The Role of Ambient Light in Shaping Public Safety: Evidence from Daylight Saving Time*

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Abstract

Darkness has long been associated with changes in criminal activity. Daylight saving time, a biannual policy that induces drastic ambient light changes, has allowed researchers to measure its causal impacts on crime. Still, we lack evidence on its mechanisms and distributional effects. This research uses data from eleven densely populated US cities to address this knowledge gap. First, it links crime and arrest incident-level data to assess whether differences in the objective versus perceived probability of apprehension could explain potential offenders' behavior changes. Second, it examines impacts on commuting patterns, measured through ridership data, to assess how potential victims' behavior explains the crime effects. Third, it studies the extent to which sleep deprivation could explain violent behavioral changes. Fourth, it evaluates whether street lighting infrastructure could moderate the impact of darkness. This study finds that ambient light influences robberies and aggravated assaults. The objective probability of apprehension does not change, suggesting that deterrence drives the results. Increased pedestrian activity partially explains the crime changes. The transitory sleep loss time cannot fully explain the alterations in sustained criminal activity. Policymakers can mitigate the impact of darkness with localized street light investments, particularly in disadvantaged communities, the areas most affected by darkness.

Keywords: regression discontinuity, crime prevention through environmental design, deterrence

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1 Introduction

Criminologists have recognized that modifying environmental factors and immediate surroundings can change people's behavior (Clarke, 1995; Jeffery, 1969; Taylor and Gottfredson, 1986). Altering situational opportunities can improve public safety by increasing the effort and risks and decreasing the rewards of committing crimes (Eck and Clarke, 2019). By focusing on the environmental design, crime prevention strategies do not need to rely solely on law enforcement and the criminal justice system, which can come at a high cost to historically marginalized communities (Chalfin et al., 2022b).

A recent body of literature has shown the impact of ubiquitous environmental factors on public safety. Criminal activities are sensitive to pollution (Carrillo et al., 2018), tree coverage (Kondo et al., 2017), temperature (Heilmann et al., 2021), and noise (Hener, 2022). A critical manipulation of the physical space and immediate surroundings lies in ambient light changes. Tactical lighting improvements can enhance public safety by deterring crime (Chalfin et al., 2022a; Mitre-Becerril et al., 2022). While jurisdictions worldwide have been making localized street light investments to modify the physical space at night with significant crime decreases (Welsh et al., 2022), there is a biannual widespread policy change that alters the natural availability of light during peak hours: daylight saving time. In the US, this policy moves clocks forward by one hour in March, and it moves them back one hour in November. Accordingly, in spring, residents trade additional light time in the evening for more darkness in the morning. During fall, the trade-off goes in the opposite direction.

Moving one hour the clocks has been shown to influence crime (Doleac and Sanders, 2015; Domínguez and Asahi, 2023; Munyo, 2018; Tealde, 2021; Umbach et al., 2017), road traffic collisions (Barnes and Wagner, 2009; Bünnings and Schiele, 2021), workplace accidents (Smith, 2016), energy consumption (Kotchen and Grant, 2011), and suicide rates (Osborne-Christenson, 2022). Sleep deprivation, reduced visibility, and routine activity changes have been proposed as prime candidates to explain the impact of ambient light. Losing sleep time has been associated with aggression and hostility, likely via reduced self-control (Haack and Mullington, 2005; Kahn-Greene et al., 2006; Semenza and Gentina, 2023). Economic and criminological theory predicts that improving visibility should increase the risk of apprehending law-breakers (Becker, 1968; Clarke and Cornish, 1985). Well-lit spaces promote a sense of security among residents (Boyce et al., 2000; Haans and De Kort, 2012). Moreover, daylight is associated with changes in foot and cyclist traffic (Fotios and Robbins, 2022). Increased pedestrian traffic could translate into 'more eyes upon the street' acting as natural surveillance mechanisms to reduce crime (Jacobs, 1961). However, it could also lead to more crime opportunities due to decreased search costs of crime opportunities by increasing the convergence of potential victims and offenders (Cohen and Felson, 1979). In short, the net effect of ambient light on crime is uncertain. Empirical evidence is needed.

Credible quasi-experimental studies have shown that daylight saving time affects crime, usually reducing robberies when there is more evening daylight, though the evidence on other crimes is mixed. Its potential mechanisms and distributional impacts are unclear. This research addresses this knowledge gap by leveraging the discrete change in ambient light at sunset caused by the daylight policy change in a regression discontinuity framework. The model controls for unobserved, time-invariant confounders and group-common seasonal variation by using city, day-of-the-week, and year-fixed effects and daily weather controls. It compares observations a few weeks apart from the daylight saving time change. The underlying idea is that after controlling for such individual, time, and weather confounders around a few weeks from the start of daylight saving time, the only difference in the evening is that people experienced an extra hour of light when it used to be dark. Accordingly, this specification captures the impact of ambient light on crime. This model has been commonly used in the literature on daylight saving time.

The regression model uses data from 11 major US cities from 2012 to 2022, linking crime to arrest records and examining mobility patterns measured by pedestrians, cyclists, and road traffic. It also relies on individual survey-level data to measure sleep behavioral modifications. Furthermore, it collects sociodemographic census tract data and built environment features to estimate heterogeneous and distributional impacts of ambient light within cities. This research finds that the start of daylight saving time (gaining one hour of evening light) leads to a 29 percent decrease in robberies and a 21 percent rise in aggravated assaults during sunset hours (6 pm to 7:59 pm). No other violent crime (murder, simple assault, and weapons violations) shows a consistent significant change. The results hold to alternative specifications and placebo tests. The impacts on robberies and assaults follow the opposite signs when assessing the effects during sunrise, when people experience more morning natural light, and when daylight saving time ends in November, though these effects are imprecisely measured.

The results suggest that robberies and aggravated assaults respond differently to widespread modifications in ambient light. This research aims to understand the underlying mechanisms behind these results. First, it examines changes in the risk of apprehension. Neither robbery nor aggravated assaults committed during sunset experienced a significant impact on the offenses cleared by arrest (measured in levels or rates), suggesting that the objective probability of apprehension does not show meaningful changes. One interpretation of this result is that the decrease in robberies is due to deterrence rather than the incapacitation of potential offenders. Next, this research assesses whether behavioral changes of potential victims could partially explain the effects on crime. It was found that more natural light leads to an increase in ridership traffic during sunset. Said differently, more people commute during evenings when there is more daylight relative to similar days with dark evenings. The change suggests that "more eyes upon the street" can be a natural surveillance mechanism to decrease robberies. However, it also induces more opportunities for altercations and conflict. This mechanism is relevant, considering that sleep patterns temporarily change during daylight saving time.

Finally, this research also explores the distributional impacts of widespread changes in ambient light by assessing crime changes between census tracts with different sociodemographics or built environment features. Neighborhoods with the highest number of street lights per square mile show no changes in robberies or aggravated assaults during sunset; the change is only experienced in the remaining neighborhoods. This analysis suggests that saturating the environment with street lighting, hence providing artificial ambient light, attenuates drastic changes in natural light, fading out any impacts on crime. Moreover, when comparing neighborhoods with different sociodemographic compositions, the high-poverty areas and majority-Black neighborhoods seem to be the ones experiencing the crime changes. In summary, widespread changes in ambient light are experienced differently across the city due to the local infrastructure and social fabric. Future research should continue exploring alternative mechanisms and other social or built environment features that could mediate the relationship between crime and ambient light.

The rest of the article is organized as follows. Section 2 reviews the literature on crime and ambient light, including a brief history of daylight saving time. Sections 3 and 4 explain the data and empirical strategy. Section 5 exhibits the results, and Section 6 discusses them and concludes.

2 Background

2.1 Daylight saving time policy

Daylight saving time has been a long-standing policy in northern hemisphere countries, where sunset and sunrise hours vary more relative to their counterparts. Over two hundred years ago, Benjamin Franklin suggested using more daylight to reduce energy expenditures (Franklin, 1931). Nonetheless, George Hudson was the first to suggest moving clocks at the equinoxes at the end of the 19th century. His idea was received with some ridicule and criticism (Hudson, 1895). Despite the initial reluctance, the idea became a public policy two decades later across Europe once World War I started, and nations needed to reduce coal consumption, the main energy source. The US adopted this policy as a wartime measure a few years later. Over the next century, the US repealed and approved daylight saving time on multiple occasions, and many more, a bill would be unsuccessfully proposed in Congress (Gray and Jenkins, 2019). Even in the last few years, there have been national and local bill proposals to end the practice of changing clocks twice a year (Olson, 2024). Such proposals are consistent with most public opinion preferring not having to change their clocks biannually and partially leaning towards adopting daylight saving time permanently (Frankovic, 2024).

Since its inception, daylight saving time has caused divided opinions. For instance, farmers have protested it because it interferes with their early daily tasks. Parents have also raised concerns about traffic accidents when sending their kids to school during dark mornings. Business owners and some labor unions have favored it as it provides longer summer evenings for working and leisure hours (Patrick, 1919). Policymakers have been responsive to their constituents, as geographical location, population composition, and political party membership predict whether Congress members will vote favorably on bill proposals supporting daylight saving time (Gray and Jenkins, 2019).

The policy discussions and citizens' preferences around moving the clock forward have centered mostly on energy consumption, traffic accidents, and biological circadian rhythms (Frankovic, 2024; Gray and Jenkins, 2019). Changes in criminal activities have not been a major factor when discussing daylight saving time. Nevertheless, since the early 1920s, some anecdotal evidence suggests that this policy may have influenced delinquency (Pollak, 1981). Daylight saving time provides an opportunity to understand the mechanisms and heterogeneous impacts of ambient light on public safety. This research contributes to this goal.

2.2 Research on crime and ambient light

Why should we expect a relationship between daylight saving time and crime? Several criminology and economic theories could answer this question. Daylight saving time affects the availability of natural light. Ambient light is a quintessential physical space factor influencing people's ability to observe and perceive their surroundings. Situational crime prevention argues that manipulating the immediate environment can reduce crime by modifying its opportunities and risks. It recognizes that a supply of potential targets is a function of the physical environment (Clarke, 1995). Crime prevention through environmental design argues that physical features can shape offenders' perceptions of residents, influencing the opportunities, risks, and convenience for committing crimes (Jeffery, 1969; Taylor and Gottfredson, 1986). By affecting our ability to distinguish individuals or situations more clearly, ambient light could increase the chances of detecting risky situations and acting against them.

Street brightness levels can also alter our perception of safety (Boyce et al., 2000; Haans and De Kort, 2012). Real and symbolic barriers, such as bright spaces, affect our attitudes and behaviors at the individual and neighborhood levels (Taylor et al., 1984; Taylor and Hale, 1986). For instance, darkness is associated with fear of crime (Painter, 1996). The idea that fear can induce behavioral changes is the cornerstone of the broken windows theory (Wilson and Kelling, 1982). Empirical evidence supports that fear of crime causes meaningful behavioral changes, such as influencing the housing market (Pope, 2008; Kim and Lee, 2018) and house location decisions (Xie and McDowall, 2008), and its effects may be different on the residents sociodemographic (Lee et al., 2022).

Ambient light could decrease crime by deterrence or incapacitation effects. Incapacitation usually responds to law enforcement inputs, while deterrence comes from a change in costs and benefits (Chalfin and McCrary, 2017). Ambient light is a non-criminal justice, non-targeted strategy that affects all individuals' apprehension probability. While there are concerns about the effectiveness of such strategies as they influence opportunities outside the realistic range of possibilities for offenders (Nagin et al., 2015), given the widespread influence of daylight saving time, economic and criminology theory would predict that a change in risks and rewards could influence criminal activity (Becker, 1968; Clarke and Cornish, 1985). Moreover, there is evidence that surveillance systems may be more effective when paired with improved lighting interventions (Piza et al., 2019). If law enforcement improves its ability to detect offenders or victims, it may be easier to identify them. Then, the probability of arresting individuals could change. This research recognizes that arrest clearance rates are an average objective probability of apprehension (Pogarsky and Loughran, 2016), and risk perceptions are influenced by idiosyncratic cognitive abilities, private information, and contextual and situational features (Barnum et al., 2021). While clearance rates may not be informative for deterrence research (Pogarsky and Loughran, 2016; Nagin et al., 2015), they can be used to assess whether incapacitation could partially explain the crime reduction of ambient light. If incapacitation is not changing, deterrence should drive the crime effects.

Behavioral changes can also explain the relationship between ambient light and crime. Darkness can affect our travel decisions, particularly walking and cycling, as they relate positively to ambient light availability. Pedestrians and cyclists may find it difficult to see and be seen in the streets under darkness, limiting their willingness to commute (Fotios et al., 2019; Fotios and Robbins, 2022). Also, public places, like public parks and green areas, close at sunset, so darkness can limit outdoor activities even if people are willing to go outside. Ambient light can modify daily routines and influence our probability of going out more often. Brighter environments could induce more potential targets for crime as potentially motivated offenders and victims converge in space and time (Cohen and Felson, 1979; Cook, 1986). Moreover, having more people outdoors means offenders' search costs for crime decrease, enabling them to identify potential victims more easily and reducing the cost of crime (Becker, 1968). Well-lit spaces could lead to 'more eyes upon the street', creating natural surveillance mechanisms (Jacobs, 1961). Accordingly, widespread luminosity changes may induce differential impacts on criminal offenses.

Sleep disruption is another behavioral change that could explain the impact of ambient light on crime. Daylight saving time temporarily reduces sleeping time (Harrison, 2013; Sexton and Beatty, 2014). Criminology research has shown a positive relationship between sleep deprivation and aggression via changes in self-control (Barnes and Meldrum, 2015; Meldrum et al., 2015; Semenza and Gentina, 2023), and self-control has been an important line of research to explain criminal behaviors (Burt, 2020; Gottfredson, 1990). Environmental psychology has also found that sleep deprivation relates to an unwillingness to solve conflicts and fewer inhibitions towards aggression (Kahn-Greene et al., 2006), exhibiting heterogeneous effects (Cote et al., 2013). Lab experiments suggest that illuminance levels can influence inclinations to approach other individuals, people's states of anger, and the willingness to inflict pain on others (Page and Moss, 1976; Veenstra and Koole, 2018).

There is empirical evidence of ambient light influencing criminal activity. Research has focused on two types of ambient light changes. One area focuses on changes in luminosity levels via street lighting interventions (or lack thereof). Street lighting focuses on targeted artificial light modifications, usually affecting the small area around the light pole or, exceptionally, a few city blocks due to blackouts. This literature measures mostly changes in nighttime criminal behaviors when public light poles are needed and noticeable when affected. Most evidence suggests that reducing darkness via street lighting causes fewer crimes (Chalfin et al., 2022a; Dominguez and Rodriguez-Martinez, 2024; Mitre-Becerril et al., 2022; Welsh et al., 2022). However, it has also been found that turning off and dimming street lights reduces crimes (Tompson et al., 2023), probably due to changes in pedestrian activity and reallocation of potential targets.

A second area of research on ambient light and crime focuses on daylight saving time, which causes an exogenous, discrete, and widespread change in natural light (Doleac and Sanders, 2015; Domínguez and Asahi, 2023; Munyo, 2018; Tealde, 2021; Umbach et al., 2017). This natural experiment allows studying larger geographical areas, so studies examine city- or nation-wide impacts. They usually focus on the effects of sunset or sunrise crimes, which are the moments when daylight saving time causes a meaningful change in ambient light. These studies commonly rely on regression discontinuity designs to compare crime a few days before and after the clocks are moved forward or backward one hour (Doleac and Sanders, 2015; Domínguez and Asahi, 2023; Munyo, 2018; Tealde, 2021). Some research has used a difference-in-differences design by taking advantage of daylight saving time extensions due to legislative changes (Doleac and Sanders, 2015; Domínguez and Asahi, 2023). Only one study used a fixed effects model to compare the first and second Mondays after daylight saving time started but measured the impacts of sleep deprivation and not natural light (Umbach et al., 2017). Research on daylight saving time and crime has consistently found a decrease in robbery when there is more ambient light. Impacts on assaults, thefts, murders, and rapes have sometimes been found significantly affected, but the evidence is mixed.

In summary, empirical evidence and theory suggest that changes in ambient light should affect criminal behaviors. However, we still lack studies on the mechanisms and distributional of ambient light on crime. This research aims to advance this line of research.

3 Data

This research collected incident-level crime and arrest data from 11 US cities between 2012 and 2022 as reported by each police department.[1] Each record has timestamped and geocoding attributes. The crime and arrest records can be linked one-to-one, so it is possible to distinguish which offenses were cleared by arrest. The crimes are categorized into murder, robbery, aggravated and simple assault, and weapons violations, which include gun discharges, illegal criminal possession, shootings, and brandishing. This study focuses only on violent offenses as they are more likely to have precise timestamp information on when the incident happened as the victim was present or a police officer witnessed the crime. In contrast, property crimes (larceny, motor vehicle, and burglary) can be committed without a victim present, so the timestamp information will be based on the victim's best guess of when the goods were stolen or realized their belongings were missing. The police department can also choose an arbitrary hour for crime.[2]

To measure changes in traffic patterns, this research collects data on the number of drivers crossing an intersection, bus riders by route, and bike-share rider users across time. Each variable was standardized (e.g., subtracting its mean and dividing by its standard deviation) and summed to create an index. While this metric loses its units of measurement, it allows examining a single outcome of traffic mobility across different cities and modes of transport.[3] Another behavioral change that can happen around daylight saving time is the disruption of sleeping patterns. This outcome is measured using the American Time Use Survey, which asks respondents about the time they spend in a day on different activities, including sleeping. This survey does not allow for identifying the city where the respondents live but provides the state of residence and whether they live in a metropolitan area. It also has the sociodemographic characteristics of the respondents, and importantly, it includes the day on which the respondent completed

[1] The research includes data from Austin, TX, Chattanooga, TN, Chicago, IL, Cincinnati, OH, Kansas City, MO, Los Angeles, CA, Louisville, KY, New Orleans, LA, Pittsburgh, PA, Rochester, NY, and San Francisco, CA. The cities were chosen based on data availability.

[2] Descriptive statistics from these 11 cities show that property crime shows atypical clustering at noon and midnight.

[3] Only Kansas City, MO, provides no information on traffic mobility. The remaining cities have data from at least one variable from car, bus, or bike riders.

the time diary.

This research also collects information on the built environment measured via street light poles in a city, a snapshot of the local infrastructure during the study period.[4] It also compiles weather information from the National Oceanic and Atmospheric Administration Integrated Surface Database, which reports surface observations from weather stations. Finally, to characterize the sociodemographic composition of the 11 cities, this study collects data from the American Community Survey.

The public safety data was aggregated to the day-city level, so each observation is the number of incidents happening at sunset (6 pm to 7:59 pm) per day and city. The traffic index measures ridership movements during sunset. The weather information was compiled at the city-daily level. Joining these variables creates a panel dataset at the day, year, and city level from 2012 to 2022.

A second analytical dataset was built to measure changes in sleeping time. Data comes from the American Time Use Survey. Only individuals who live in the metropolitan areas of the states of the cities included in this research were kept in the dataset.[5] Given that the cities included in this research are located in metropolitan areas, this subsample is the closest proxy to measure changes in sleeping time for the geographical areas used in the main results. This second dataset is a repeated cross-sectional dataset at the individual, day, year, and state level from 2012 to 2022.

A third dataset was built to study whether the built environment attenuates the relationship between ambient light and crime and examine intra-city distributional impacts. Public safety data was aggregated to the neighborhood level to measure the number of incidents in a census tract per day at sunset. City-daily weather information was used for this analytical dataset so all neighborhoods experience the same weather controls. Sociodemographics at the census tract level are only available at the year level. The number of light poles is a cross-sectional snapshot of the built environment features in each city. These two last variables were aggregated to the census tract level and were used to build percentiles to classify the neighborhoods based on the heterogeneity dimension of interest. This third dataset is a panel at the day, year, and census tract level from 2012 to 2022.

Table 1 exhibits descriptive statistics of the mean number of public safety incidents between 2012 and 2022 at the daily level around three weeks from the start of daylight saving time in the 11 cities. Aggravated and simple assaults account for most of the daily violent offenses. There are 6.3 daily robberies. Nearly 11 percent (0.72) occur between 6 pm and 7:59 pm, which is more than what we would expect if the crime were distributed uniformly across the day. Around 2.9 weapons violations happen daily, with 0.35

[4] Only Rochester, NY, provides no data on street lights. The remaining cities have information on street lights. In a few instances, the location of street lights was proxy via service calls to light fixtures.

[5] The states are California, Illinois, Kentucky, Louisiana, Missouri, New York, Ohio, Pennsylvania, Texas, and Tennessee.

occurring near sunset. The clearance rate is different between crimes. Over half of the weapons violations during sunset are cleared by arrest. The high clearance rate is consistent with weapons violations being an offense usually discovered by police proactivity, so arrests are likely to happen (Moore, 1980). Forty-two percent of the murders around sunset are cleared by arrest. This rate decreases to around 30 percent for aggravated and simple assaults. Only 20 percent of sunset robberies are solved by arrest. These statistics are consistent with national data from the FBI's Uniform Crime Reporting and suggest that the crimes most costly to society are more likely to be cleared by arrest.

Appendix Table A.1 shows the sociodemographic composition of the 11 cities. The average city has around one million inhabitants, with half identifying as White, one-fourth as Black, and one-sixth as Hispanic. One-fifth have a high school diploma, one-fourth have some college education, and around two-fifths have at least a college degree. The unemployment rate went from 10.7 in 2012 to 5 percent in 2022, consistent with the national downward trend experienced after the Great Recession.

4 Empirical strategy

Studying the causal relationship between ambient light and crime is challenging due to unobserved confounders creating endogeneity biases. These biases mean that instead of measuring the impact of ambient light on crime, we would be measuring the effect of a third unobserved variable on crime. For example, comparing crimes between day and night hours would likely suggest that darkness increases crimes. However, given that people's routines and lifestyles differ between these two periods, this approach is unlikely to capture a causal effect. Another approach would be to contrast the number of crimes between summer (when there is more sunlight) and winter (when there is less sunlight). The issue is that people behave differently across these seasons, even after controlling for the weather.

To address these endogeneity concerns, this research leverages the drastic ambient light change caused by daylight saving time. **Figure 1** shows the average amount of daylight over a year in the 11 cities, marked by the hours between sunrise and sunset. Winter has shorter days, and summer experiences longer days. Two times a year, there is a discontinuous change in ambient light when clocks move by one hour due to daylight saving time. Daylight saving time starts on the second Sunday in March and ends on the first Sunday in November. Accordingly, between 6 pm and 7:59 pm in spring, there is an extra hour of sunlight when it used to be dark. The same situation happens between 6 am and 7:59 am in the fall. In contrast, mornings in spring and evenings in fall experience one extra hour of darkness when it used to be bright.

The research design compares the number of crimes a few days before and after the start (or end) of daylight saving time, removing confounders that could be biasing the relationship between ambient light and crime. The main analysis focuses on the impact of the start of daylight saving time on public safety outcomes during sunset. The effects at sunrise, at the start of daylight saving time, and at the end of the daylight regime are estimated as a robustness check. The main econometric specification uses the following regression discontinuity design, restricting the sample within a small bandwidth h:

$$y_{idt} = \alpha_0 + \beta_1 DST_t + \alpha_1 f(r_t) + \alpha_2 DST_i g(r_t) + \gamma_t + \mu_i + wday_d + X_{it}\omega_X + u_{idt} \tag{1}$$

where y_{idt} is the main outcome (e.g., count of crimes, clearance rate, or traffic index) in city i, in day d, and year t. DST_t indicates whether daylight saving time is in place, which affects all cities simultaneously. The running variable, r_t, is the number of days until the start of daylight saving time, centered around zero, so a negative value means that the clocks have not moved forward yet. Daylight starts on the second Sunday of March, which falls between the 8th and 14th of March, depending on the year. γ_t are year-fixed effects to control for time-varying, city-invariant confounders (e.g., national yearly economic shocks). μ_i are city-fixed effects to account for time-invariant, city-specific unobserved variables (e.g., stable city policies and regulations). $wday_d$ is a day-of-the-week fixed effect to control for different daily patterns and crime risk within a week (e.g., more crime happens on Friday and Saturday than on other days). X_{idt} includes daily weather covariates (temperature, precipitation, humidity, and visibility) as weather influences crime and traffic patterns. The functions $f(r_t)$ and $g(r_t)$ allow flexible polynomial forms on either side of the threshold. The error term is represented by u_{idt}, using robust standard errors. This assumption is later relaxed by clustering the standard errors at different levels. β_1 is the main coefficient of interest and provides the average effect for experiencing an additional hour of ambient light on days that otherwise would have experienced darkness. The regression is estimated using ordinary least squares.

Previous studies on daylight saving time have also used regression discontinuity (Bünnings and Schiele, 2021; Doleac and Sanders, 2015; Domínguez and Asahi, 2023; Munyo, 2018; Osborne-Christenson, 2022; Smith, 2016; Sexton and Beatty, 2014; Tealde, 2021). More broadly, regression discontinuity has also been used in criminology to study impacts on the age of criminal responsibility (Loeffler and Grunwald, 2015), private policing (MacDonald et al., 2016), prison sentences (Mitchell et al., 2017), and prison facility security classification (Tahamont, 2019). This method also forms part of the quasi-experimental toolbox that can strengthen the link between rigorous evidence and policy evaluation in criminology (Berk et al., 2010; Blumstein, 2013; Braga and Weisburd, 2013).

5 Results

5.1 Main results

This research first provides descriptive evidence of differences in crime counts near the start of daylight policy change. **Figure 2** compares the average daily count of crimes at sunset (6 pm to 7:59 pm) between 2012 and 2022, around three weeks from the start of daylight saving time. Second-order polynomials fit the data points. Robbery shows a drastic decrease. Aggravated assault shows the opposite change, suggesting more offenses due to changes in ambient light. Simple assault suggests a monotonic, non-discontinuous relationship as time goes by. Murder and weapons violations show no change.

These descriptive results suggest a discontinuous change but do not account for seasonal variations or daily weather differences that could impact crime. These results are estimated using an ordinary least squares regression discontinuity design to account for these concerns. The specification includes second-order polynomial functions controlling for seasonal variations and weather changes following Equation 1. The model was estimated using only observations around three weeks from the start of daylight saving time. This bandwidth is similar to the ones used in other ambient light research; the robustness checks relax this assumption. **Table 2** shows 0.209 fewer robberies during sunset due to the new daylight time, which, relative to a mean of 0.72, translates into a 28.9 percent decrease. Aggravated assaults during sunset increased by 0.215, equivalent to a 20.9 percent change. No other crime shows a significant change.

5.2 Robustness checks

This section assesses the robustness of the main findings. The results are presented in a specification curve that includes the point estimate and 90 and 95 confidence intervals. This approach identifies, if any, the most consequential analytical decisions for changing the findings. It also helps to increase the precision of the statistical inference by providing a range of estimates (Simonsohn et al., 2020). **Figure B.1** presents 193 alternative models by modifying the polynomial function (linear and quadratic), the number of days to include in the regression (from two to seven weeks), the presence of covariates (with and without weather controls), period of estimation (including and excluding the COVID-19 pandemic era), and different standard errors assumptions (robust and clustering at the city, year, or day-of-the-week level).

First, the median estimate for robberies using a second-order polynomial function order is larger than a linear function (-0.105 vs. -0.159). Aggravated assaults experience a similar pattern (0.096 vs. 0.204). Still, their confidence interval overlaps. Second, expanding the bandwidth (number of days to include in the regression) increases the selection bias but makes the estimates more precise, a phenomenon called the variance-bias trade-off (Imbens and Lemieux, 2008). For example, using two weeks of data leads to a -0.169 [0.193] median estimate for robberies [aggravated assaults] but changes to -0.115 [0.113] when using seven weeks of data. Third, using controls may eliminate small sample biases and improve precision. The median estimate for aggravated assaults follows this pattern, decreasing from 0.156 to 0.139 when adding weather covariates. This pattern does not hold for robberies, as including controls leads practically to the same median estimate (-0.142 vs. -0.129). Fourth, the COVID-19 pandemic has not affected the relationship between ambient light and crime. Excluding the post-COVID-19 period (2020 onwards) has no meaningful impact on the median estimates (robberies: -0.136 vs. -0.129; aggravated assaults: 0.156 vs. 0.145).

Default standard errors can overstate the coefficient precision by not accounting for serial correlation. Robust standard errors are usually the norm in regression discontinuity. However, this research uses panel data, so the results are assessed under standard error clustering (city, year, and day of the week). The proportion of significant estimates at the 90 percent level ranges from 18.8 to 97.9 percent for robberies and 77.1 to 97.9 percent for aggravated assaults. The clustering unit may seem to affect the estimates' statistical precision. However, the cluster-robust standard errors asymptotic theory assumes that the number of clusters goes to infinity. Having a few clusters downward biases the covariance matrix. This research design has only seven to eleven clusters, and the rule-of-thumb requires at least 50 (Cameron and Miller, 2015). To address this concern, **Figure B.2** shows the distribution of estimates by randomly assigning the start of daylight saving time to a placebo date: different Tuesdays, Thursdays, and Sundays in the year, excluding March and November (months on which the daylight time changes). The location of the estimate in the distribution of hypothetical treatment assignments provides an implied p-value. Robberies and aggravated assaults coefficients are among the largest in the distribution, implying a randomization inference p-value of 0.019 and 0.044. This method reassures that the estimates are statistically significant.

Next, **Figure B.3** assesses the existence of discontinuities at values other than the threshold. It shifts daylight saving time to a placebo date ranging from one to six weeks before and after the real policy change. None of the placebo dates is significant for robberies, and only two out of twelve specifications are significant for aggravated assaults, which is within the expected false discovery rate.

Finally, another way to assess the robustness of the results is to examine the impacts at other moments also affected by discrete changes in ambient light. **Figure A.2** and **Table A.2** show point estimates and visual regression discontinuity estimates of the start of daylight saving time on crime at sunrise (6 am to 7:59 am), which now experiences darkness when it used to be bright. Simple assaults show a significant decrease, and robberies show an imprecise increase. Changes in crime are more muted when assessing the impacts at the end of daylight saving time in November. Appendix **Table C.1** and **Figure C.1** show that sunrise robberies decrease. Robberies at sunset seem to increase, but the impact is not statistically significant.

5.3 Potential causal mechanisms

One contribution of this research is exploring the potential underlying mechanisms driving the effect of ambient light on criminal activity. This section examines three possible mechanisms: changes in the probability of apprehension, urban mobility, and sleep deprivation.

5.3.1 Probability of apprehension

Daylight saving time provides natural light in the evening when it used to be dark. Well-lit spaces could influence people's ability to observe individuals, increasing the probability of giving a description that could help police officers identify the offender. Law enforcement could also be better equipped to catch people breaking the law in the act, as offenders cannot use darkness to conceal their activities. The proportion and number of crimes cleared by arrest are used to assess whether incapacitation rather than deterrence could drive the results. **Figure 3** compares the average proportion of crimes at sunset cleared by arrest around three weeks from the start of daylight saving time. A smooth transition in robberies and aggravated assaults can be observed before and after daylight saving time, suggesting that a drastic ambient light change does not cause a meaningful impact on the probability of solving a crime. This null result is confirmed in **Table 3**, Panel A, once the regression discontinuity regression controls for seasonal variations and idiosyncratic shocks. The point estimates can rule out a 5.7 percentage increase in the probability of solving a robbery and an equivalent 7.1 percentage point change for aggravated assaults at a 95 percent confidence level.

The previous model only includes days when a crime occurred during sunset as the denominator divides by the number of crimes to estimate the clearance rate. This situation reduces the sample size, so one can be concerned that the null effects are due to a lack of statistical power. Panel B presents the specification estimating a change in the number of cleared crimes by arrest, which preserves a larger sample size. The results are also statistically insignificant. The results suggest that the decrease in robberies may be due to deterrence rather than incapacitation, as the police are not arresting more individuals. The perceived change in the risk of apprehension is enough to hinder robberies.

5.3.2 Mobility patterns

Another factor that could explain the main results is traffic and mobility pattern changes. Previous evidence has shown that daylight saving time can influence people's time spent outdoors (Fotios et al., 2019; Fotios and Robbins, 2022; Sexton and Beatty, 2014). This research is consistent with past literature. Using the traffic index, a standardized daily count of drivers per intersection, bus riders per bus line, and bike-shared users, **Figure 4** visualizes a discrete discontinuity at sunset when daylight saving time starts (Panel B). This change is not present when measuring the traffic patterns during the entire day (Panel A). This result is confirmed in **Table 4** once the model controls for seasonal and idiosyncratic fixed effects in a regression framework.

Not observing changes throughout the day but only during sunset is consistent with the idea that ambient light is the driving mechanism. Ambient light is drastically different in the evening when now it is bright but used to be dark. The results suggest that people are taking advantage of the extra hour of light to be outside without altering their activities meaningfully during the rest of the day. The additional "eyes upon the street" seem to contribute to a decrease in robberies by providing natural deterrence options. However, more people in the street seem to be creating additional opportunities for conflicts and altercations, which could explain the increase in aggravated assaults.

5.3.3 Sleep deprivation

Finally, to the extent that individuals sleep less due to moving the clocks forward, aggression could also be impacted, as literature has suggested (Haack and Mullington, 2005; Kahn-Greene et al., 2006; Semenza and Gentina, 2023). A regression discontinuity design was estimated using individual responses from the American Time Use Survey. The regression discontinuity follows Equation 2.

$$y_{idst} = \alpha_0 + \beta_1 DST_t + \alpha_1 f(r_t) + \alpha_2 DST_i g(r_t) + \gamma_t + \mu_s + wday_d + X_i \omega_X + u_{idt} \tag{2}$$

where y_{idst} is the minutes spent sleeping by respondent i, in day d, in state s, and year t. It includes state (μ_s), day-of-the week ($wday_d$), and year (γ_t) fixed effects. It also controls for the respondents' characteristics (X_i: age, income, sex, marital status and employment status, race, ethnicity, and schooling level). The ordinary least squares regression compares individuals with similar sociodemographics living in the same state and year, but some were interviewed under different daylight regimes by a few days difference. The model uses robust standard errors. **Appendix Figure A.1** shows descriptive evidence of a slight decrease in sleeping time when daylight saving time starts. This result is confirmed in **Table**

5 using the regression discontinuity specification. The average respondent slept 30.5 minutes (6.3%) less daily within two weeks of the clocks moving forward. This impact seems temporal as within three weeks of the policy change, the effect decreases to 22.7 fewer minutes of daily sleep (4.7 percent), becoming a statistically insignificant decrease of 11.7 minutes (2.3 percent) within one month.

One possible explanation for the change in the magnitude and statistical significance of the sleep time treatment effect could be the bias-variance trade-off. As observations further away from a few weeks of the intervention are compared, some bias is introduced. Alternatively, the outcome experiences time-varying treatment effects, so the impact of sleep deprivation is only short-term. This last hypothesis is consistent with previous evidence (Smith, 2016). The effect of daylight saving time on sleep deprivation cannot completely explain the change in aggression measured via aggravated assaults. The sleep impact decays over time, but not the changes in assaults. Other mechanisms should also influence them, such as increased pedestrian activity.

5.4 Heterogeneity analysis

This research makes two additional contributions. First, it examines how localized environmental features moderate the impact of daylight saving time on crime. Then, it measures the distributional crime changes within cities. To this end, this project uses the analytical dataset that measures the count of crimes during sunset at the census tract, day level, from 2012 to 2022. Survey data and administrative records were used to classify the neighborhoods by quintile within a city based on 1) the number of street lights per square kilometer, 2) the percent of people living under the poverty line, and 3) the proportion of Black residents. Then, an ordinary least squares regression discontinuity is estimated using only the census tracts of each quintile. This process ensures an equal representation of census tracts per city in each model (around 600 census tracts per quintile). The regression uses a modified version of Equation 1, adding census tract fixed effects to measure within-variation (e.g., neighborhood changes across time) and clusters the standard errors at the census tract to account for serial correlation.

Figure 5 presents the regression discontinuity point estimate and 90 and 95 percent confidence intervals for sunset robberies and aggravated assaults for the three heterogeneity dimensions across each quintile. The number of daily crimes between 6 pm and 7:59 pm per census tract becomes rare, even for cities with around a million inhabitants. Lower baseline levels make it harder to estimate treatment effects (Hinkle et al., 2013). Accordingly, this subsection highlights the heterogeneity dimension trends across quintiles rather than the point estimates' specific value.

First, this research assesses whether street lighting can attenuate the natural light changes due to daylight saving time. Panel A shows that the regression discontinuity estimates of robberies and aggravated assaults in the fifth quintile are very close to a zero-point estimate. In contrast, the coefficients for the first fourth quintiles are considerably larger and more likely to be statistically significant. Neighborhoods with the largest concentration of street lights per square kilometer seem unaffected by discrete changes in natural ambient light. To contextualize this result, the top quintile has over 400 street lights per square kilometer, substantially larger than the bottom quintiles, which go from 66 to 279 street lights per square kilometer. The results suggest that neighborhoods with a large infrastructure to illuminate the urban landscape can partially substitute natural light changes, attenuating the impacts of darkness. This finding resembles the unequal impact of light found in Latin America (Tealde, 2021).

Next, this research assesses the distributional impacts of daylight saving time across census tracts with different poverty levels. Poverty was chosen because of its long-standing association with criminal activity (Merton, 1938; Patterson, 1991), and places with concentrated disadvantage are at risk of having simultaneously high crime victimization and incarceration rates (Sampson and Loeffler, 2010). Consistent with this idea, the impacts of ambient light on crime are not distributed equally within cities. Neighborhoods with the highest poverty levels drive the observed changes in crime. The regression discontinuity estimates on sunset robberies are close to zero and statistically insignificant for the bottom fourth quintiles. At the same time, the coefficient is negative, significant, and considerably large for the top quintile (e.g., the poorest neighborhoods). An opposite effect is observed for aggravated assaults, though its changes are more nuanced. The census tracts in the top quintile have around 30 percent of their residents living below the poverty line. This number goes down to 14 percent in the fourth quintile, decreasing by half at each following quintile. In short, poverty seems to drive the impacts of darkness on crime.

Finally, the differential impacts of darkness on crime are also examined based on the proportion of Black residents in the neighborhood. Majority-Black census tracts experience the largest crime changes. The neighborhoods in the top two quintiles, where nearly 40 percent of the population identifies as Black, experienced a significant reduction in sunset robberies. In contrast, the remaining neighborhoods face no significant crime differences. For aggravated assaults, the opposite effect is found. The neighborhoods in the top quantile based on the prevalence of Black residents experienced an increase in aggravated assaults, while the remaining areas saw no significant change. The similar observed patterns between poverty and majority-Black neighborhoods are unsurprising given the overlap between race and class in the US (Wilson and Aponte, 1985; Wilson, 2003). For example, in this analytical sample, poverty levels and Black residents are highly correlated ($\rho = 0.53$, p-value < 0.001). Accordingly, ethnic and racial disparities, which are correlated with unequal income levels, lead to differential effects of ambient light on crime. This empirical exercise highlights that disadvantaged areas should receive first street light investments to reduce the impact of darkness on crime.

6 Discussion and conclusions

The discrete change in ambient light caused by daylight saving time has been used previously as a natural experiment to measure its impact on crime. Evidence has consistently found a decrease in robberies at sunset. Impacts on other crimes are mixed (Doleac and Sanders, 2015; Domínguez and Asahi, 2023; Munyo, 2018; Tealde, 2021; Umbach et al., 2017). However, we lack evidence on its mechanisms and distributional effects. This research relies on a regression discontinuity design to compare observations a few days apart from daylight saving time, controlling for seasonal, idiosyncratic, and weather confounders. The start of daylight saving time, which brings an extra hour of natural light in the evening, causes a 28.9 percent decrease in sunset robberies and a 20.9 percent increase in aggravated assaults. The results are robust to alternative specifications and placebo tests. The results suggest that crime responds to different situational cues. It is important to highlight that changes in assaults have been studied less in the daylight saving time literature. Using the same empirical strategy, only one study focuses on them with a positive estimate. However, it is not significant at conventional levels (Doleac and Sanders, 2015).[6]

How should we understand the opposite impacts of ambient light on these two violent crimes? First, it is important to highlight that these violent offenses have different motivations. Robberies are considered financially driven. Individuals committing robbery look for immediate cash due partially to a lack of legitimate ways to earn money, though some do it for other social rewards. They usually use violence as a means to get rewards (Dickinson et al., 2023; Wright et al., 2006). As in acquisitive crimes, the individuals judge the anticipated benefits against potential risks, so these offenses require planning and calculated decision-making (Deakin et al., 2007). In contrast, aggravated assaults are thought of as crimes of passion. They are committed in the heat of the moment due to altered emotions and an escalation of a verbal argument. Commonly, individuals do not think of the consequences as they are focused only on the present (Berkowitz, 1978; Felson and Steadman, 1983). Moreover, assaults usually happen on the street with strangers or slight acquaintances (Pittman and Handy, 1964). Accordingly, assaults are more likely to be unplanned and contingent on the number of potential arguments or interactions they face with other people.

Second, the underlying mechanisms driving the relationship between ambient light and crime tested in

[6] One daylight saving time study finds a decrease in assaults, but the authors compare the first Monday post daylight saving time to the following Monday to capture changes in sleep patterns, not due to ambient light (Umbach et al., 2017).

this research can provide some guidance on these differential effects. Well-lit spaces make distinguishing situations easier so individuals can avoid being in harm's way, and offenders are deterred from crime. Law enforcement could catch more people breaking the law as offenders' ability to use darkness to conceal their activities decreases, leading to incapacitation. This research finds no change in the sunset cleared crimes, measured as rate or absolute levels. At a 95 percent confidence level, the results can rule out a 5.7 percentage increase in the probability of solving a robbery and an equivalent 7.1 percentage point change for aggravated assaults. The objective probability of apprehension was not affected. The perceived risk could be changing, explaining the decrease in robberies. In other words, deterrence rather than incapacitation seems to explain the impact of ambient light on robberies. Moreover, persons committing robberies plan and premeditate their actions to reduce risks and maximize rewards, so a deterrence effect via a change in the uncertainty on whether they will be caught may explain the treatment effect. Assaults, on the other side, driven by provocations and intense emotions, may be less sensitive to a deterrence effect caused by environmental changes, which could explain why assaults did not decrease.

Daylight saving time leads to an additional hour of light when it used to be dark, so changing routine activities, traffic patterns, and the amount of "eyes upon the street" could be another mechanism affecting crime. Ridership data helps to test whether this hypothesis holds to evidence. This research finds that daylight saving time increases traffic and mobility patterns at sunset but not during the rest of the day. This result is consistent with previous research (Fotios et al., 2019; Fotios and Robbins, 2022; Sexton and Beatty, 2014). It is thought that pedestrian activity increases the probability of convergence in space and time of potential victims and offenders (Cohen and Felson, 1979), which would decrease the search cost of crime, encouraging more crime (Becker, 1968). Empirical evidence shows that increased mobility can lead to a higher victimization risk, particularly for public aggression (Massenkoff and Chalfin, 2022). Higher victimization risk, particularly for offenses that depend on interactions with strangers, could explain the apparent paradox of observing an increase in assaults due to ambient light. It is relevant that this result is not new in the literature. The relationship between increased mobility and crime seems to explain the effects of public transit closures or driving restrictions on crime, which change the number of people in the street (Carrillo et al., 2018; Phillips and Sandler, 2015; Wu and Ridgeway, 2021).

Natural light influences peoples' internal clock, regulating cycles of alertness and sleepiness, also called circadian rhythms. Sleep deprivation is associated with reduced self-control, which could lead to more criminal activities, particularly aggression (Barnes and Meldrum, 2015; Semenza and Gentina, 2023). This underlying mechanism is examined by measuring changes in the time spent sleeping around daylight saving time. The results suggest that there is a 6.3 percent loss of sleep. This effect is consistent with an increase in aggravated assaults. The coefficient for aggravated assault is also slightly larger (in absolute terms) when the bandwidth is smaller. However, the sleep disruption is transient. Beyond three weeks, the coefficient is still negative but shrinks and is no longer statistically significant. Said differently, the sleep treatment effect decays over time, but not the impact on aggravated assaults. Accordingly, sleep deprivation can partially explain the effect of ambient light on aggravated assaults.

Ambient light affects the physical space and our perception of it. This research finds that light impacts neighborhoods differently. Census tracts with a more extensive street lighting infrastructure seem impervious to the drastic changes in ambient light. This result is consistent with street light being an imperfect substitute for natural light. Still, this analysis also reveals that the crime changes seem to come from poor and majority-Black neighborhoods. These areas are the ones that benefit the most from a decrease in robberies when we have more daylight; they also experience the largest increase in assaults, though this effect is more nuanced. Given that robbery is a more costly crime than aggravated assaults (Cohen and Piquero, 2009), fewer robberies offset the cost of more aggravated assaults. Overall, this research suggests that disadvantaged places would benefit the most from having better-illuminated spaces.

Finally, this study is not without limitations. First, future research should explore the impact of ambient light on crime and its mechanisms using a larger, ideally national sample. It would allow the impact on smaller cities and rural areas to be examined. Second, it is worth remembering that "absence of evidence is not evidence of absence", so not finding an effect of perceived risk due to more natural light does not mean it could be found in other contexts. Future research should continue assessing this mechanism. Finally, survey and qualitative data on the impacts of ambient light on perceived risk is a key area of study, as well as, more broadly, how modifications to the built environment impact potential offenders' decision-making.

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Table 1: Descriptive statistics when daylight saving time starts, 2012-2022

	Mean [std. dev]		
	Daily crimes	Sunset crimes	Sunset clearance rate (%)
	(1)	(2)	(3)
Violent	16.16	1.79	27.98
	[20.23]	[2.66]	[35.08]
Murder	0.34	0.04	42.14
	[0.72]	[0.22]	[48.16]
Robbery	6.35	0.72	19.47
	[8.48]	[1.31]	[33.29]
Aggravated assault	9.49	1.03	30.52
	[12.33]	[1.69]	[37.97]
Simple assault	32.63	3.46	28.82
	[45.51]	[5.03]	[31.33]
Weapons violations	2.92	0.35	56.20
	[4.86]	[0.86]	[45.79]

Notes: Mean [standard deviation of] daily crimes from 11 US cities between 2012 to 2022. The data covers three weeks before and after daylight saving time starts. Sunset refers to incidents ocurring between 6:00 pm and 7:59 pm. Clearance rate refers to the proportion of crimes where an arrest happened multiplied by 100. Weapons violations refer to gun discharges, illegal criminal possession, shootings, and brandishing.

Table 2: Regression discontinuity estimates of daylight saving time on sunset crime

	Murder	Robbery	Aggravated assault	Simple assault	Dangerous weapons
	(1)	(2)	(3)	(4)	(5)
DST starts	−0.017	−0.209***	0.215**	−0.209	−0.045
	(0.022)	(0.080)	(0.098)	(0.207)	(0.063)
Change (%)	-42.0%	-28.9%	20.9%	-6.0%	-12.6%
Mean dep. var.	0.04	0.72	1.03	3.46	0.35
Bandwidth (days)	21.0	21.0	21.0	21.0	21.0
Observations	4,601	5,074	5,074	4,601	4,601

Notes: Ordinary Least Squares regression discontinuity estimates of the impact of the start of daylight saving time on sunset crime (between 6:00 pm and 7:59 pm). The model follows equation (1), which includes city, day-of-the-week, and year fixed effects, and daily weather controls (temperature, precipitation, humidity, and visibility). It uses a second-order polynomial function, and data from three weeks around the start of daylight saving time. Robust standard errors in parentheses. The bottom rows exhibit the percentage change (estimate/mean*100), followed by the daily mean between 2012-2022, the bandwidth (in days), and the number of observations. *p<0.1; **p<0.05; ***p<0.01.

Table 3: Regression discontinuity estimates of daylight saving time on sunset cleared crimes

	Robbery	Aggravated assault
	(1)	(2)
A. Proportion of cleared crimes by arrest (clearance rate)		
DST starts	-0.052	-0.037
	(0.056)	(0.055)
Change (%)	-26.8%	-12.0%
Mean dep. var.	0.19	0.31
Bandwidth (days)	21.0	21.0
Observations	1,366	1,750
B. Number of cleared crimes by arrest		
DST starts	-0.041	0.042
	(0.032)	(0.051)
Change (%)	-31.1%	13.3%
Mean dep. var.	0.13	0.32
Bandwidth (days)	21.0	21.0
Observations	5,074	5,074

Notes: Ordinary Least Squares regression discontinuity estimates of the impact of the start of daylight saving time on sunset (between 6:00 pm and 7:59 pm) crimes cleared by arrest. The model follows equation (1), which includes city, day-of-the-week, and year fixed effects, and daily weather controls (temperature, precipitation, humidity, and visibility). It uses a second-order polynomial function, and data from three weeks around the start of daylight saving time. Robust standard errors in parentheses. Panel A uses the proportion of sunset crimes cleared by arrest. Panel B uses the number of sunset cleared by arrest. The bottom rows exhibit the percentage change (estimate/mean*100), followed by the daily mean between 2012-2022, the bandwidth (in days), and the number of observations. *p<0.1; **p<0.05; ***p<0.01.

Table 4: Regression discontinuity estimates of daylight saving time on traffic patterns

	All day (1)	Sunset hours (2)
DST starts	0.145	0.453***
	(0.145)	(0.159)
Bandwidth (days)	21.0	21.0
Observations	2,389	1,956

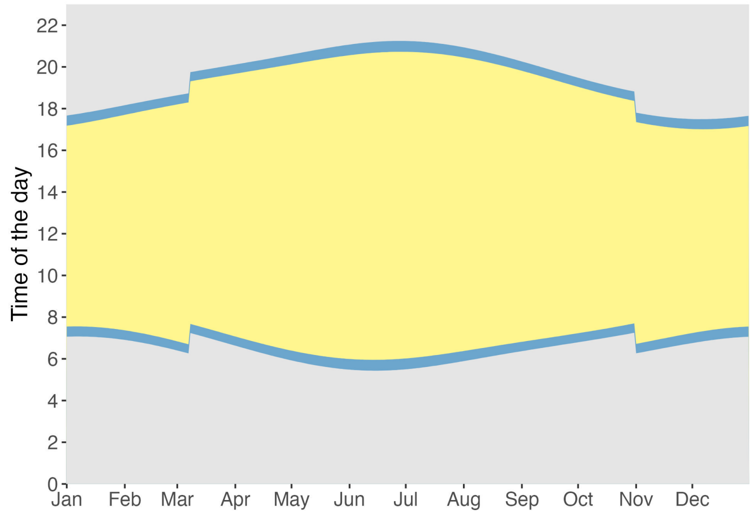
Notes: Ordinary Least Squares regression discontinuity estimates of the impact of the start of daylight saving time on the traffic index during all day and sunset (between 6 pm and 7:59 pm). The traffic index is the standardized average daily count of drivers per intersection, bus riders per bus line, and bike-shared users (each component was standardized and summed into an index). The model follows equation (1), which includes city, day-of-the-week, and year fixed effects, and daily weather controls (temperature, precipitation, humidity, and visibility). It uses a second-order polynomial function, and data from three weeks around the start of daylight saving time. Robust standard errors in parentheses. The bottom rows exhibit the bandwidth (in days) and the number of observations. *p<0.1; **p<0.05; ***p<0.01.

Table 5: Regression discontinuity estimates of daylight saving time on sleep time

	Sleep time (minutes)			
	(1)	(2)	(3)	(4)
DST starts	-30.52^{**}	-22.78^{**}	-11.17	-7.44
	(13.33)	(10.51)	(9.04)	(8.09)
Change (%)	-6.3%	-4.7%	-2.3%	-1.5%
Mean dep. var.	482.79	483.47	483.05	483.41
Bandwidth (days)	14.0	21.0	28.0	35.0
Observations	3,479	4,904	6,580	8,237

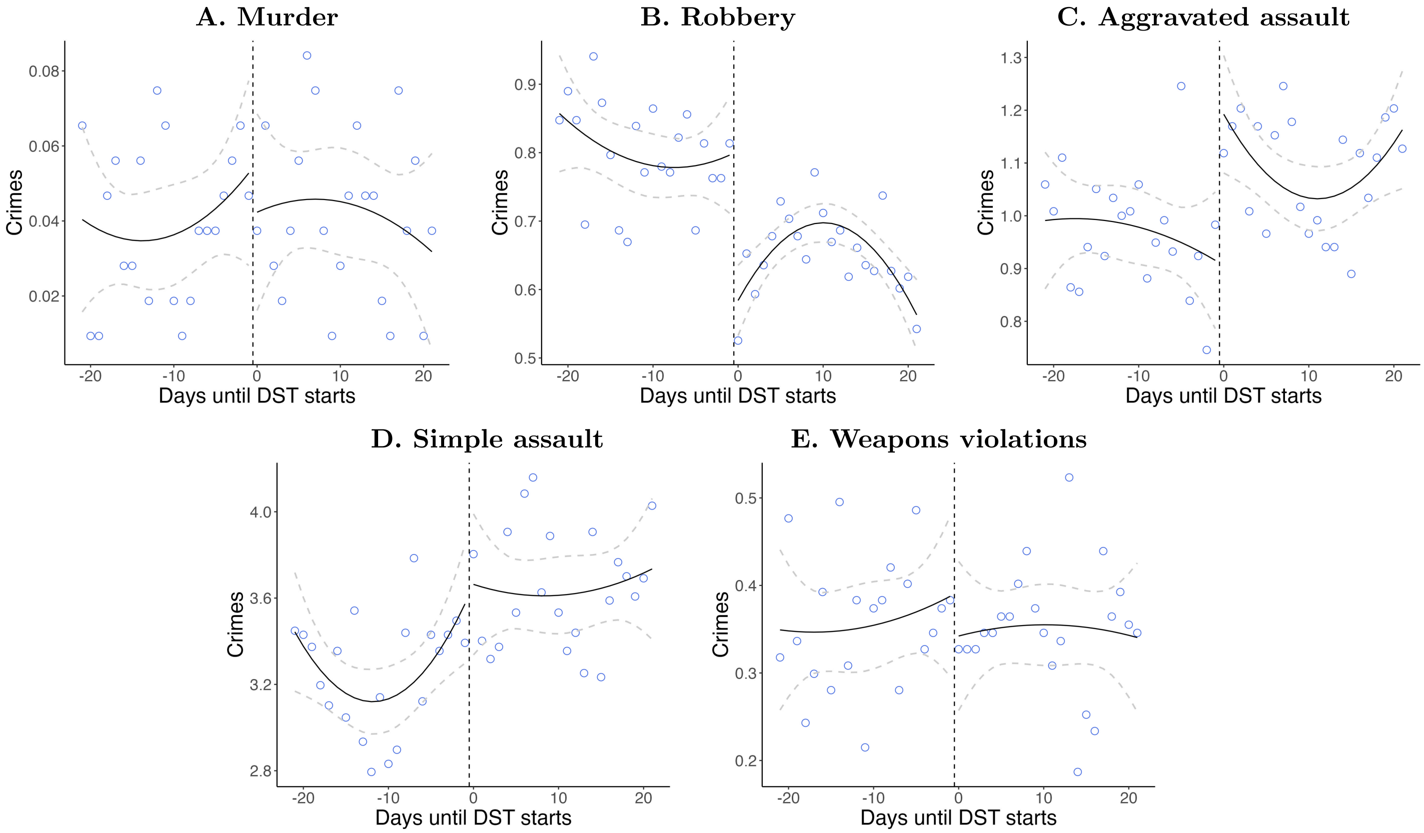
Notes: Ordinary Least Squares regression discontinuity estimates of the impact of the start of daylight saving time on sleep time (in minutes). Sleep time comes from the American Time Use Survey. The model follows equation (3), which includes state, day-of-the-week, and year fixed effects, and individual sociodemographics (age, income, sex, marital and employment status, race, ethnicity, and schooling level). It uses a second-order polynomial function. Robust standard errors are in parentheses. The bottom rows exhibit the percentage change (estimate/mean*100), followed by the daily mean between 2012-2022, the bandwidth (in days), and the number of observations. *p<0.1; **p<0.05; ***p<0.01.

Figure 1: Discontinuity on ambient light due to daylight saving time



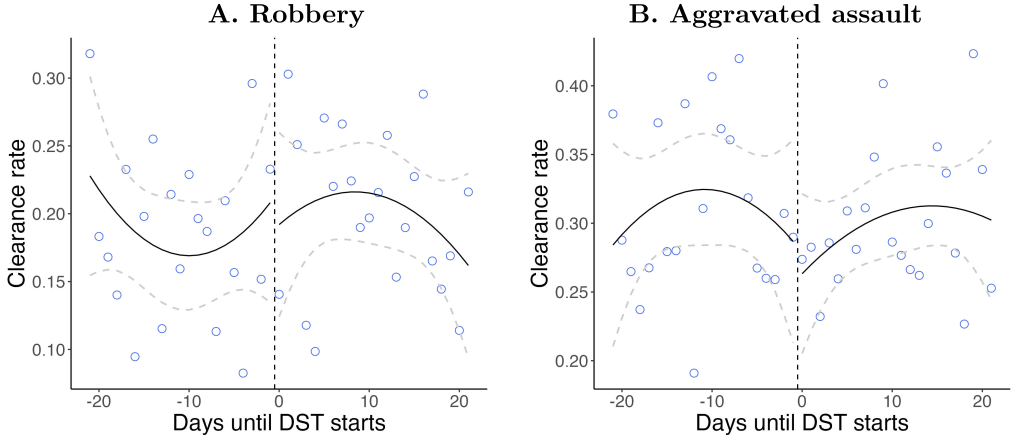
Notes: Average daylight in 2015 in the 11 cities. The bottom and top grey areas represent the night period. The blue bands at the top and bottom represent the twilight period, which is the period before sunrise and after sunset when there is partial illumination by the sun (neither complete darkness nor complete brightness). The middle yellow area represents the daylight period.

Figure 2: Discontinuity on sunset crimes when DST starts



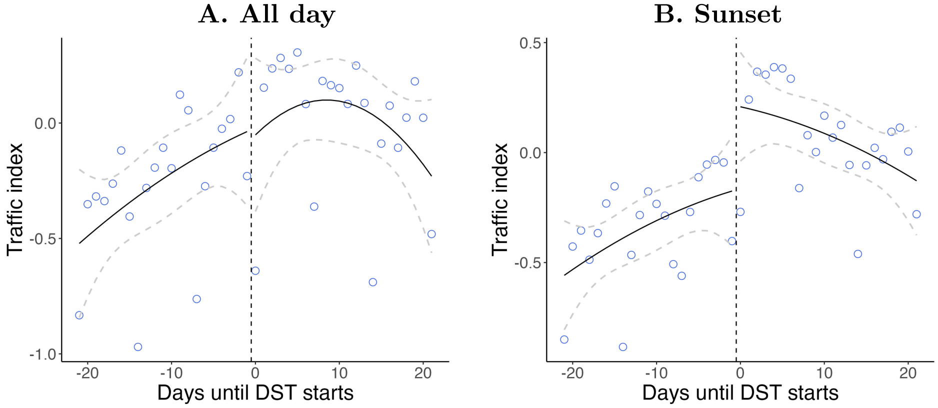
Notes: Mean number of daily crimes happening during sunset (6 pm to 7:59 pm) between 2012 and 2022, around three weeks of the start of daylight saving time, using second-order polynomials (solid line) and 95 percent confidence intervals (dash lines). A positive distance means daylight saving time has started. Weapons violations refer to gun discharges, illegal criminal possession, shootings, and brandishing.

Figure 3: Discontinuity on sunset clearance rate by arrest when DST starts



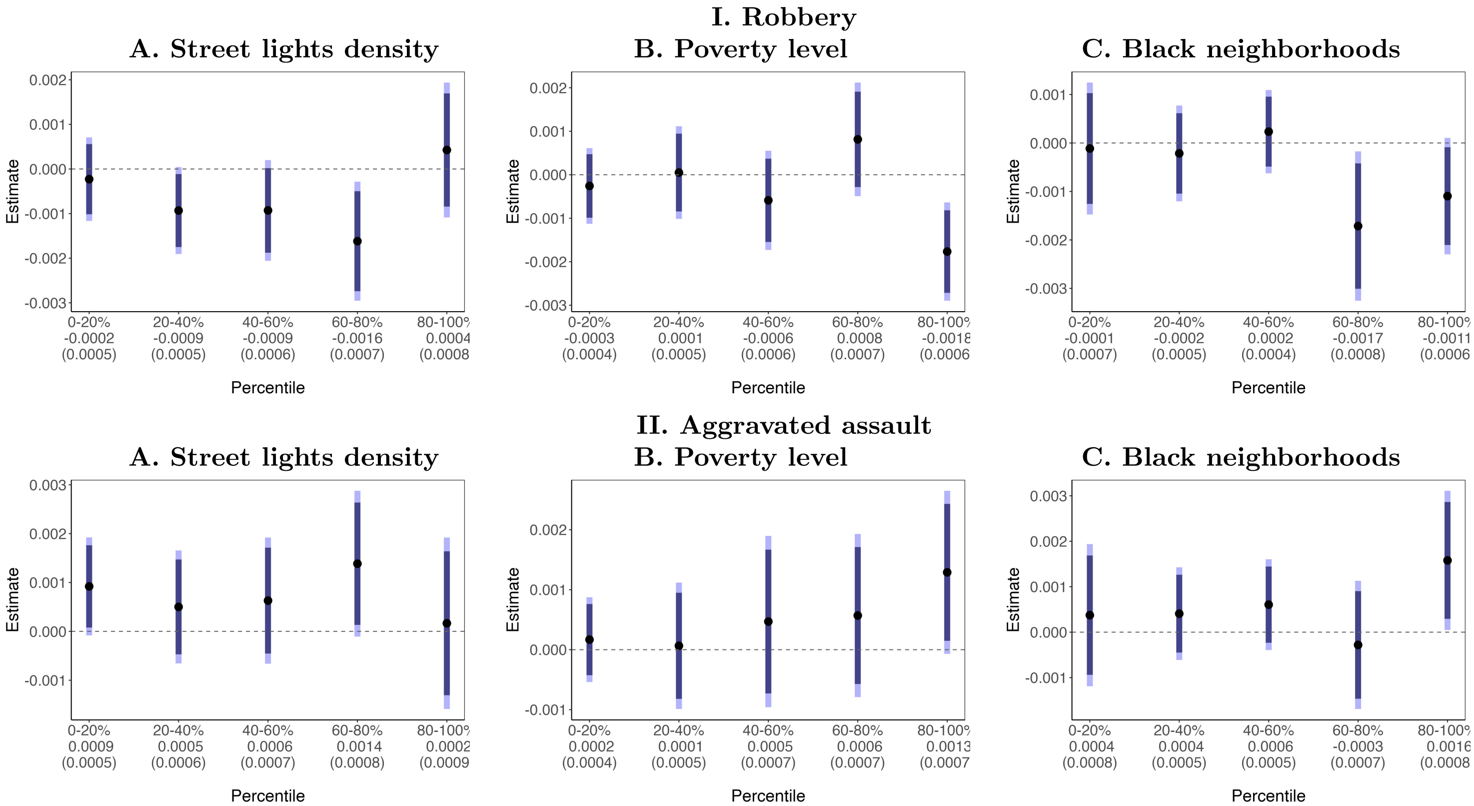
Notes: Proportion of crimes clearance by arrest during sunset (6 pm to 7:59 pm) between 2012 and 2022, using second-order polynomials (solid line) and 95 percent confidence intervals (dash lines) around three weeks of the start of daylight saving time. A positive distance means daylight saving time has started.

Figure 4: Discontinuity on traffic patterns when DST starts



Notes: The traffic index is the standardized daily count of drivers per intersection, bus riders per bus line, and bike-shared users (each component was standardized and summed into an index). The figure shows the second-order polynomials (solid line) and 95 percent confidence intervals (dash lines) around three weeks from the start of daylight saving time. A positive distance means daylight saving time has started.

Figure 5: Regression discontinuity estimates of daylight saving time on sunset crimes, heterogeneous effects



Notes: Ordinary least squares regression discontinuity estimates of the impact of the start of daylight saving time on sunset crime (between 6 pm and 7:59 pm). The model includes census tract, day-of-the-week, and year-fixed effects, and city-level daily weather controls (temperature, precipitation, humidity, and visibility). Each data point is a different specification using only data from the census tracts in its percentile group. The specification uses data from three weeks around the start of daylight saving time. Clustered standard errors at the census tract level are in parentheses. 90% and 95% confidence intervals are included as vertical lines. The bottom rows present the percentile group, regression discontinuity estimate, and standard error in parenthesis.

ONLINE APPENDIX

A Appendix: Additional estimates

Table A.1: Descriptive statistics at the city level, selected years

	Mean (std. dev)		
	2012	2017	2022
Population (thousands)	948.0 (1,121.5)	982.1 (1,150.0)	958.1 (1,099.9)
Age 0-18 (%)	21.2 (3.1)	20.0 (2.9)	19.2 (2.5)
Age 18-64 (%)	67.1 (2.7)	66.5 (2.6)	65.5 (3.0)
Age 65+ (%)	11.7 (2.1)	13.5 (2.3)	15.3 (2.1)
Male (%)	48.8 (1.1)	48.7 (1.5)	49.0 (1.5)
White (%)	55.5 (12.0)	54.8 (11.3)	47.4 (12.0)
Black (%)	28.6 (16.2)	27.7 (16.1)	25.0 (14.4)
Hispanic (%)	15.9 (14.6)	16.4 (14.4)	17.3 (13.7)
Less than high school (%)	14.9 (4.4)	12.8 (4.4)	10.7 (4.0)
High school (%)	23.7 (5.1)	23.2 (5.3)	21.0 (5.4)
Some college (%)	26.7 (3.4)	25.7 (3.5)	24.2 (4.1)
College+ (%)	34.7 (8.3)	38.3 (9.1)	44.0 (9.4)
Unemployment rate (%)	10.7 (2.1)	5.8 (1.8)	5.0 (1.6)

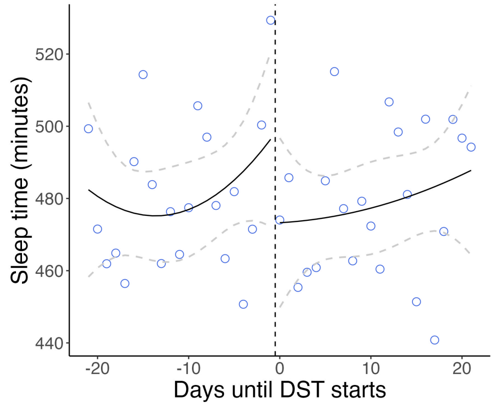
Notes: Mean (standard deviation of) sociodemographic characteristics of 11 US cities. Data comes from the American Community Survey one-year estimates. Standard deviations are in parentheses.

Table A.2: Regression discontinuity estimates of daylight saving time on sunrise crime

	Murder	Robbery	Aggravated assault	Simple assault	Dangerous weapons
	(1)	(2)	(3)	(4)	(5)
DST starts	0.005	0.056	0.054	-0.231^{**}	0.045^{*}
	(0.012)	(0.047)	(0.058)	(0.111)	(0.024)
Change (%)	30.0%	22.1%	15.7%	-18.6%	61.9%
Mean dep. var.	0.02	0.25	0.35	1.24	0.07
Bandwidth (days)	21.0	21.0	21.0	21.0	21.0
Observations	4,601	5,074	5,074	4,601	4,601

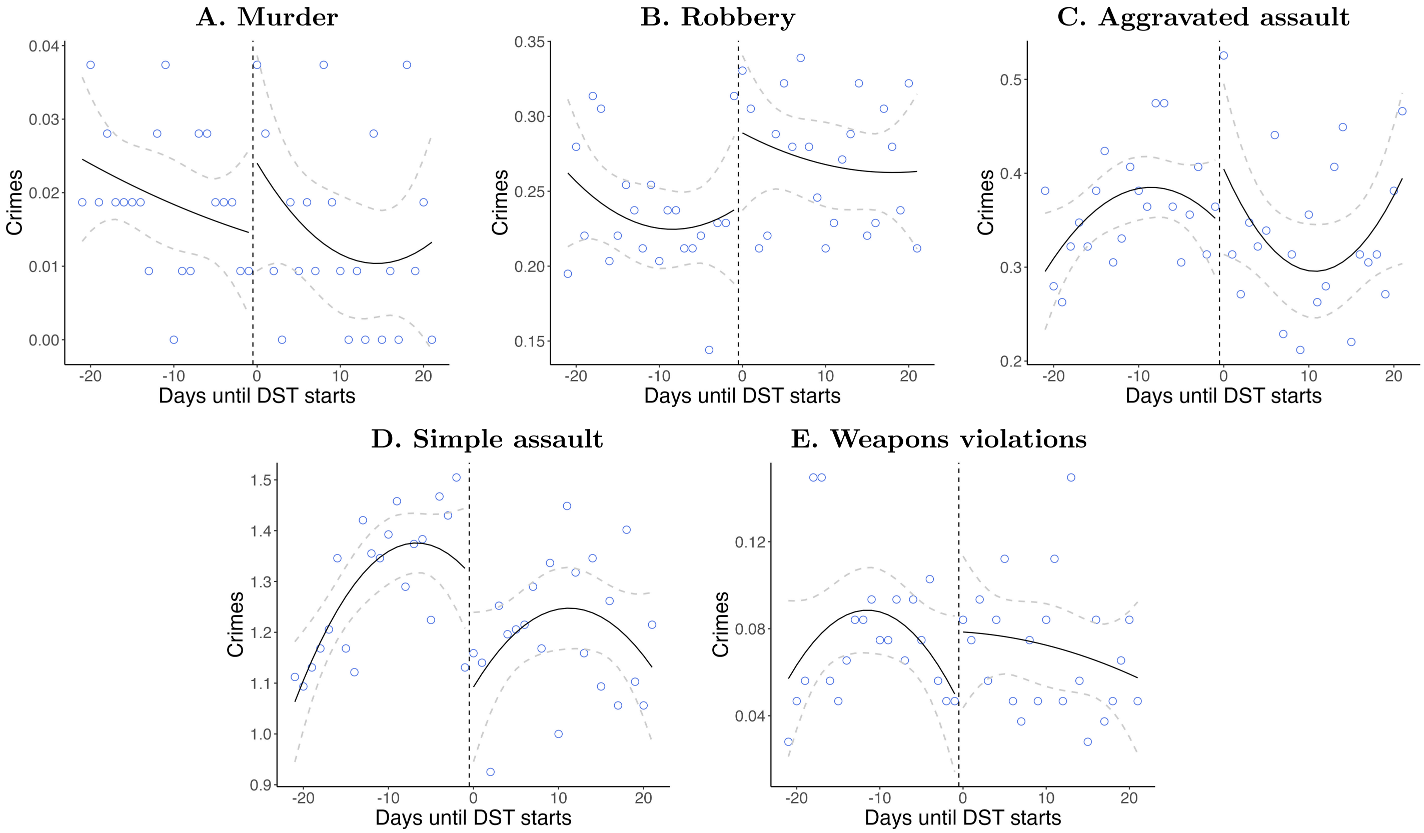
Notes: Ordinary Least Squares regression discontinuity estimates of the impact of the start of the daylight saving time on sunrise crime (between 6:00 am and 7:59 am). The model follows equation (1), which includes city, day-of-the-week, and year fixed effects, and daily weather controls (temperature, precipitation, humidity, and visibility). The specification uses data from three weeks around the start of daylight saving time. Robust-standard errors are in parentheses. The bottom rows exhibit the percentage change (estimate/mean*100), followed by the daily mean between 2012-2022, the bandwidth (in days), and the number of observations. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Figure A.1: Discontinuity on sleep time when DST starts



Notes: Average daily sleep time between 2012 and 2022 around three weeks of the start of daylight saving time, using second-order polynomials (solid line) and 95 percent confidence intervals (dash lines). A positive distance means daylight saving time has started. Sleep time comes from the American Time Use Survey.

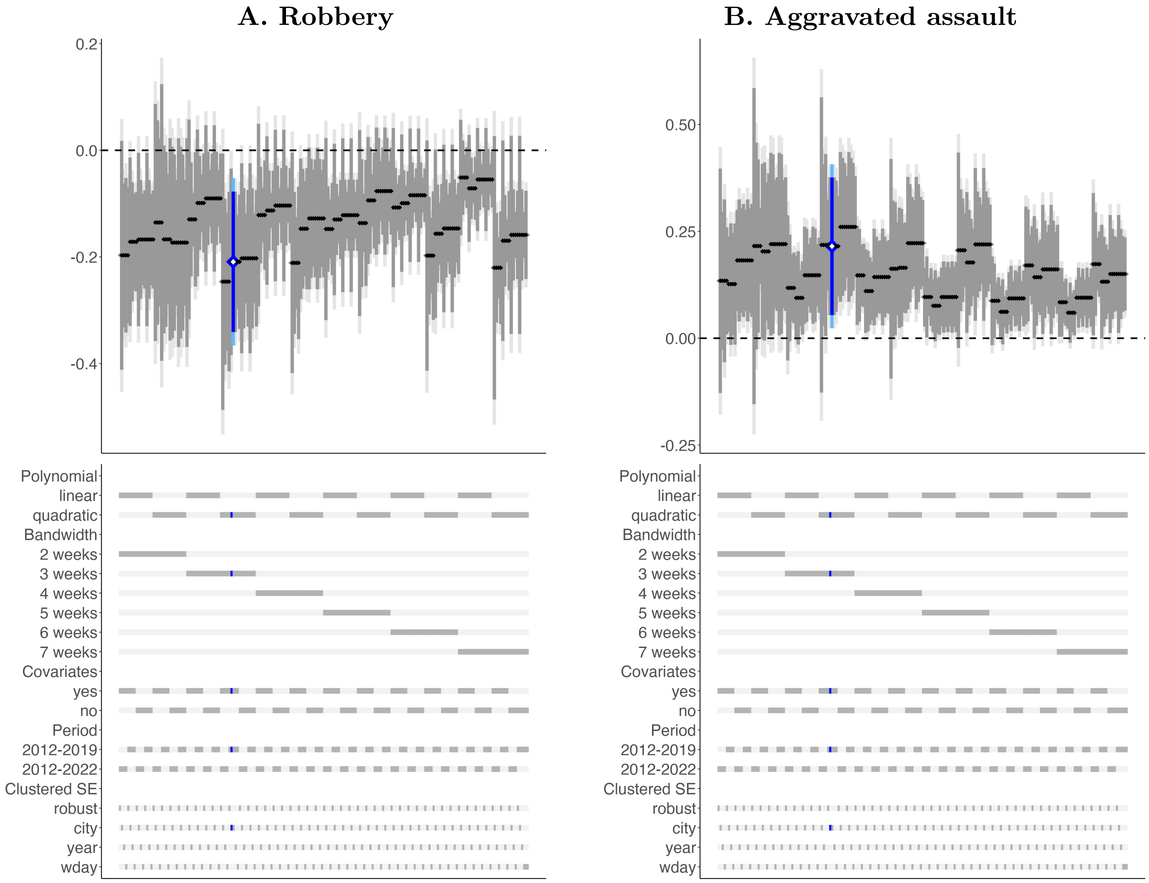
Figure A.2: Discontinuity on sunrise crimes when DST starts



Notes: Mean number of daily crimes happening during sunrise (6 am to 7:59 am) between 2012 and 2022, using second-order polynomials (solid line) and 95 percent confidence intervals (dash lines) around three weeks of the start of daylight saving time. A positive distance means daylight saving time has started. Weapons violations refer to gun discharges, illegal criminal possession, shootings, and brandishing.

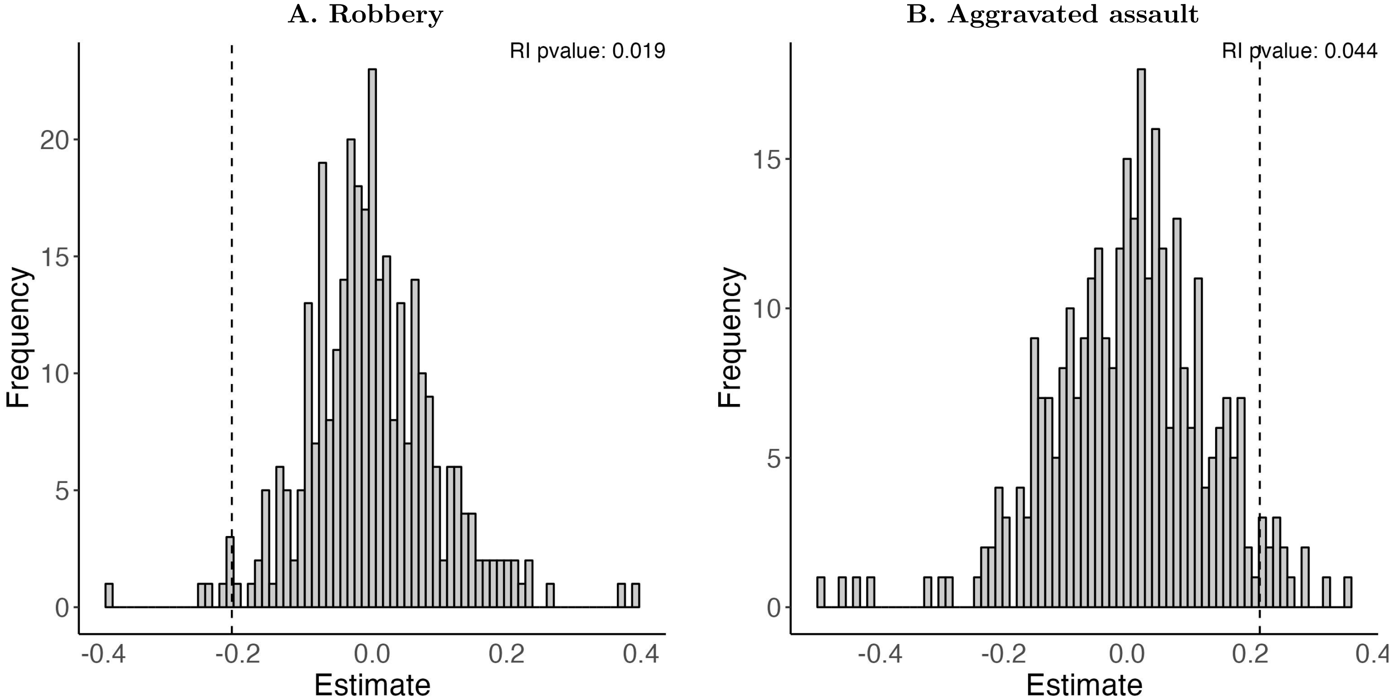
B Appendix: Robustness checks when daylight saving time starts

Figure B.1: Regression discontinuity of daylight saving time on sunset crime, alternative specifications



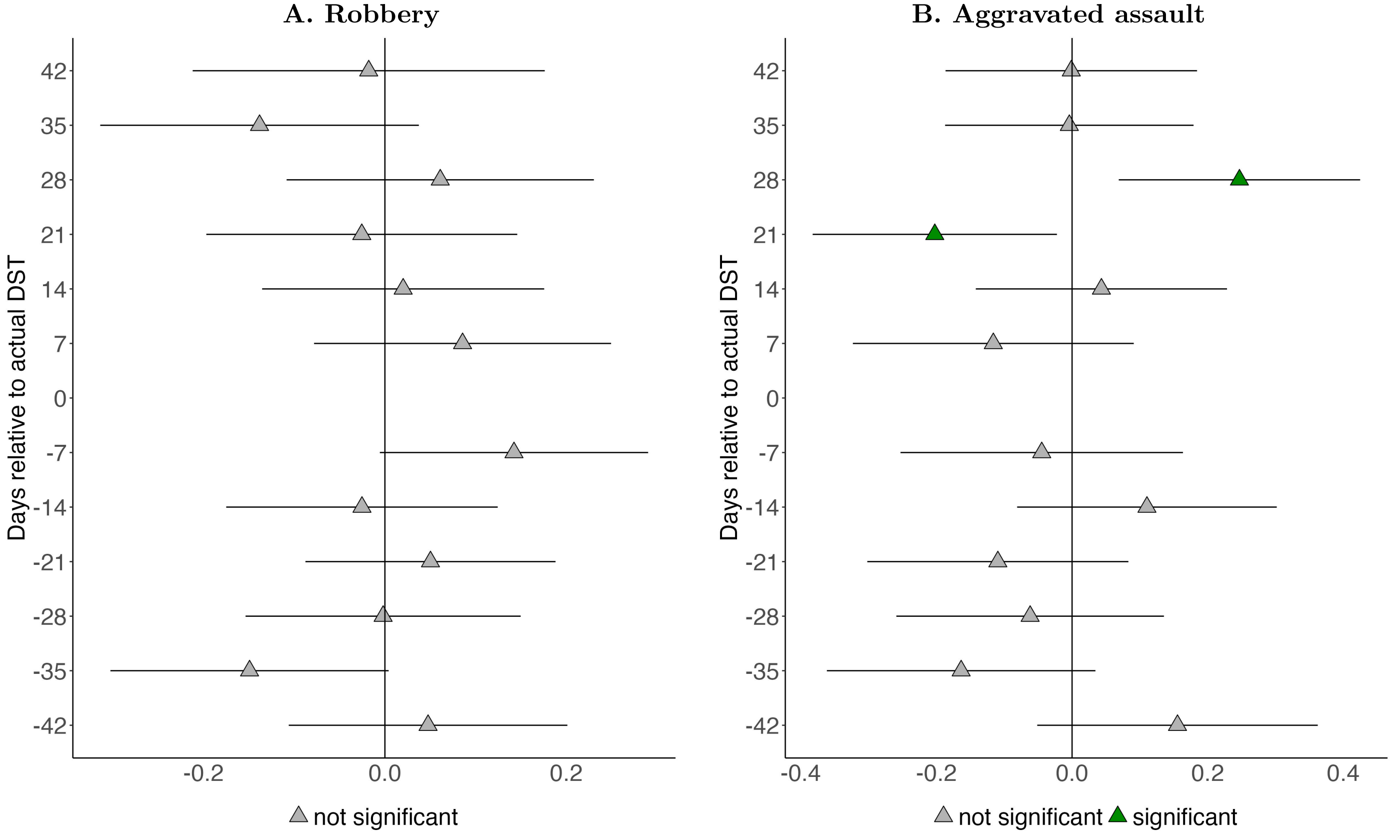
Notes: Ordinary Least Squares regression discontinuity estimates on sunset crime (between 6 pm and 7:59 pm). The specification modifies its bandwidth (two to seven weeks), polynomial function (1st, 2nd, and 3rd), controlling for weather conditions (with and without covariates), and standard errors estimation (robust and clustered at the city, year, and day-of-the-week). The main specifications, highlighted in blue, are estimated using Calonico et al. (2015) and Imbens and Kalyanaraman (2012) bandwidths.

Figure B.2: Regression discontinuity of daylight saving time on crime, Randomization inference



Notes: Ordinary least squares regression discontinuity estimates of the impact of the start of daylight saving time on sunset crimes (between 6 pm and 7:59 pm). The model follows equation (1), which includes city, day-of-the-week, and year-fixed effects and daily weather controls (temperature, precipitation, humidity, and visibility). The specification uses a second-order polynomial function. The randomization inference (RI) shifts the 'start' of daylight saving time to the different Tuesdays, Thursdays, and Sundays in the year, excluding March and November (months on which daylight saving time changes). The main specifications, highlighted in vertical dashed lines, are estimated using Calonico et al. (2015) and Imbens and Kalyanaraman (2012) bandwidths.

Figure B.3: Regression discontinuity of daylight saving time on sunset crime, placebo cut-off values



Notes: Ordinary Least Squares regression discontinuity estimates of the impact of the start of daylight saving time on sunset crimes (between 6 pm and 7:59 pm). The model follows equation (1), which includes city, day-of-the-week, and year-fixed effects and daily weather controls (temperature, precipitation, humidity, and visibility). The specification uses a second-order polynomial function. The placebo test shifts the actual change of daylight saving time to a placebo date, ranging from one to six weeks in seven-day increments, and estimates the optimal bandwidth following Calonico et al. (2015). The 95 percent confidence intervals and their statistical significance are marked in the figure.

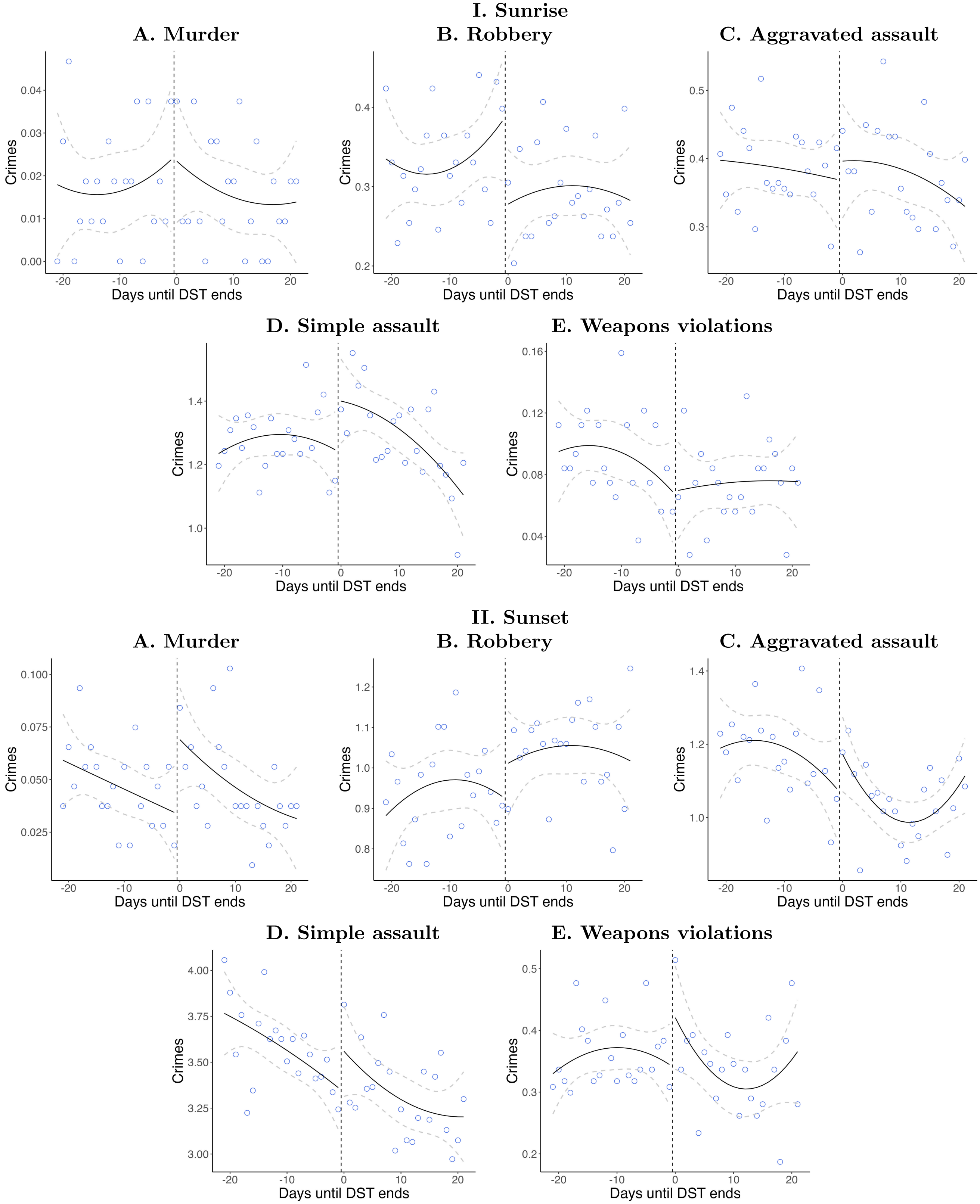
C Appendix: Public safety impacts when daylight saving time ends

Table C.1: Regression discontinuity estimates of daylight saving time on crime, Fall DST ends

	Murder	Robbery	Aggravated assault	Simple assault	Dangerous weapons
	(1)	(2)	(3)	(4)	(5)
A. Sunrise (6 am to 7:59 am)					
DST ends	−0.005	−0.119**	−0.023	0.126	0.004
	(0.014)	(0.056)	(0.061)	(0.110)	(0.028)
Change (%)	-31.1%	-38.0%	-6.2%	9.9%	4.6%
Mean dep. var.	0.02	0.31	0.38	1.28	0.08
Bandwidth (days)	21.0	21.0	21.0	21.0	21.0
Observations	4,601	5,074	5,074	4,601	4,601
B. Sunset (6 pm to 7:59 pm)					
DST ends	0.035*	0.070	0.066	0.040	0.093
	(0.020)	(0.093)	(0.104)	(0.194)	(0.060)
Change (%)	74.8%	7.1%	5.9%	1.2%	26.8%
Mean dep. var.	0.04	1.00	1.10	3.44	0.34
Bandwidth (days)	21.0	21.0	21.0	21.0	21.0
Observations	4,601	5,074	5,074	4,601	4,601

Notes: Ordinary Least Squares regression discontinuity estimates of the impact of the end of the daylight saving time on crime. The model follows equation (1), which includes city, day-of-the-week, and year fixed effects, and daily weather controls (temperature, precipitation, humidity, and visibility). The specification uses data from three weeks around the ends of daylight saving time. Robust-standard errors are in parentheses. The bottom rows exhibit the percentage change (estimate/mean*100), followed by the daily mean between 2012-2022, the bandwidth (in days), and the number of observations. *p<0.1; **p<0.05; ***p<0.01.

Figure C.1: Discontinuity on crimes when DST ends by time of the day



Notes: Mean number of daily crimes happening during sunrise (6 am to 7:59 am) or sunset (6 pm to 7:59 pm) between 2012 and 2022, using second-order polynomials (solid line) and 95 percent confidence intervals (dash lines) around three weeks of the end of daylight saving time. A positive distance means daylight saving time has started. Weapons violations refer to gun discharges, illegal criminal possession, shootings, and brandishing.