. The graphs show a decrease in robbery and rape rates across DST but an increase in aggravated assault and murder rates. These trends follow the trends that we see in the results of running the regression discontinuity model. Figures A.1 and A.2 in the appendix illustrate the effect of DST on crime rates on Rural and Urban population respectively.

Figure 2: Daily Estimates RD Impact on Total Population



Note: Linear specification of average daily crime rates before and after DST. Graphs do not include weekends to make it more readable.

V. Results

Table 2 displays the results from running the RD with jurisdiction by year and jurisdiction by week fixed effect, where crime is at the daily level and each unit of the data is jurisdiction by day. It displays the daily totals of crimes per million for robbery, rape, aggravated assault and murder. The coefficients encapsulate the causal effect of DST (which measures ambient light) on each crime rate. The regression shows that the effect of having a change in daylight decreases robbery overall by 0.0868 per million, by 0.0457 per million in rural areas and by 0.192 per million in urban areas. The table shows that an increase in ambient light through DST causes rape rates to decrease as well. On the other hand, with daylight savings in effect, aggravated assault increases significantly in rural areas by 0.339 per million and for total population by 0.240 per million. Aggravated assault decreases in urban areas by 0.0128 per million. It is, however, not significant, thus we cannot make any strong conclusions about the effect of ambient light in urban populations. Finally, rate of murder increases very slightly in all population subgroups.

Table 2: RD Daily Totals with Jurisdiction by Year and Jurisdiction by Week Fixed effects

Crimes per 1,000,000	Robbery	Rape	Aggravated Assault	Murder
Total Population	-0.0868	-0.000837	0.240**	0.0112
	(-1.29)	(-0.02)	(2.08)	(0.74)
Rural Population	-0.0457	-0.0138	0.339**	0.00370
	(-0.66)	(-0.27)	(2.52)	(0.22)
Urban Population	-0.192	0.0321	-0.0128	0.0303
	(-1.23)	(0.50)	(-0.06)	(0.95)

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table represents the effect of ambient light on crime(s) per million at the daily level from an RD specification. This model includes day-of-week, jurisdiction-by-year and jurisdiction-by-week fixed effects with standard errors clustered by jurisdiction. Daily totals were calculated by summing hourly data across all hours within a day.

Next, shifting our focus on the hours most affected by DST, the hours around sunset. I think the effect of a change in ambient light is felt most on these hours, hence the conclusion drawn from these results would be the strongest. Notice from Table 3 that in this specification the rate of robbery decreases in the hours after sunset by 0.135 per million in the total population, 0.156 in rural population and 0.0302 in the urban population. However, here the coefficients are significant at the 1% level and are high in magnitude for both the total population and the rural population. As hypothesized earlier, even though robberies reduce in urban areas, the change is not significant and the magnitude of the change is much smaller. Next, rate of rape decreases across all groups, but not significantly. Aggravated assault also does not change statistically significantly, but it increases in the hours after sunset, which follows a similar direction to the daily level crime rates. Murder seems to reduce by a really small amount. Thus, the effect of an increase in ambient light in the hours most affected by the DST shows a significant decrease in robbery, a decrease in rape and murder, but an increase in aggravated assault.

Table 3: RD Sunset Hour with Jurisdiction by Year and Jurisdiction by Week Fixed effects

Crimes per 1,000,000	Robbery	Rape	Aggravated Assault	Murder
Total Population	-0.135***	-0.0216	0.0960	-0.00268
	(-4.00)	(-1.20)	(1.44)	(-0.78)
Rural Population	-0.156***	-0.0197	0.0888	-0.00242
	(-3.92)	(-1.01)	(1.18)	(-0.63)
Urban Population	-0.0302	-0.0312	0.133	-0.00399
	(-0.57)	(-0.71)	(0.93)	(-0.51)

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note: The table represents the effect of ambient light on crime(s) per million at the hourly level from an RD specification in the hours most affected by daylight. This model includes day-of-week, jurisdiction-by-year and jurisdiction-by-week fixed effects with standard errors clustered by jurisdiction.

The direction of change in crime rates in both the hourly and daily levels are similar (except that of murder, which is really small and highly insignificant in both models), however there is a difference in what change is statistically significant. While robbery decreases statistically significantly at the hour level, aggravated assault increases significantly at the daily level.

The most striking result from the change in crimes at hourly and daily level is the fact that there is an increase in aggravated assault, albeit small. I hypothesize that the reason this happens is because these are probably robberies gone wrong. An increase in light might make the criminal more prone to getting caught and being recognized, thereby incentivizing them to subsequently assault the person motivated by fear. Further, if there is an increase in aggravated assault based on robberies gone wrong, NIBRS does not report those events as robberies. Maybe, the reason why we see a decrease in robberies, is not because there was a decrease in robberies that were attempted, but because those robberies might have turned into aggravated assault. I think a possible mechanism at play could be that the increase in aggravate assault is corresponding to the decrease in robberies.

VI. Robustness checks

The running variable for the RD specified is time. One of the effects of this is that crime can be inherently different on weekends versus weekdays with people having more of a propensity to stay out later on weekends. In order to make sure my results were robust to weekends I ran a model with DST x Weekend interaction term. Notice from Tables A.1-A.3 in the appendix that the coefficient of the DST with DST x Weekend is not very different from the model without the interaction term. Thus, I conclude that my model is robust to the differences between weekdays and weekends.

In the specification used by Doleac and Sanders (2015) they had weather controls, because of which they did not include week by jurisdiction fixed effects. I ran a model with just jurisdiction by year fixed effects in order to gauge the difference between a model which does not include any weather controls and the model in this paper (jurisdiction by week and jurisdiction by year fixed effects). As can be seen by Table A.4 in the Appendix, I find that rape rates now decrease significantly in total and rural populations, however aggravated assault still increases significantly. There does seem to be differences in the direction and magnitude of the coefficients of crimes. Next, on simply running a jurisdiction by week fixed effects (Appendix Table A.5) I find that the coefficients are almost the same as a model with both the kinds of fixed effects. Hence, I think jurisdiction by week fixed effects absorbs the effect of variations across years, thereby making it redundant to include a jurisdiction-by-year fixed effect as well. Despite this, I included the year and week fixed effects model in my paper to appeal to the logic laid out in Doleac and Sanders (2015). The same patterns are there in the hourly level data as seen in Appendix Table A.6 and A.7.

VII. Conclusion

This paper looks at the effect of ambient light on crime rate across 2007-2016, both for urban and rural places. Overall, there is an ambiguous effect of change in crime in response to change in ambient light. One can see that there is a significant decrease in robbery in the hours most affected by daylight as a result of an increase in ambient light. There is also a significant rise in aggravated assault at the daily level, which might be because of robberies gone wrong. Further, there are no statistically significant results for urban populations across all crimes at daily and hourly level. This can be explained by the fact that urban places usually have artificial ambient light so a change in DST might not have the intended significant effect. On the other hand, all the impacts that are observed in the total population are observed in similar direction and magnitude in the rural population. Thus, the changes in the overall population are biased as a result of the impact of ambient light on crime in rural locations.

The main goal of the paper was to look at the effect of ambient light in urban and rural locations separately. However, even though the data sets for both the groups were big, urban populations formed only 10% of the overall dataset. On average, more crimes occur in urban places than in rural areas, hence the data set is not an accurate representation of the ratio of crime rates across the country. This prevents us from reading too much into the total population results, which is not a true representation of total crime in the United States. Another limitation of this paper is the fact that time is used as a running variable, which has been addressed by using fixed effects and conducting robustness checks to ensure the identifying assumption is not violated.

These results do have policy implications in terms of what natural ambient light could do in rural places. This provides evidence that any kind of increase in ambient light will have the initial impact of reducing crime. Crime is very expensive to the economy; a reduction would have social and economic benefits to the economy. The effect of ambient light was felt mostly in rural areas in contrast to urban areas. A potential hypothesis for this is the presence of artificial ambient light in urban areas. Thus, a policy suggestion that comes about as a result of this would be to invest more energy in setting up sources of light in rural areas, so we do not have to rely on a natural, possibly ambiguous shock to decrease crime. A potential future research would be to calculate the cost of crime and see if ambient has any real effects in terms of reducing costs. Further, DST works as a good exogenous shock, however an analysis that must be looked at is the effect of a permanent change in light levels on crime rates, and not just a one-hour shock.

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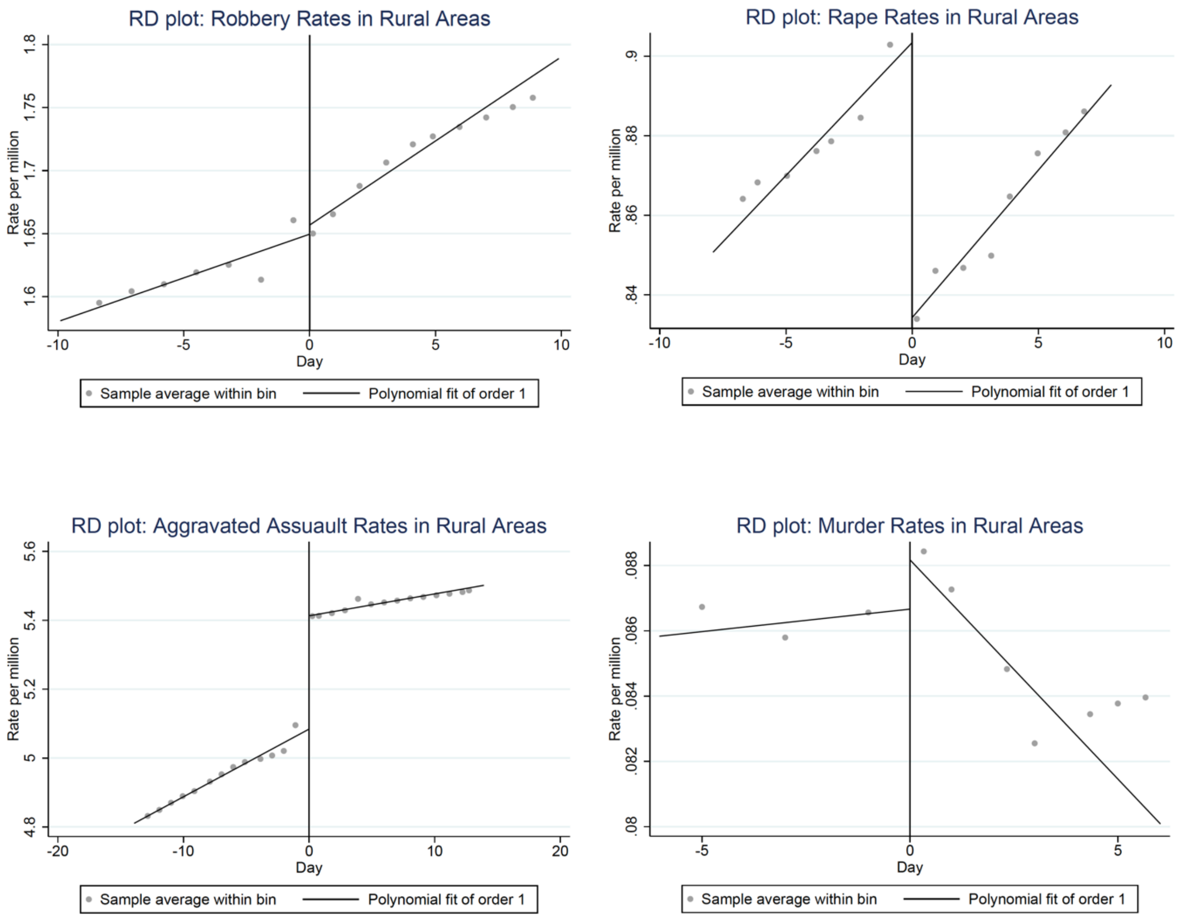
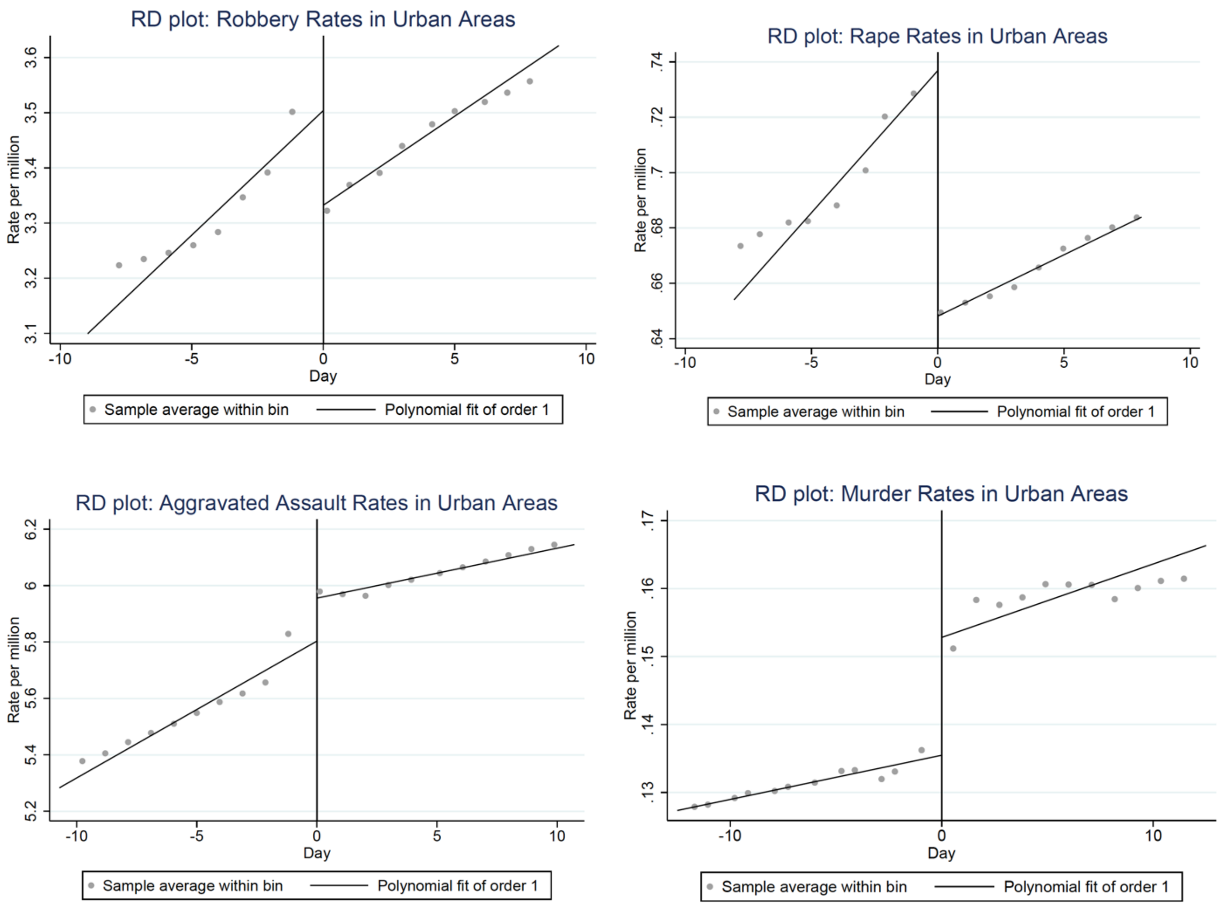
Appendix

Figure A.1: Daily Estimates RD Impact on Rural Population



Note: Linear specification of average daily crime rates before and after DST. Graphs do not include weekends to make it more readable.

Figure A.2: Daily Estimates RD Impact on Urban Population



Note: Linear specification of average daily crime rates before and after DST. Graphs do not include weekends to make it more readable.

Table A.1: Daily Totals with DST x Weekend for Total Population

	Robbery	Rape	Aggravated Assault	Murder
DST x Weekend	-0.0729	-0.121***	0.0892	0.0142
	(-1.49)	(-3.79)	(1.03)	(1.25)
DST	-0.00940	-0.0364	0.344***	-0.000185
	(-0.17)	(-1.18)	(4.04)	(-0.02)
Total Observations	515844	515844	515844	515844

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note: The table represents the effect of ambient light on crime(s) per million at the daily level from an RD specification. This model includes an interaction term, DST x Weekend. Daily totals were calculated by summing hourly data across all hours within a day.

Table A.2: Daily Totals with DST x Weekend for Rural Population

	Robbery	Rape	Aggravated Assault	Murder
DST x Weekend	-0.0900*	-0.183***	0.0525	0.0348***
	(-1.66)	(-4.68)	(0.51)	(2.61)
DST	0.0131	-0.0356	0.423***	-0.0104
	(0.24)	(-0.94)	(4.39)	(-0.90)
Total Observations	433566	433566	433566	433566

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note: The table represents the effect of ambient light on crime(s) per million at the daily level from an RD specification. This model includes an interaction term, DST x Weekend. Daily totals were calculated by summing hourly data across all hours within a day.

Table A.3: Daily Totals with DST x Weekend for Urban Population

	Robbery	Rape	Aggravated Assault	Murder
DST x Weekend	-0.0293	0.0383	0.183	-0.0386*
	(-0.28)	(0.74)	(1.15)	(-1.82)
DST	-0.0670	-0.0387	0.139	0.0260
	(-0.52)	(-0.76)	(0.78)	(1.07)
Total Observations	82278	82278	82278	82278

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note: The table represents the effect of ambient light on crime(s) per million at the daily level from an RD specification. This model includes an interaction term, DST x Weekend. Daily totals were calculated by summing hourly data across all hours within a day.

Table A.4: RD Daily Totals with Jurisdiction by Year Fixed Effects

Crimes per 1,000,000	Robbery	Rape	Aggravated Assault	Murder
Total Population	-0.0302	-0.0711**	0.369***	0.00387
	(-0.60)	(-2.38)	(4.41)	(0.36)
Rural Population	-0.0126	-0.0880**	0.438***	-0.000485
	(-0.24)	(-2.40)	(4.63)	(-0.04)
Urban Population	-0.0753	-0.0277	0.192	0.0150
	(-0.63)	(-0.56)	(1.08)	(0.61)

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table represents the effect of ambient light on crime(s) per million at the daily level from an RD specification. This model includes day-of-week and jurisdiction-by-year fixed effects with standard errors clustered by jurisdiction. Daily totals were calculated by summing hourly data across all hours within a day.

Table A.5: RD Daily Totals with Jurisdiction by Week Fixed Effects

Crimes per 1,000,000	Robbery	Rape	Aggravated Assault	Murder
Total Population	-0.0843	-0.000675	0.244**	0.0111
	(-1.26)	(-0.02)	(2.11)	(0.74)
Rural Population	-0.0439	-0.0136	0.343**	0.00367
	(-0.64)	(-0.26)	(2.55)	(0.22)
Urban Population	-0.188	0.0325	-0.0125	0.0303
	(-1.21)	(0.50)	(-0.06)	(0.95)

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table represents the effect of ambient light on crime(s) per million at the daily level from an RD specification. This model includes day-of-week and jurisdiction-by-week fixed effects with standard errors clustered by jurisdiction. Daily totals were calculated by summing hourly data across all hours within a day.

Table A.6: RD Sunset Hour with Jurisdiction by Year Fixed Effects

Crimes per 1,000,000	Robbery	Rape	Aggravated Assault	Murder
Total Population	-0.110***	-0.0144	0.0439	0.00190
	(-4.17)	(-0.84)	(0.82)	(0.51)
Rural Population	-0.122***	-0.0116	0.0443	0.00268
	(-4.00)	(-0.58)	(0.71)	(0.63)
Urban Population	-0.0462	-0.0294	0.0418	-0.00221
	(-1.08)	(-1.30)	(0.55)	(-0.33)

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table represents the effect of ambient light on crime(s) per million at the hourly level from an RD specification in the hours most affected by daylight. This model includes day-of-week and jurisdiction-by-year fixed effects with standard errors clustered by jurisdiction.

Table A.7: RD Sunset Hour with Jurisdiction by Week Fixed Effects

Crimes per 1,000,000	Robbery	Rape	Aggravated Assault	Murder
Total Population	-0.135***	-0.0216	0.0966	-0.00266
	(-3.99)	(-1.21)	(1.45)	(-0.77)
Rural Population	-0.155***	-0.0198	0.0896	-0.00241
	(-3.92)	(-1.01)	(1.19)	(-0.63)
Urban Population	-0.0299	-0.0313	0.133	-0.00399
	(-0.57)	(-0.71)	(0.93)	(-0.51)

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table represents the effect of ambient light on crime(s) per million at the hourly level from an RD specification in the hours most affected by daylight. This model includes day-of-week and jurisdiction-by-week fixed effects with standard errors clustered by jurisdiction.