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Abstract[*]

This paper studies the effect of ambient light on crime, taking advantage of the daylight saving time (DST) policy, which imposes exogenous variations in daylight exposure at specific hours of the day. The paper uses a rich administrative database managed by Chile's national police, a centralized agency that collects detailed information regarding each crime incident. A 20% decrease (increase) in crimes is found when the DST transition increases (decreases) the amount of sunlight by one hour during the 7-9 p.m. period. Importantly, no significant response is detected induced by DST associated with a plausible demand-side response such as the population's commuting time pattern, and no substantial short-term displacement is found. Most of the changes in property crime due to the DST policy are driven by robbery in residential areas.

JEL classifications: K42, R41, D01
Keywords: Economics of crime, Daylight Saving Time, Rational choice

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1. Introduction

Popular wisdom often identifies darkness with criminal activity. In Charles Dickens' novels, for example, crime usually happens under the so-called "cover of darkness." This association is not confined to fiction. In a famous case, as a young lawyer Abraham Lincoln tried a case in which the alleged amount of light was very important. The future President of the United States discredited one of the key testimonies against his defendant showing that the light provided by the moon would not have actually allowed the witness to identify the murderer from around 100 yards away, as he had previously declared. [1] In spite of that belief, empirical evaluations documenting this effect are scarce. Part of the limitation is because comparisons of crime patterns during a day will offer a spurious estimate of this relationship because ambient light and other determinants of crime may spuriously correlate in the course of a day.

In this study, we present several estimates of the effect of ambient light in a highly populated dense and urban area as Santiago, Chile. We find that reducing (increasing) the amount of ambient light substantially increases (reduces) criminal activity. We take advantage of the Daylight Savings Time (DST) policy, which imposes exogenous variation in ambient light during certain hours of the day, to analyze how ambient light impacts criminal activity. In particular, we find that in the vicinity of the DST transition, crime decreases by 20% when DST increases the amount of sunlight by one hour during the 7-9 p.m. period. These findings are mainly driven by robbery, and to some degree, theft and motor vehicle theft. On the other hand, we find a 17% increase in overall criminal activity when the DST transition sharply decreases the daylight exposure for the same time of the day. Our results are valid under several specification checks, including two different sources of exogenous variation.

We use a rich administrative database provided by the Chilean Government and collected by the national police (Carabineros de Chile). The main advantages of this database are that it covers the full universe of reported crimes and is collected by a centralized police agency. Both factors are crucial for comparability purposes (e.g., when comparing different years and times of day within a large urban area). We have detailed information about each crime incident (day, time, georeferenced location geocoded) for the 2005–2010 period, and the two main Chilean metropolitan areas: Santiago and Valparaíso.

This paper attempts to make several contributions. We successfully replicate many of the findings presented by Doleac and Sanders (2015) who offers the most rigorous study of the

[1] By using an almanac Mr.Lincoln shows that the moon had set before the time of the incident. For more details, see Henry Fonda and John Ford's film *Young Mr. Lincoln* (1939)

effect of variation in ambient light caused by DST on crime in a notably different setting. We focus on a large and densely populated urban area, which represents an important setting for discussing the replicability of previous results. By relying on the NIBRS database, Doleac and Sanders (2015) estimates are representative of a large population and a relatively diverse geographic area, but highly concentrated in low-density and rural areas in the United States that may not necessarily be representative of large urban settings where most of the population live. Despite notorious differences across countries, [2] an examination of the results in a highly urbanized city such as Santiago, Chile can be informative not only for cities in less industrialized countries but also in many large metropolitan areas across the world. With a population of over 6 million people, Santiago is the sixth largest city in Latin America and among the 50 most populated cities in the world, as well as the 28th most densely populated city on earth. [3]

In terms of the results, as opposed to Doleac and Sanders (2015), we do detect a consistent response when DST imposes a reduction in ambient light during sunset hours. The fall DST transition offers a natural way to test the relationship between ambient light and crime. In a previous and extended version of the paper Doleac and Sanders (2012) report a small and barely significant reduction in robbery during sunset hours. It is hard to reconcile this finding through the sunlight mechanism, however, since the fall DST transition imposes a reduction in ambient light during sunset hours. [4] Doleac and Sanders (2015) claim that the coincidence of the fall DST transition with Halloween is confounding the relationship between criminal activity and sunlight due to an unusual activity at sunset hours that may prevent them for detecting a consistent effect. In our case, we do detect a significant increase in crime when DST imposes a reduction in ambient light at sunset hours. Consistent with the spring DST transition, this result is especially driven by robbery, and to a lesser degree by motor vehicle thefts. Importantly, in terms of the magnitude of the variation the response is symmetric, which reinforces the negative relationship between ambient light and criminal activity.

We also analyze potential temporal re-allocations of criminal activity associated with the variation in sunlight imposed by DST policy. We find no evidence of substantial displacement to other periods of the day. Although we cannot rule out all other possible types of

[2]Both areas differ in many regards, but a particularly important one is the pattern of criminal activity. The average annual murder rate (incidents per 100,000 inhabitants) is considerable lower in Santiago (2.05) than the average value of Doleac and Sanders (2015) database (5.14), while the comparison in robbery rates reverses: 507.56 in Santiago versus 120 annual incidents per 100,000 population in the sample used by Doleac and Sanders (2015)

[3]Source: City Mayors ranking available at www.citymajors.com. Extracted on May 6, 2019.

[4]However, they do report a positive and economically significant response in shoplifting and burglary. See Table 7 for details on each crime category

displacement (e.g., across crime types, level of violence exhibited by offenders and kind of victims), our results suggest that evidence in favor of short-term displacement within a day is at most weak, and not consistent when comparing opposite DST transitions. Only a portion of the crime reduced at sunset hours, if any, seems to be compensated by an increase during nighttime hours; this coincides with the fact that the overall daily variation associated with DST policy is similar in magnitude to the variation observed at sunset hours.

By focusing on a single large city we are able to discuss several novel issues regarding the effect of ambient light on crime. We take advantage of other sources of information to analyze the degree to which our reduced-form results on criminal activity could be driven by other types of responses. In particular, we focus on victim's behavior that, according to Cook, Ludwig, and McCrary (2011), has been "largely neglected in the economics literature" (Cook et al., 2011, p.10). Using high-frequency data from Santiago's subway ridership, we analyze whether the variation in ambient light is also associated with changes in ridership, and we do not find significant variation induced by the DST transition. Of course, this piece of information cannot rule out other possible endogenous responses associated with victim or police behavior; however, that information is at least suggestive that potential offender or supply-side responses, rather than victims' endogenous reactions, could be driving our results.

Furthermore, we combine detailed information on crime incidents with property tax administrative databases to study treatment effect heterogeneity by land use. Crime responses in areas that are intense in different uses can differ for a set of reasons. We hypothesize that environmental differences across areas can affect the way ambient light impacts criminal activity and temporal displacement. In particular, we study whether our estimates differ across areas, using the exact location of crimes to classify the type of land where each incident took place. We highlight two important findings from this analysis. First, we observe that our results are mainly driven by what happens in residential areas. A plausible explanation has to do with differences in how residential and non-residential areas are served by public and street lights. This result is consistent with Chalfin, Hansen, Lerner, and Parker (2019) who find that communities that were assigned more lighting experienced sizable reductions in crime. We further discuss the implications of this finding, which could reinforce the negative relationship between ambient light and criminal activity. Finally, by analyzing heterogeneity across land-use types we also observe that any temporal displacement of criminal activity is more likely to take place in commercial and service areas.

This paper is organized in seven sections. First, we discuss some theoretical implications of daylight for crime, and review some similar empirical estimations in the literature. In the third and fourth sections, we describe the crime data, the empirical strategies and their

results. The fifth section of extension presents several robustness tests of our identification strategy focusing on a different DST transition and estimates for each hour of the day. We also include heterogenous responses estimating several coefficients by each crime category. The fifth section is the conclusion. Finally, we offer a rich Appendix with tables and figures that complement the basic results of this paper.

2. Daylight and Criminal Activity

In the economics of crime literature scholars usually refer to Becker (1968)'s framework to analyze the theoretical avenues through which criminal activity is deterred. Although its theoretical foundations can be traced back to the much earlier work on deterrence theory of Beccaria and Bentham, Becker (1968) developed an analytical framework for optimal crime control policy that assumes a specific model for criminal behavior. [5] Becker's economic approach does not rely on ad hoc concepts such as differential association or *anomie* to explain criminal behavior; rather, he focused on incentives. He assumed that criminal behavior can be modeled as a choice made by a person whose expected utility exceeds what he could achieve at other activities. In that sense, "persons become *criminals*, therefore, not because their basic motivations differ from that of other persons, but because their benefits and costs differ" (Becker, 1968, p.176).

Briefly, Becker's formulation characterizes the decision to commit an offense as a function of three groups of variables: i) his/her probability of conviction and punishment if convicted, ii) income available for that person in legal and illegal activities, and iii) his/her willingness to commit an illegal act [6]. Under this framework, variation in daylight hours may affect the chances that an offender is identified and consequently his or her probability of capture.

Following Becker, we hypothesize that the likelihood of committing a crime will depend on the costs and benefits of offending at a particular time of the day. Thus, offender's likelihood of committing a crime can be written as follows:

$$P[U(\text{Criminal Activity}) > U(\text{Non-criminal Activity})] = P[B - pC > U_{NC}] \tag{1}$$

where B represents the benefits of offending, p the probability of capture, and C the costs of offending, including all perceived monetary and non-monetary costs associated with

[5] For an overview of the evidence on the deterrent effect of police, imprisonment, and capital punishment see Nagin (2013)

[6] Since then, many efforts have been made to incorporate other legal and non-legal aspects of crime, such as the feeling of shame and embarrassment as an explicit cost of crime (Williams and Hawkins (1989); Grasmick and Bursik Jr (1990); Hechter and Kanazawa (1997) and notions of human agency and decision-making skills (Cornish and Clarke (1987).

offending. We can argue that a sharp variation in the amount of light during a certain period of the day may affect B, C and p. U_{NC} represents the net utility of a non-criminal activity available to the potential offender [7]. A reduction in ambient light may reduce an offender's probability of being identified and then prosecuted, which subsequently affects the probability of capture: $\frac{\partial p}{\partial Light} > 0$. In that sense, ambient light deters criminals from offending, thus reducing criminal activity.

On the other hand, since B and C are determined by all crime opportunities available at a particular time h we could anticipate two additional reactions to an increase in ambient light. Victims may react to the lower perceived risk (as a result of the increase in offender's probability of capture) by i) decreasing the level of effort they devote to protecting their goods, which will decrease the costs of offending $\frac{\partial C}{\partial Light} < 0$, or ii) increasing the likelihood of circulating with more valuable goods, which will increase the benefits of offending either by increasing the value of the (potential) stolen good $\frac{\partial B}{\partial Light} > 0$ or decreasing offender's costs of searching $\frac{\partial C}{\partial Light} < 0$. In all these cases, criminal activity may increase as a result of an increase in ambient light. In a way, since we cannot define a priori which effect will be larger, the effect of ambient light on crime is an empirical matter [8].

Regarding empirical estimates, Van Koppen and Jansen (1999) offers one of the first attempts to measure the effect of ambient light on criminal activity. They compare daily, weekly and seasonal variations of the number of commercial robberies in the Netherlands between 1988 and 1994 and find that the crime rate is higher in winter than in summer. They attribute that gap to the difference in the number of dark hours during the day. However, by relying on OLS analysis using observational data from both summer and winter seasons their estimates are subject to a set of potential confounders.

A crucial innovation in this literature is Doleac and Sanders (2015) who offers the most rigorous study of the effect of variation in ambient light caused by DST on crime. Their research strategy relies on two different sources of variation: a change in the timing during the year when the DST policy was implemented for some particular years, and a regression discontinuity (RD) design using the DST transition to identify sharp variation in sunlight. They focus on felony robbery and other violent crimes such as rape, aggravated assault, and murder. Doleac and Sanders (2015) find a 27% decrease in the robbery rate during sunset hours that drives much of the overall 7% decrease in the robbery rate.

[7] To actually calculate offender's likelihood of offending, we can follow Glaeser (2008), in which gains in the non-criminal sector equal $U = U + u$, where u is distributed across the population with a cumulative distribution $F(u)$ and a density $f(u)$. Thus, the marginal criminal is represented by $B - pC > U_{NC}$, and the total number of criminals can be approximated by $F(B - pC - U)$

[8] In a similar way, Doleac and Sanders (2015) interpret their results as "the net effect of an increase in ambient light from DST" (Doleac and Sanders, 2015, p.10)

One potential limitation of Doleac and Sanders (2015) has to do with the external validity of the results. National Incident-Based Reporting System (NIBRS) is a rich database of 558 United States jurisdictions, which covers a total population of approximately 22 million for years 2005-2008. However, most of the jurisdictions covered in the NIBRS survey are in low-density and rural areas. To the extent that urban and rural areas differ in terms of criminal activity (Glaeser and Sacerdote (1999), Grogger and Willis (2000), and especially in the way ambient light shapes criminal activity, Doleac and Sanders (2015)' estimates may not necessarily reproduce in high-density and urban areas where most people live.

Finally, another closely related study is Chalfin et al. (2019) who conduct the first experimental evaluation on the effect of street lighting on crime. They randomized the provision of street light by installing temporary lighting towers to housing developments across New York City. Although their intervention is very different to the one-hour variation in ambient light at sunset hours imposed by DST, they also find a strong negative relationship between light and criminal activity; in particular they find that provision of street light led to at least 36 percent reduction in outdoor index crime during night hours.

3. Empirical Analysis

We use administrative data from all crime reported to police between 2005 and 2010. Each crime report contains information about the time and location where the crime was perpetrated, and it classifies each crime according to 10 different categories. Our analysis is mainly focused on Santiago, Chile, a city of more than 6 million inhabitants. Crime reports are collected by the Chilean police, which is a very centralized organization (Carabineros de Chile). They collect detailed information directly from the victims that includes crime category, location and time of the incident among other characteristics. Table 1 summarizes the major crimes reported for the years of our analysis. We excluded from the analysis injuries and domestic violence offenses since they are unlikely to be affected by changes in sunlight hours.

We also collect information on actual DST implementation for each year in Santiago. We obtained the precise day of DST implementation for each year based on the 1489 Act records (Decreto 1489). In "normal" years DST transitions occurs after the second Saturday of March (fall transition) and October (spring transition). In addition, we collected data on exact sunset and sunrise hours in 2005, in which we can observe the sharp variations in terms of sunlight exposure associated with a particular DST transition during a "normal" year. Figure 1 shows the daily evolution of sunset (blue line) and sunrise hours (red line) in 2005.

Table 1: Total Crimes by Year: Region Metropolitana, Chile

Year	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Robbery	30,921	33,050	37,948	33,249	31,754	27,983
Larceny	8,708	9,510	12,335	11,663	12,914	12,445
Vehicle Theft	7,494	9,357	12,931	13,555	16,837	18,529
Theft from a Motor vehicle	23,692	20,706	23,848	24,567	27,528	30,902
Burglary w/people	22,783	21,518	22,308	21,544	21,302	20,104
Burglary w/o people	10,704	12,672	12,459	12,583	13,074	12,951
Other Robberies	1,409	3,028	1,921	1,598	1,513	2,282
Theft	30,523	30,609	33,122	34,337	35,687	36,797
Murder	131	148	166	123	128	95
Rape	934	963	919	1,091	1,019	879
Total	**137,299**	**141,561**	**157,957**	**154,310**	**161,756**	**162,967**

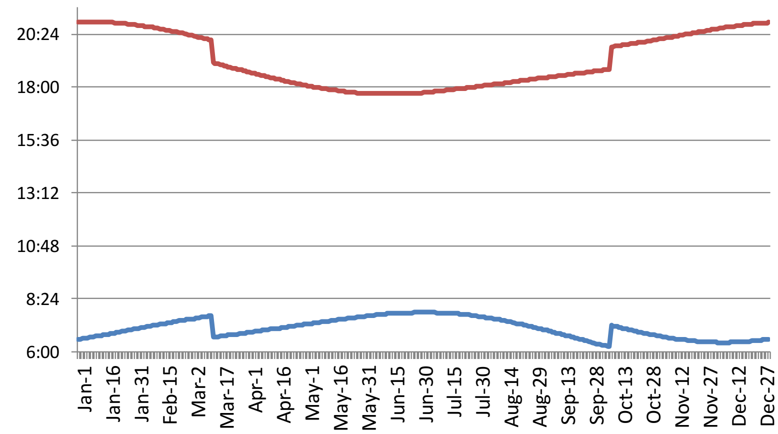
Source: AUPOL, Carabineros de Chile, Subsecretaría del Delito, Ministerio del Interior, Chile.

Importantly, we found two exceptional episodes in 2008 and 2010 DST when the March transition was delayed for three weeks due to natural causes: the 2008 drought and the 8.8 Richter scale earthquake (2/27/2010) that largely affected the central part of the country. In the empirical strategies section we discuss these two exceptions, which are crucial to one of our identification strategies.

The empirical challenge of this paper is to analyze the relationship between daylight exposure and criminal activity. As we discussed earlier, the main problem is that it is hard to disentangle the extent to which sunlight modifies people's behavior in terms of their decision and activities, which may affect opportunities for crime and the behavior of potential offenders. Rather than an attempt for a complete description of the criminal behavior where sunlight exposure may be an important factor, we rely on two exogenous variations that offer an opportunity to empirically estimate the causal effect. Given the data we have available we are able to estimate this effect for different situations. In particular, we estimate the effect of DST transition on crime for different times of day and in two different periods of the year. In addition, we offer a complementary identification strategy that also relies on exogenous variation in ambient light across the calendar year.

First, we describe a regression discontinuity design that takes advantages of the sharp variation in daylight exposure that DST transition produces around sunrise and sunset hours. We use this approach to test whether an increase/reduction in daylight exposure causes a reduction/increase in crime when the two DST transitions of each year are considered. We complement that approach by implementing a second identification strategy which relies on

Figure 1. Sunrise and Sunset Hours in 2005



Note: Red and blue lines represent respectively the exact sunset and sunrise times for each day of the year. Source: Astronomical information extracted on February 2, 2016 from www.tutiempo.net.

a different source of variation due to an exogenous delay in the DST transition that occurred during the period for which data are available. As we mentioned before, in 2008 and 2010 the Government decided to delay the fall transition (March) by three weeks. We believe that this exogenous variation offers another research opportunity to analyze the effect of daylight on crime. In this section we describe the details of each approach.

3.1. Sharp Regression Discontinuity Design

The potential outcomes framework or the so called Neyman-Rubin causal model (Sekhon (2008)) offers a simple way to specify why, under certain circumstances, a regression discontinuity design yields a causal estimate of a particular effect (Imbens and Lemieux (2008)). Its basic identification assumption is that the conditional expectation functions of potential outcomes are continuous in the vicinity of a certain cutoff. Our dependent variable Y_i represents the amount of criminal activity observed during a particular period of the day, and X_i is some temporal measure that indicates proximity to DST transition. Formally, we can write:

$$E[Y_i(0)|X_i = x] \text{ and } E[Y_i(1)|X_i = x] \text{ are continuous in } x \tag{2}$$

Thus, we can estimate the average treatment effect ρ around a certain point c as follows:

$$\rho = \lim_{x \to c^+} E[Y_i|X_i = x] - \lim_{x \to c^-} E[Y_i|X_i = x] = E[Y_i(1) - Y_(0)|X_i = c] \tag{3}$$

In our case we implement this strategy for causal inference since we know the exact rule that describe the treatment assignment, which in this case is determined by the time-schedule imposed by Daylight Saving Time policy. The continuity assumption requires smoothness in a small neighborhood of the DST transition, so any discontinuity of the conditional distribution of the outcome at the threshold value can be interpreted as evidence of a causal effect (Imbens and Lemieux (2008)). In this case the treatment can be defined as a sharp variation in daylight exposure, which is precisely determined by the DST transition. In particular, we focus on the one-hour variation imposed by DST transition twice a year. In terms of sunlight exposure, for each DST transition there are two times of day that are highly exposed to this source of variation; and we call them sunset (19:00-20:59) and sunrise (6:00-7:59) hours. There is no reason to believe that other times of day (nighttime and daytime) are exposed to this particular treatment during that same period. Following Angrist and Pischke (2008), we propose a simple model whose specification directly estimates the causal effect of DST transition on crime at the period of the day h, so we run several regressions depending on the period of the day (h) we focus on:

$$\log(Crime_{i,t,h}) = \alpha_h + \beta_{1,h}X_{i,t,h} + \beta_{2,h}DST_{i,t,h}X_{i,t,h} + \rho_h DST_{i,t,h} + \omega_{i,h} + \psi_{t,h} + \epsilon_{i,t,h} \quad (4)$$

The dependent variable $\log(Crime_{i,t,h})$ measures the log of total crimes for a particular day i, year t, during the daytime period h. Unless otherwise specified, $Crime_{i,t,h}$ considers all robbery, larceny, theft, vehicle theft, burglary, murder, and rape incidents in day i, year t, and daytime period h. The running variable $X_{i,t,h}$ indicates the number of days before and after the DST transition and is centered to zero, meaning the day when the DST transition actually occurred for each particular year t. $DST_{i,t,h}$ is an indicator function of whether a day i in year t was exposed to the DST transition or not, and we also include an interaction term $DST_{i,t,h} \times X_{i,t,h}$ to control for any change in slope at each side of the threshold. In order to have a more flexible function we consider additional functional forms such as a quadratic specification of the running variable $X^2_{i,t}$, and an interacted term $DST_{i,t,h} \times X^2_{i,t,h}$. We further include $\omega_{i,h}$ (day of the week) and $\psi_{t,h}$ (year fixed effects) to better approximate the cyclical structure of crimes, and finally $\epsilon_{i,t,h}$ represents the idiosyncratic error term. The parameter ρ_h is our coefficient of interest which captures the effect of sunlight variation on the percentage of total crimes during a particular period of the day defined by h.

3.2. *Difference-in-Differences Approach*

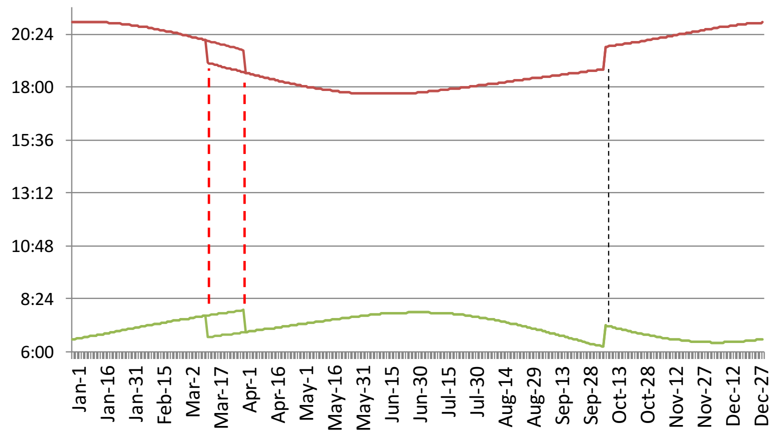
As a complementary analysis, we estimate the effect of this sharp variation in daylight exposure under a second identification strategy. Here we exploit another source of exogenous variation, namely a delay in the DST transition. In particular, we take advantages of the fact that for two particular years the Chilean Government decided to delay the DST fall transition, which by law must occur after the second Saturday of March. Under the assumption that this decision was orthogonal to our dependent variable we can build a natural counterfactual for our treatment group determined by those years where the DST fall transition was implemented as the law regularly establishes it.

A reasonable concern of the RD identification strategy may raise the issue that crime incidence may also be affected by the period of the year itself. This can be particularly relevant for the estimates based on the fall season (DST transition in March). In Chile, March is the first "regular" month of the year for the basic activities of the population. The academic year for all school levels as well as many jobs regularly begin during the first two weeks of March, right after the end of vacation period during January and February. If people are learning how to adjust to their schedules during these two weeks of March, the difference between these two weeks and the following two may capture more than simply the effect of the DST schedule. In that sense, the RD estimates might be biased.

The difference-in-differences strategy offers a robustness check for this concern since it relies on the timing where this exogenous variation happens for two specific years. In particular, Act 1498 establishes that March transition must be implemented after the second Saturday of March each year. However, in 2008, due to a hard drought the government decided to delay the implementation of the winter schedule by three weeks with the hope of reducing energy consumption. Similarly, in 2010, after the strong earthquake, the government likewise decided to postpone the implementation of the winter schedule by three weeks in order to help families, volunteer and organization groups that were working on the first steps of the reconstruction process and taking full advantages of sunlight hours in the evenings. Figure 2 illustrates the variation in terms of the sunrise and sunset hours across days of the year.

We follow Doleac and Sanders (2015), taking advantage of the variation in the day of the year where the DST transition was implemented and the variation in the impact of DST across different hours of the day. For this case, we restrict the sample to the earliest DST transition in March for the treatment years (after Saturday, March 8 in 2005) and for the control years (after Saturday, March 29 in 2008). We collapse all the data to day-by-sunset level, where "sunset" represents a two-hour period in which sunset-time actually happened for that year. Our basic regression can be described as follows:

Figure 2. Sunrise and Sunset Hours in 2005, Fall DST Transition Delay



Notes: Red and green lines represent respectively the exact sunset and sunrise times for each day of the year. Source: Astronomical information extracted on February 2, 2016 from www.tutiempo.net.

$$\log(Crime_{i,t}) = \alpha + \beta_1 DST_{i,t} + \beta_2 Sunset_{i,t} + \gamma DST_{i,t} \times Sunset_{i,t} + \epsilon_{i,t,h} \tag{5}$$

where the dependent variable represents the log of total crimes in a particular day-hour period and $DST_{i,t}$ indicates whether observation i corresponds to years where regular DST transition was implemented (2005, 2006, 2007, 2009), as opposed to the "control years" which are 2008 and 2010. In other words, β_1 accounts for average permanent differences between years with and without DST policy in place. $Sunset_{i,t}$ indicates whether observation i corresponds to "sunset-hours", as opposed to the rest of the hours of the day, so it enters this model as a common-trend effect for treatment and control groups as is usual in difference-in-differences specifications. γ represents in this case our parameter of interest; it captures the double difference between treatment and control groups and sunset-hours versus other hours of day.

4. Results

The main results of this project are presented in three parts. First, we present a set of stylized facts comparing the distribution of criminal activity across hours of the day for a short period of time before and after DST transition. Then, we move to RD estimations beginning with a graphical representation for our preferred RD estimate. We present regressions coefficient under different model specifications. The last part of this section shows

the difference in differences estimates. For the first two parts, the results are based on the spring DST transition during sunset hours since this transition incorporates the most stable bandwidth. Results for other times of day and periods of the year are fully reported in the extension section and in the Appendix.

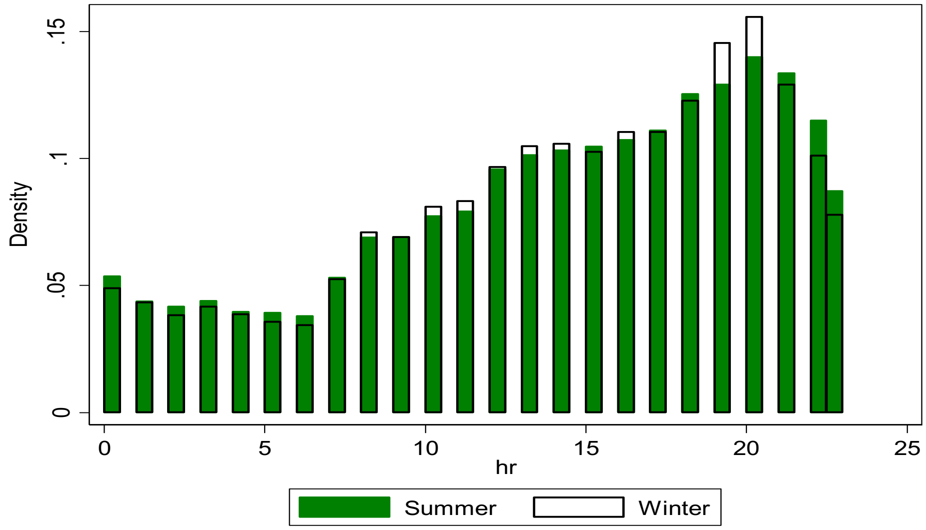
4.1. Graphical Analysis

The first feature of crime distribution over time that we want to highlight is its large variation across time during an average day. Figure 3 plots a histogram of crime distribution over hours of the day for two different periods: three weeks before (winter) and three weeks after (summer) the DST spring transition. For the two periods the distribution of crime incidents is very similar and shows a general pattern with a small proportion of incidents during nighttime hours (midnight to 6 a.m.), followed by a period of an increasing rate until 1 p.m. After 1 p.m. the rate of incidents remains stable until 6 p.m. In contrast, the period between 7 p.m. and 9 p.m. displays the highest crime rate. If the variation in light is affecting criminal activity, we may expect to see an important variation during these hours of the day. Indeed, we observe a sharp reduction in crime incidents around 7 p.m. and 8 p.m., which can be associated with the implementation of a new time schedule. Figure 14 in the Appendix shows the same pattern for the fall (March) DST transition. Similar histograms for each year and its DST transitions can additionally be found in Figures 15 and 16. Finally, the Appendix further includes Figures 17 and 18, also with histograms, but modifying the window period for “summer” and “winter” seasons.

Our primary focus is the discontinuity associated with the vicinity of sunset hours. Similarly, we may expect variations around the period of the day that includes sunrise hours. In addition, analyzing similar responses for other periods of the day that are not affected by variations in ambient light are also relevant. Based on the variation in ambient light imposed by the DST policy, we define four relevant periods of analysis: nighttime hours (9:00 p.m. to 5:59 p.m.), daytime hours (10 a.m. to 5:59 p.m.), sunset hours (7:00 p.m. to 8:59 p.m.), and sunrise hours (6:00 a.m. to 7:59 a.m.).

Figure 4 plots the residuals from a regression that adjusts for the variation of crime incidents relative to the day when DST transition occurred for sunset hours. Similar plots for night, day, and sunrise hours can be found in Figures 19- 22 in the Appendix. We include six different figures that show the discontinuity associated with DST at sunset hours but not at other hours of the day. For graphical purposes, and given the cyclical pattern of criminal activity, in Figure 4 we plot the residuals of a regression that controls for year and day-of-week fixed effects.

Figure 3. Distribution of Crime by Hour of Day: 2005-2010 around Spring DST Transition

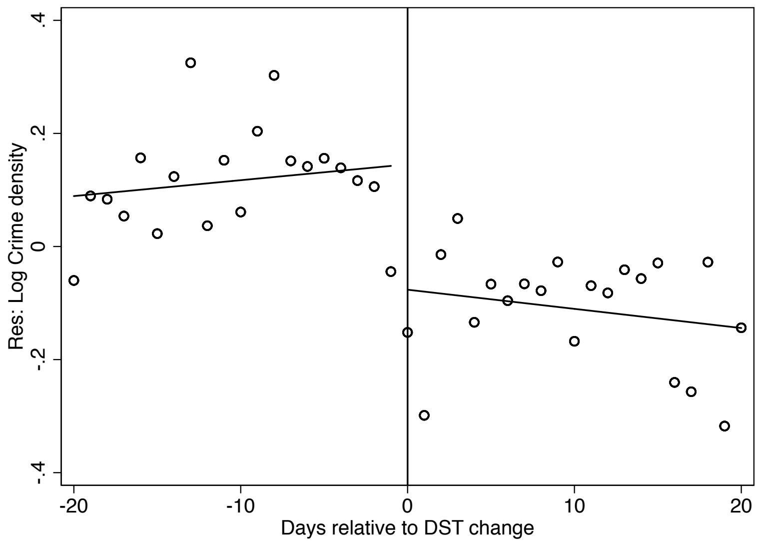


Notes: Histogram of crime reports by hour of day, including robbery, larceny, theft, vehicle theft, burglary, murder, and rape incidents. Summer and winter refer to the DST schedule, which always occurred after the second Saturday of October. Sample considers a window of three weeks after (summer) and before (winter) the DST transition.

We interpret the sharp discontinuity at the threshold in Figure 4 as the effect of ambient light on criminal activity. More specifically, we observe a 20% reduction in crime incidents associated with reducing by one hour the amount of ambient light exposure during sunset hours (7 p.m. to 9 p.m.). In order to clarify this, we can consider that on Saturday 10/8/2005 sunset was at 18:49, while the immediate following day (after the DST transition), Sunday 11/8/2005, sunset was at 19:49. Conversely, during sunrise hours we experience a sharp decrease of one hour of sunlight for the same transition. Importantly, we do not observe similar discontinuities in criminal activity for other different periods of the day (see Figures 19- 22 in the Appendix).

In the Appendix, we include similar results exploiting the variation in ambient light induced by the DST fall transition. Interestingly, we find similar results in magnitude but with the opposite sign. We interpret this finding as consistent with the fact that variation in ambient light is directly affecting the amount of criminal activity observed in the urban space, since the direction of the variation imposed by the DST transition goes in the opposite direction. As in Figure 4, Figure 23 in the Appendix plots the linear fit of the residuals on each side of the threshold. In addition, Figures 24- 27 displays in different ways the discontinuity around a threshold defined by DST transition for the four periods of the day.

Figure 4. Crime Variation during Spring DST Transition: Sunset Hours



Notes: Linear adjustments at each side of the threshold at sunset hours using residuals from a regression that controls for year and day-of-week fixed effects. Horizontal axis is the number of days away from DST transition, and the sample is restricted to 21 days at both sides of the threshold. Similar figures for others daytime periods, using different adjustment of the running variable and its interaction with the treatment variable, are in the Appendix (Figures 19- 22).

4.2. Basic Estimates

4.2.1. RD Estimates

Table 2 shows the results for our variable of interest, which is the start of summer season based on the DST spring transition that takes place in October. We can see under different functional specifications a reduction of 20% that can be attributed to the extra hour of sunlight during that period. Similar results for the other relevant periods of the day are shown in Appendix Table 8. Our preferred estimation considers a sample that exclude days related to the September holiday season (Chilean national day). Later, we discuss how robust to sample selection our results are. Interestingly, we do not see significant variation that can be attributed to the new time-schedule during other day periods, except during sunrise hours, which are also affected by a sharp variation in sunlight hours.

We reproduce RD estimates of Table 2 exploiting the fall DST transition, which imposes

Table 2: RD Estimates: Sunset Hours during Spring DST Transition

	Sunset	**Sunset**	**Sunset**	**Sunset**
Summer (D)	-0.259***	-0.205***	-0.205***	-0.173
	(0.09)	(0.06)	(0.06)	(0.12)
Days	Y	Y	Y	Y
Days^2	N	N	N	Y
Summer*Days	Y	Y	Y	Y
Summer*Days^2	N	N	N	Y
DoWeek FE	N	Y	Y	Y
Year FE	N	N	Y	Y
N	210	210	210	210
R2	0.027	0.092	0.141	0.141

Notes: Coefficients using equation (4) at sunset hours. Running variable is days before and after spring DST transition. Summer captures the discontinuity imposed by the DST schedule, which usually takes place after the second Saturday of October. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

variations in ambient light in similar hours of the day but in the opposite direction across days. In this case we exclude February days from the sample due to the strong seasonality effects related to summer vacations in Chile. Interestingly, we find a consistent increase in crime during sunset hours, which coincides with a sharp decrease in ambient light during that time of day. Again, we find no significant crime variation associated with other periods of the day. Table 3 shows the results for the DST transition in fall during sunset hours. Since this transition is from summer to winter, the coefficient of interest in this case is "winter."

Consistent with the results exploiting the spring DST transition, we find no significant effect for other periods of the day, and these results are displayed in Appendix Table 9.

Although the similarity of the results can clearly be presented as a robustness check, we believe that regarding this particular DST transition a possible caveat should be taken into account. In Chile, March is the first regular month of the year for the basic activities of the population. The academic year at all school levels, for example, beings during the first week of March, and jobs usually do as well. That particular feature of March may affect our estimation, which relies on variation of stable patterns for crime activities on each side of the threshold. DST March transitions usually occur after the second Saturday of March. However, as we have mentioned earlier, there are two years where the DST implementation was delayed substantially. In 2008, due to a hard drought the government decided to delay the implementation of the winter schedule with the hope of reducing energy consumption. Similarly, in 2010, after the strong earthquake, the government decided to postpone the implementation of the winter schedule in order to help volunteer and organization groups

Table 3: RD Estimates: Sunset Hours during Fall DST Transition

	Sunset	**Sunset**	**Sunset**	**Sunset**
Winter	0.185**	0.185***	0.170**	0.236**
	(0.08)	(0.07)	(0.07)	(0.11)
Days	Y	Y	Y	Y
$Days^2$	N	N	N	Y
Summer*Days	Y	Y	Y	Y
Summer*$Days^2$	N	N	N	Y
DoWeek FE	N	Y	Y	Y
Year FE	N	N	Y	Y
N	221	221	221	221
R2	0.059	0.236	0.253	0.256

Notes: Coefficients using equation (4) at sunset hours. Running variable is days before and after fall DST transition. Winter captures the discontinuity imposed by the DST schedule which usually takes place after the second Saturday of March; see text for exceptions. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

that were assisting people in need to take full advantage of sunlight hours. Thus, since our RD estimates are calculated using the actual DST transition dates, we believe they likely reflect the effect of ambient light on crime imposed by this policy.

4.2.2. Difference-in-Differences Estimates: Fall DST Transition, March

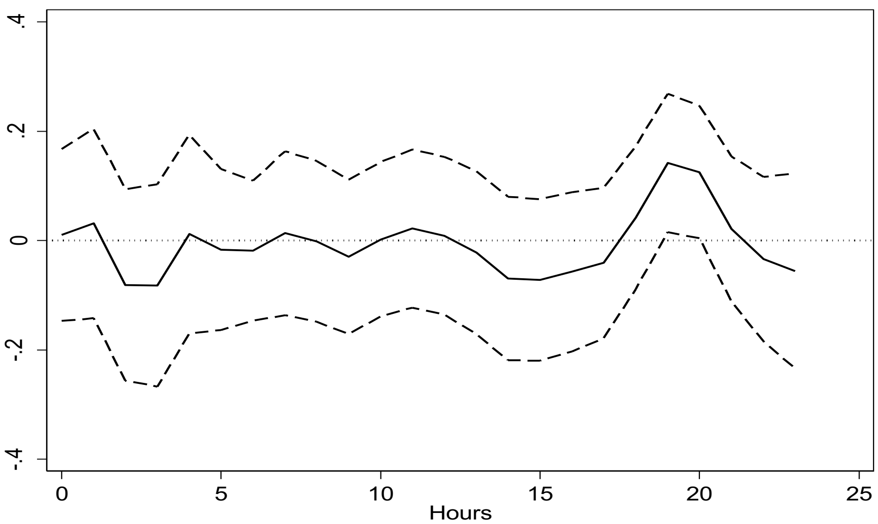
We know evaluate the robustness of the results under a different identification strategy. As we previously discussed, the fact that the DST transition takes place in a particular period of the calendar year can bias our RD coefficients – if other things that affect criminal activity also change at that time of the year. Although limited, this concern could be important during the fall DST transition that usually takes place after the second Saturday in March, which is a period of the year where people are typically learning to adapt to their time-schedules. [9]. Our difference-in-differences estimates address that concern by capturing the double difference between years where the DST transition was implemented as usual and years when there was a delay of three weeks. Our estimates also control for the difference between sunset-hours and the rest of the day. Under the assumption of common-trend between these two groups of years we can interpret our estimate as the causal effect of a variation in daylight exposure on crime. It is important to keep in mind that this particular source of variation is available only for the fall DST transition, which usually occurs in March. During this DST transition, sunlight period decreases sharply during sunset hours.

[9] Most Chileans take vacations in February, and most schools and colleges begin the academic year on the first of March

Conversely, during sunrise hours we experience a sharp increase of one extra hour of sunlight.

We run specification (5), after collapsing the data to day-by-sunset level, where "sunset" represents a two-hour period when sunset-time actually happened for that year. We additionally repeated that procedure, considering "sunset-hours" or the relevant period each hour of the day, which directly offers a falsification test for the effect of daylight variation on crime. Figure 5 summarizes all those estimates with their respective confidence intervals.

Figure 5. Difference-in-Differences Estimates by Hour of Day: Fall DST Transition



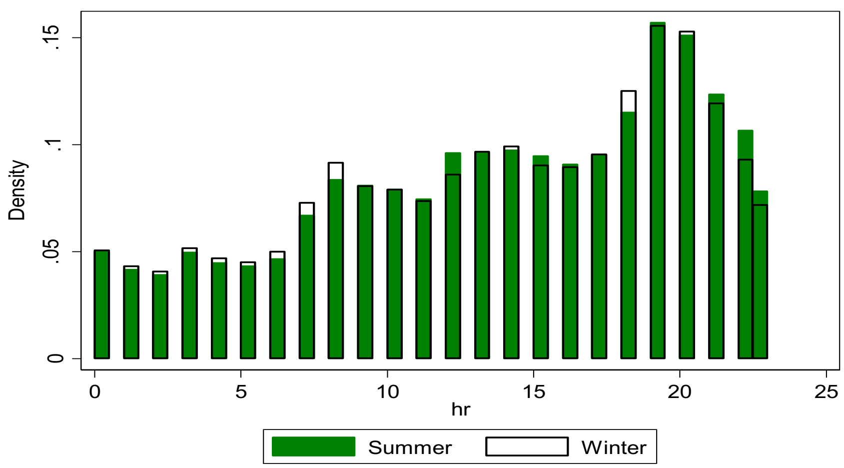
Notes: Figure represents hourly estimates of 24 difference-in-differences regressions as defined by equation (5). Each regression is estimated using a two-hour window period and the coefficient is plotted at the initial hour of the period. Sample is restricted to the period between the earliest DST March transition between the treatment (March 8th) and control groups (March 29th).

As we can see in Figure 5, it is very clear that we see no significant effect except for the estimates that are based on the real sunset-hours. These estimates represent a 15% increase in crime, which is slightly smaller in absolute value than our previous RD specification based on the spring DST transition (18% decrease), but quite similar to our RD estimate based on the same fall DST transition (17% increase). Interestingly, we estimated the same diff-in-diff model for the city of Valparaiso and we found very similar values. See Figure 35 in the Appendix.

4.3. Robustness and Falsification Tests

So far, we have interpreted our results as the effect of ambient light on crime. In addition to the observed change in criminal activity at sunset hours, we have detected no significant effect for periods of the day where DST does not induce a sharp variation in ambient light. We interpret this as a basic robustness check. As a stylized fact, we can analyze Figure 6, which resembles the previous histograms but considers a false DST transition that would have happened after the second Saturday of May. In this case, no sharp variation in criminal activity is observed for the three weeks before and after the false DST transition. In the Appendix, Figures 28 and 29 show similar results for other months of the year. No important variations are related to any of those false DST transitions.

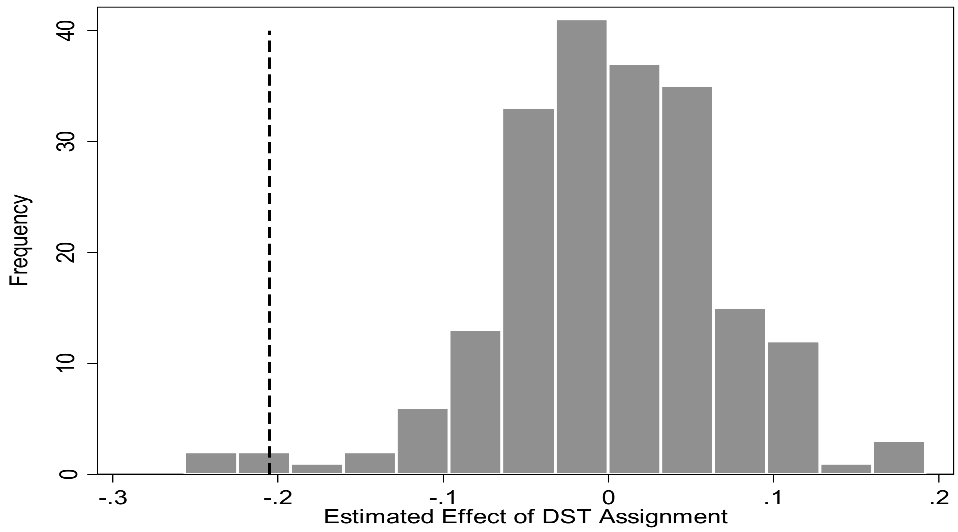
Figure 6. Distribution of Crime by Hour of Day: 2005-2010 around False DST Transition



Notes: Histogram of crime reports by hours of day. It considers robbery, larceny, theft, vehicle theft, burglary, murder, and rape incidents. Summer and winter refer to a false DST schedule set to begin after the second Saturday of May. Sample considers a window of three weeks after (summer) and before (winter) the DST transition.

A general falsification test in that regard is Figure 7, which shows a histogram of multiple estimations of our basic model modifying the transition. Only one estimate represents the true effect of DST transition, whereas the rest of the coefficients are calculated using false DST transitions. The dashed line represents the coefficient for our true DST transition. In the appendix, Figure 30 shows similar result for robbery incidents. In both cases we have that our "true coefficient" represents a singular value on the distribution of the possible "treatment" variables across days of the year.

Figure 7. Histogram of Sunset RD Estimates by Day of the Year: 2005-2010

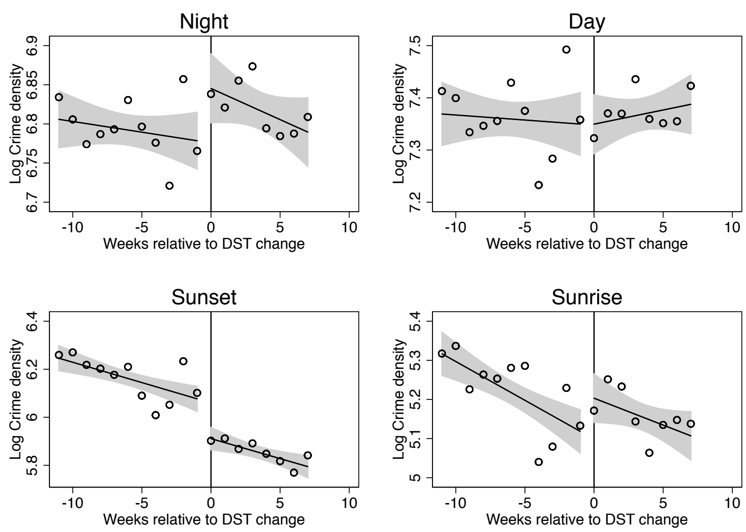


Notes: Histogram of RD coefficients estimates using equation (4) during sunset hours for every day of the year. We exclude days after December 15 and before April 15 to avoid both strong seasonality effects during the calendar year. All regressions consider a window of three weeks after (summer) and before (winter) the false DST transition. Dashed line represents the value of our true DST transition in spring.

Another possible concern could be related to the unit of analysis and the size of the bandwidth we use in the specifications. We discuss the robustness of our results to those concerns in Figures 8 and 9. Figure 8 graphically displays the results from an RD comparing the amount of crime observed at the weekly level. We can observe that part of the day-of-week variation goes away since we are collapsing every point at the weekly level. Again, results are consistent in terms of the basic pattern for every period of the day, and the magnitude of the coefficient at sunset hours is very similar. Again, we find no significant effects at other times of day.

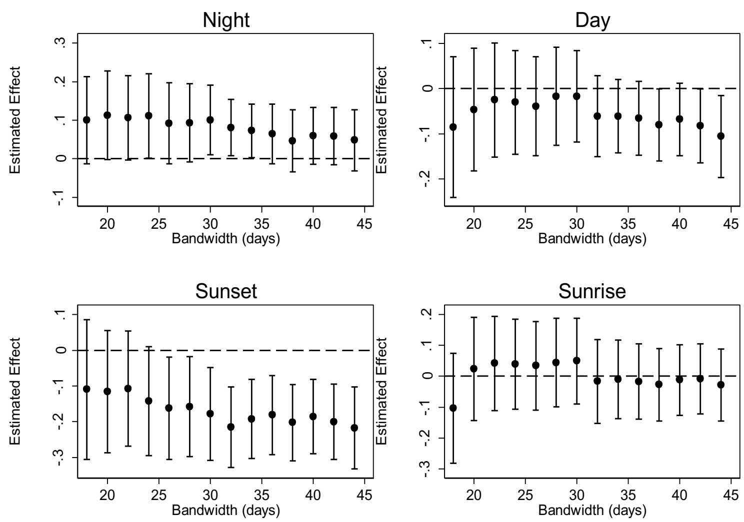
Then, Figure 9 shows how robust to bandwidth size are the coefficients we have presented. Generally speaking, we observe that coefficients are robust to the bandwidth choice. Estimates using more flexible functional forms as well as a similar figure for the fall DST transition can be found in the Appendix, Figures 31-33.

Figure 8. Crime Variation during Spring DST Transition by Daytime Period



Notes: Linear adjustments at each side of the threshold for different periods of the days using residuals from separate regression that controls for year fixed effects. Shadowed areas represent 95% confidence intervals. Horizontal axis is the number of weeks away from DST spring transition.

Figure 9. RD Spring Coefficients Sensitivity to Bandwidth Size by Daytime Period



Notes: Each point represents RD estimates of summer coefficient using a sample of days indicated on x-axis. It includes 95% confidence intervals for each estimate using robust standard errors. Regressions consider log of crime incidents as dependent variable as specified in equation (4), considering a linear specification of the running variable.

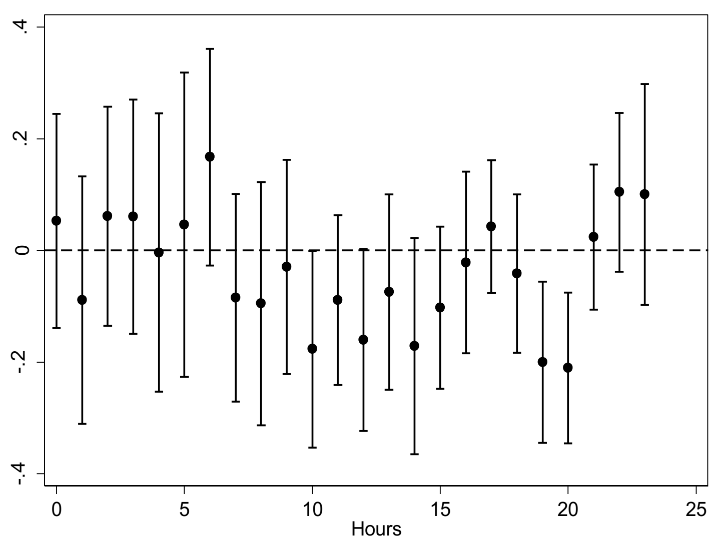
4.4. Further Results

In order to analyze variations in criminal activity associated with DST policy in a more general way, we present different estimates by hour of the day. By doing this we confirm our previous results that most of the crime variation is associated with those periods of the day that are affected by variations in ambient light imposed by DST policy. Then, we extend our results by distinguishing effects by specific types of offense. We find that robbery is by far the most responsive crime to the changes in ambient light imposed by the DST policy. Although we cannot rule out the importance of ambient light for other types of crime, we discuss why in this particular case we are able to detect a clear effect on robbery.

4.4.1. Sensitivity to Hours Using Spring Transition

A natural generalization of our aggregate results for different hours of the day that we discuss in Table 2 and Table 8 is presented in Figure 10. We estimate 24 separate estimates by each hour of the day.

Figure 10. RD Estimates by Hour during Spring DST Transition



Notes: Each point represents the RD estimate of a regression using a sample restricted to the hour indicated on x-axis as specified in equation (4). It includes 95% confidence intervals for each estimate using robust standard errors. Summer refers to the DST schedule, which takes place after the second Saturday of October. Sample is also restricted to 17 days before and after the DST transition in October.

As we can see in Figure 10, the largest variation in criminal activity is associated with sunset hours (7 p.m. and 8 p.m.), when we see a 20% decrease. Although some noisy

estimates are observed during the rest of the day, we find no consistent pattern that can be associated with the variation in ambient light. Interestingly, we find a positive but not significant effect at 6 a.m., which suggests an increase in crime that could be related to a reduction in ambient light during that period of the day.

4.4.2. Heterogenous Responses by Crime Type: Spring DST Transition

Table 4 presents separate estimates for each crime category and period of the day. There are many possible ways ambient light can differently affect different types of crimes. Among the most crucial distinctions for the purposes of our identification strategy is the accuracy of the reported time of each crime category. Since we are using reports that are mostly made by victims, the accuracy of the time reported is influenced by the type of offense he/she suffered. For instance, a victim can clearly recall the time when he/she was robbed, while in the case of "burglary without people" he/she needs to make an estimation based on some basic facts (last time he/she was there, when he/she noticed the incident, etc.). A similar claim can be made for the rest of the crime categories identified in the sample.

Table 4: RD Estimates by Offense and Daytime Period: Spring DST Transition

	Night	**Day**	**Sunset**	**Sunrise**
All Crimes	0.059	-0.0811	-0.205***	0.0154
	(0.04)	(0.05)	(0.06)	(0.07)
Robbery	0.0693	-0.128	-0.334***	0.318*
	(0.05)	(0.07)	(0.10)	(0.12)
Larceny	0.0501	-0.236**	0.084	0.0704
	(0.13)	(0.09)	(0.13)	(0.17)
Vehicle Theft	0.093	-0.118	-0.203	-0.0301
	(0.09)	(0.08)	(0.14)	(0.17)
Theft from vehicles	0.126	-0.0546	-0.263	-0.182
	(0.07)	(0.07)	(0.16)	(0.17)
Burglary w/People	-0.0618	0.0405	-0.309*	-0.277
	(0.07)	(0.06)	(0.14)	(0.17)
Burglary w/o People	0.0197	0.0428	-0.169	0.0207
	(0.11)	(0.08)	(0.17)	(0.16)
Other robbery	-0.0221	-0.151	-0.0382	-0.253
	(0.18)	(0.17)	(0.19)	(0.19)
Theft	0.0463	-0.124	-0.184	-0.0924
	(0.09)	(0.07)	(0.10)	(0.18)

Notes: Estimates from 36 regressions using equation (4) by crime category and daytime period. Sample size considers 17 days before and after DST transition as in Table 2. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

At first glance, almost all estimates are not significant except for the case of robbery. We believe that robbery is likely driving our previous estimates when we pool all crime categories together, especially considering both its high incidence in the overall crime category and its sensitivity to each different time period. Indeed, for the case of robbery we find an even larger response in sunset hours (33% decrease), and we also find a similar response in the opposite direction (32% increase) during sunset hours.

In the Appendix we complement this analysis with three additional tables. First, in Table 10 we reproduce Table 4 estimates for the fall DST transition, and we detect a significant response (30% increase) for robbery during sunset hours, which is consistent with the sharp decrease in ambient light in that particular DST transition. We also find no clear pattern associated with the remaining crime categories. In addition, we include Tables 11 and 12, which contain hourly estimates by each crime category. While these estimates are presumably much noisier, we still find significant effects on criminal activity associated with robbery during sunset hours separately for both DST transitions.

5. Extensions

In this section, we discuss three additional features of the findings. First, we carefully analyze our results to discuss the degree to which we can detect temporal reallocation of criminal activity that could be interpreted as evidence of short-term displacement. Second, we analyze the extent to which our findings are driven by a possible demand-side response regarding potential victims' behavior. Particularly, we study how DST affects the time-commuting pattern of the population using high-frequency data from Santiago's subway network. Third, we analyze the heterogeneity of the effect of ambient light on crime by land use.

5.1. Evaluating Possible Temporal Reallocation of Criminal Activity

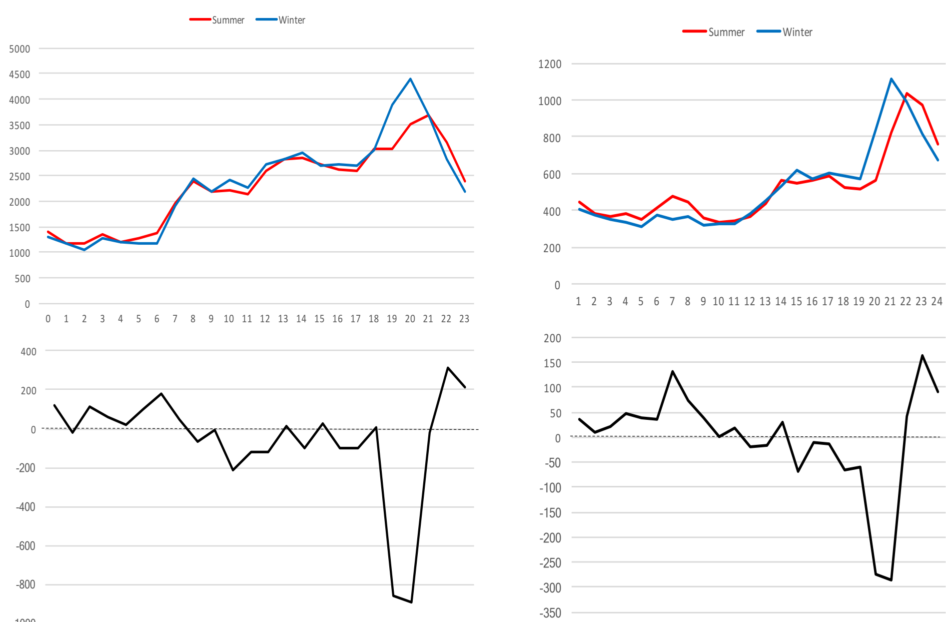
In the previous section, we find no significant responses regarding criminal activity at times of day when the amount of light was arguably not affected by the DST transition. In a way, this evidence alone can be indicative of no short-term displacement in crime. In this section, we further discuss possible scenarios of temporal displacement. Evidence of displacement is important since it can substantially alter the evaluation of a particular policy. An interesting case in this regard is Jacob, Lefgren, and Moretti (2007). They found substantial temporal displacement exploiting weather shocks that significantly alter the amount of criminal activity across U.S. cities. They present a dynamic model of criminal

behavior and show that for long periods (across different weeks) displacement is consistent with wage fluctuations with a meaningful income effect that persists across periods. In this study, we discuss temporal displacement of criminal activity during a shorter period—across hours of the day within a certain day.

If no temporal displacement occurs, we can expect that the effect at sunset hours—when a considerable portion of criminal activity takes place—strongly influences the overall variation in crime induced by the DST policy. Thus, RD estimates using (4), with overall daily crime incidents as the dependent variable, should yield a similar variation in the amount of reported crimes.

Figure 11 puts together two sets of data. It compares the distribution of criminal activity for two crime categories: all crimes (left) and robbery (right) incidents. The top figures show the criminal activity for every hour of the day for two periods before and after the spring DST transition; bottom figures show the difference in criminal activity between those two periods at every hour of the day. We focus on the spring DST transition. According to Figure 34, it is more likely to detect displacement in the spring DST transition.

Figure 11. All Crimes vs. Robbery during Spring DST Transition



Notes: Figure shows distribution of incidents across hours of the day between three weeks before (winter) and after (summer) spring DST transition. Figures at the left are built using a sample that pools all crimes, whereas figures at the right refer to robbery incidents. Top panels illustrate differences in terms of number of incidents, whereas panels at the bottom describe differences between summer and winter for every hour of the day. Summer refers to the DST schedule, which always occurred after the second Saturday of October.

Consistent with the set of histograms in section 4, Figure 12 shows that the largest variation in criminal activity takes place at sunset hours. Using a simple test for short-term temporal displacement, we compare the daily variation in criminal activity with the one observed at hours of the day affected by variation in ambient light. The overall daily observed variation in incidents is -2.5% and -0.3% for all crimes and robbery, respectively. We estimate the overall daily effect of the DST transition using specification 4; in most specifications, we find for both all crimes and robbery incidents a small and nonsignificant decrease. Figures 36, and 37 in the Appendix show the coefficients for the overall daily estimates using both the spring (October) and fall (March) DST transitions.

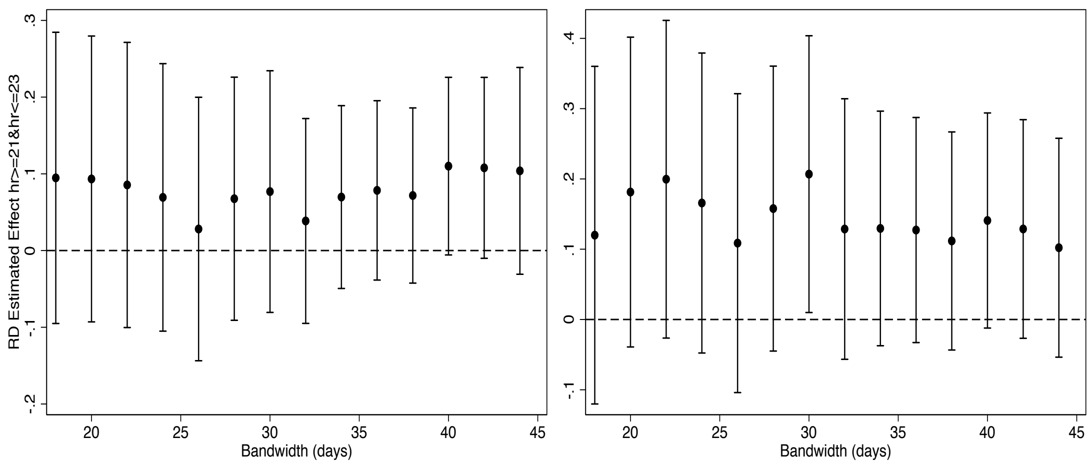
Interestingly, the overall daily variation in all crimes due to the DST transition in spring is similar in magnitude to the variation experienced during sunset hours. We also find no significant variation of crimes during DST at other periods of the day. These two facts suggest that events during the sunset hours drive the overall observed differences in all crime rates. By contrast, we observe that in the case of robbery, the overall daily variation is lower in magnitude than the difference observed at sunset hours; this could indicate some displacement of crimes across hours of the day. However, we find a substantial reaction at sunrise hours that partially offsets the effect at sunset hours. Nevertheless, the latter evidence alone is not sufficient to show that there is temporal displacement. In the Appendix, we show similar estimations for the case of the DST transition in fall. These last estimations yield consistent results with the (previously mentioned) results for the DST transition in spring.

Although our estimates from Tables 4, 11, 12, and Figure 10 suggest that substantial displacement across all hours of the day is not detected, an alternative test might look at a particular period of the day where displacement is more likely to happen. If criminals set a target of money to be collected in a day in the spirit of the NYC taxi drivers studied in Camerer, Babcock, Loewenstein, and Thaler (1997), we may expect that a sharp reduction in criminal activity at sunset hours may incentivize them to increase their efforts during the following period (e.g., night hours before midnight). We test for the presence of substantial displacement during this period of the day.

Figure 12 shows bandwidth sensitivity of RD estimates using both all crimes (left) and robbery incidents (right) as the dependent variable. We restricted the analysis to the period 9–11 p.m. Again, we focus on the DST transition in spring. Most coefficients for all crimes are positive but non-significant. Interestingly, robbery coefficients are slightly larger, and indeed for a specific bandwidth size (30 days), there is a significant increase in robberies. This provides some evidence of crime displacement to later hours during a day. However, it is important to keep in mind that even in the case of that particular coefficient (bandwidth of 30 days), the crime reduction at sunset hours (-5.76%) exceeds the crime increase during

the 9-11 p.m. period (+4%).

Figure 12. RD Spring Coefficients Sensitivity to Bandwidth Size, 21-23 Hrs.: All Crimes (Left) versus Robbery (Right)



Notes: Figures show RD estimates using different bandwidth sizes according to equation (4). Sample is restricted to the period 21-23hrs., right after sunset hours. Left and right figures show estimates for all crimes and robbery, respectively. All coefficients are estimated considering days before (winter) and after (summer) during the spring DST transition.

5.2. Evaluating a Response in the Commuting Pattern of the Population

Most empirical studies in the economics of crime literature take victims' behavior as given. But potential victims can affect criminal activity in different ways, especially when they perceive changes in the risk of suffering a property crime. They can avoid circulating in certain areas or during particular periods of the day, harden a particular target or simply offer a higher level of resistance when attacked [10]. Ideally, we may incorporate into our estimation a full specification of victims' behavior for every hour of the day. Considering that most criminal activity takes place when people return home in the evening, we analyze the extent to which a variation in victims' commuting timing drives our estimates. Hence, we run the following regression for every period of the day.

[10]See Domínguez (2017) for a more detailed discussion of this issue

$$\log(M_{i,t,h}) = \alpha_h + \beta_{1,h} X_{i,t,h} + \beta_{2,h} DST_{i,t,h} X_{i,t,h} + \rho_h DST_{i,t,h} + \omega_{i,h} + \psi_{t,h} + \epsilon_{i,t,h} \quad (6)$$

In this equation, $M_{i,t,h}$ represents the number of people who entered the Santiago subway system in period of the day h, day i, and year t. Equation (6) also controls for year and day-of-week fixed effects. To estimate equation (6), we use Santiago subway ridership data. The Santiago subway system transports 2.5 million passengers per day, which represents around 18% of all total trips in an average day (calculations by the authors using data from Munoz et al [2016]). In 2010, the Santiago subway had 108 stations with a total network of approx. 100 km. Our data include the number of commuters who entered the subway system during every hour and span the same years for which our crime data are available.

Table 5: RD Estimates of Metro Ridership during Spring DST Transition, Santiago 2005-2010

	Night	Night	Day	Day	Sunset	Sunset	Sunrise	Sunrise
Summer (D)	0.0029	0.0217	-0.124	-0.232*	-0.0908	-0.152	-0.436	-1.013**
	(0.040)	(0.064)	(0.078)	(0.117)	(0.062)	(0.092)	(0.244)	(0.362)
Days	Y	Y	Y	Y	Y	Y	Y	Y
Days^2	N	Y	N	Y	N	Y	N	Y
Winter x Days	Y	Y	Y	Y	Y	Y	Y	Y
Winter x Days^2	N	Y	N	Y	N	Y	N	Y
DoWeek FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	210	210	210	210	210	210	210	210
R2	0.958	0.96	0.878	0.886	0.904	0.912	0.849	0.861

Notes: Regressions coefficients using equation (6). Dependent variable is log of metro ridership at each daytime period. Summer and winter refer to the DST schedule that switches in fall and spring. Sample size considers 17 days before and after (summer) DST transition as in Table 2. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Results from regression (6) are displayed in Tables 5 and 7.2. We find no significant variation associated with the variation in ambient light. This suggests that our results are not fully driven by a change in the commuting pattern of the population. In a way, this finding contrasts with the conclusion of Wolff and Makino (2012), who evaluate the effect of the DST policy on people's time allocation using the American Time Use Survey (ATUS). They find a modest variation associated with the DST transition. When ambient light increases during evening hours, people report spending 3% more of their time in outdoor recreational activities and reducing TV watching time by 9 minutes.

5.3. *Evaluating Different Responses by Land Use*

We finally explore a potential heterogeneity of the main results by land use. A heterogeneous effect of daylight on property crime depending on the type of land use could potentially inform about some mechanisms through which ambient light affects crime. We hypothesize that differences between areas in the provision of urban amenities can affect crime response to variations in ambient light. In that sense, if streetlights serve better commercial rather than residential areas, the effect of ambient light on crime should be stronger in the latter areas.

To analyze the effect of ambient light on criminal activity by land use we matched the crime dataset with information about land use provided by Chile's Transportation Planning Office (know under the acronym "Sectra"). The information about land use used by Sectra divides Santiago's metropolitan area in the *Estraus* database. *Estraus* disaggregates Santiago into 707 zones and identifies the area of land devoted to different uses. Based on the exact location of crime incidents and the zone they belong to, we characterized the locations of each incident according to the share of land devoted to each use. We were able to identify *Estraus* zones for an 79.12% of all reported crimes. Table 6 describes land use distribution in Santiago by percentiles of land-use intensity.

Table 6: *Estraus* Zones Distribution by Land Use, Region Metropolitana

	Panel A: Geographical Areas Distribution					
	Other-uses	Services	Industrial	Residential	Educational	Commercial
p1	0.000	0.000	0.000	0.000	0.000	0.000
p25	0.044	0.005	0.001	0.481	0.008	0.015
p50	0.110	0.017	0.009	0.736	0.026	0.034
p75	0.196	0.049	0.076	0.863	0.047	0.070
p99	0.939	0.366	0.413	0.991	0.224	0.358

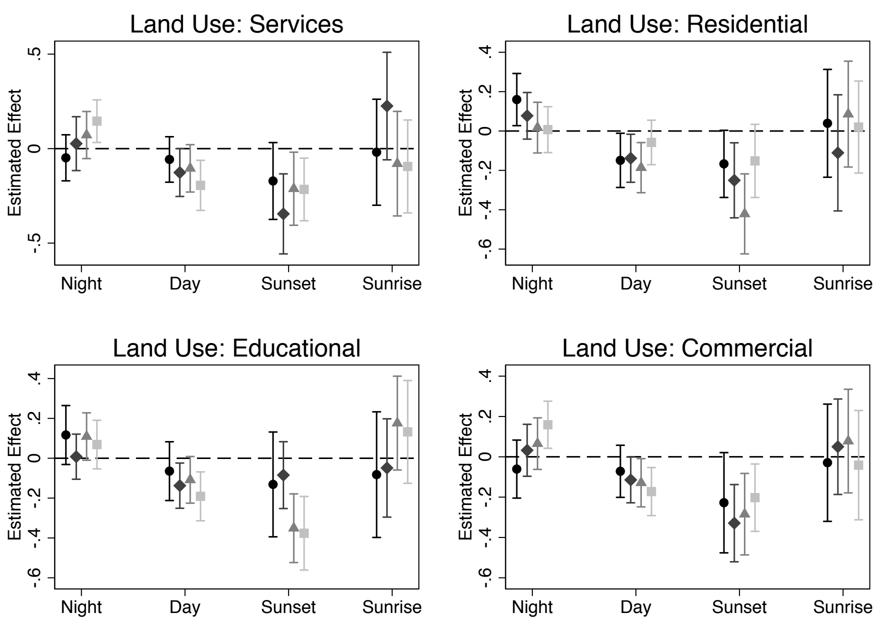
Notes: Columns show land distribution by different uses identified at the top. Rows indicate percentiles of the sample when sample of zones is sorted by each particular use. Values indicate the proportion of the land devoted to each particular use for each percentile of the sample. Sample is defined by all zones identified in the *Estraus* database.

Each column in Table 6 can be read as the share of land devoted to the type of use identified at the top. In Appendix Table 14 we also include similar calculations using the actual sample of crimes we consider for both DST fall and spring transition. Panel A considers *Estraus* zones as a sample, and it reports land use shares by percentiles of *Estraus* zones. Panels B and C considers a sample of crime incidents. A comparison between the three panels shows almost no variation in the type of location where crimes take place, and its distribution across land uses fairly resembles the one identified using *Estraus* zones.

To examine heterogeneity by type of land use, we run our preferred RD specification on

separate samples defined by quartiles of land use intensity. For each land use category, we run our model considering a sample of incidents that took place in areas defined by quartiles of land use identified in Table 6. Figure 13 reports 64 RD estimates. For each period of the day, we run separate regressions using different samples, according to quartiles of land use intensity where crimes took place; coefficients from left to right reflect how RD estimates change when restricting the sample to crimes committed in areas from less to more intensive use of the land. Across different types of land use intensity we observe an important degree of treatment effect heterogeneity that suggest that the effect of ambient light on crime is mediated by the characteristics of the land.

Figure 13. RD Spring Coefficients by Land Use



Notes: RD coefficients by land use using equation (4). Coefficients represents the effect of DST transition using different samples. For each period of the day, coefficients are estimated using separate samples, sorted by quartiles of land-use intensity. Circles coefficients are estimated using a sample of the bottom quarter of *Estraus* zones, whereas squared coefficients are estimated using a sample of the top quarter of *Estraus* zones. Each coefficient includes a 95% confidence interval.

In Table 7 we test whether coefficients across samples are different. For simplicity, instead of splitting the sample into quartiles of land use intensity, we consider only two categories for land use intensity (below and above the median for each type of land use). Column [4] shows whether the impact of ambient light on property crime is heterogeneous across areas with different intensities in the same land use. In most comparisons, apart from the two situations we discuss below, we detect no significant heterogeneities in the previously mentioned impact.

Table 7: RD Coefficients by Land Use: Spring DST Transition

	Land Use < Median	Land Use > Median	Difference	Difference
Panel A: Services	(1)	(2)	(1) - (2)	P-Value
Night	0.033	0.078	0.045	0.365
	(0.051)	(0.040)		
Day	-0.085	-0.081	0.004	0.931
	(0.047)	(0.052)		
Sunset	-0.235	-0.198	0.036	0.666
	(0.083)	(0.064)		
Sunrise	0.099	-0.034	-0.132	0.251
	(0.095)	(0.090)		
Panel B: Residential				
Night	0.138	0.004	-0.134	0.016
	(0.053)	(0.041)		
Day	-0.104	-0.063	0.041	0.334
	(0.060)	(0.040)		
Sunset	-0.134	-0.258	-0.124	0.097
	(0.077)	(0.063)		
Sunrise	-0.034	0.022	0.056	0.645
	(0.124)	(0.077)		
Panel C: Educational				
Night	0.053	0.063	0.010	0.844
	(0.055)	(0.040)		
Day	-0.082	-0.082	0.000	0.994
	(0.054)	(0.046)		
Sunset	-0.061	-0.294	-0.233	0.003
	(0.082)	(0.067)		
Sunrise	-0.107	0.099	0.206	0.095
	(0.116)	(0.089)		
Panel D: Commercial				
Night	-0.005	0.091	0.096	0.054
	(0.053)	(0.041)		
Day	-0.062	-0.089	-0.027	0.560
	(0.051)	(0.050)		
Sunset	-0.223	-0.202	0.021	0.808
	(0.090)	(0.067)		
Sunrise	-0.067	0.063	0.131	0.300
	(0.116)	(0.085)		

Notes: Coefficients represents the effect of DST transition using different samples. Coefficients are estimated using equation (4) by daytime period and considering crimes that takes place in zones identified by each column and panel. Column (1) and (2) considers crimes that take place in areas where land use of the zone indicated in the respective panel is below (above) the median of Santiago. The hypothesis tests are Wald chi-square tests of the type $H_0 : \beta_{below} - \beta_{above} = 0$ on SUR models including the respective above and below median regressions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Coefficients in Table 7 suggest that our main finding (crime reduction at sunset hours and no significant variation in other periods of the day) seems to be driven by what happens in residential and to some degree in educational areas. Sunset estimates are larger in these areas, whereas the reverse pattern is observed in services and commercial areas. This finding is consistent with the urban amenities explanation that may attenuate crime responses in commercial areas through more intense street lights.

Also, Table 7 shows an important feature regarding potential time displacement of criminal activity. Evidence of time displacement towards night during the spring DST transition can be indicative of a potential supply-side reaction. This suggests that potential offenders are exhibiting a larger effort that could partially compensate the crime reduction imposed by the DST transition at sunset hours. Results in Table 7 show significant differences at night in residential and commercial areas, which suggests that crime displacement towards night hours is much more likely to take place in commercial rather than residential areas.

6. Conclusion

In this paper, we present new estimates of the causal effect of ambient light on criminal activity. We extend the previous evidence in the literature to a highly dense and populated urban area. Following the strategy adopted by Doleac and Sanders (2015), we discuss the validity of our results under two different sources of variation and confirm the magnitude and direction of many of their findings. We find that a one-hour increase (reduction) in the amount of light at sunset hours (between 7-8:59 PM) reduces (increases) the amount of criminal activity by 20%. Our results are also robust to a variety of model specifications. Particularly, we find no significant responses associated with placebo variations across hours of the day during the DST transition, or using false DST transitions across days of the year. Moreover, our results are robust to the bandwidth definition as well as the level of aggregation of the data (daily or weekly level).

Our findings not only confirm previous estimates of the literature in a novel setting but also reinforce the negative relationship between ambient light and criminal activity. As opposed to Doleac and Sanders (2015), our estimates for the two DST transitions are similar in absolute value, and we do observe a significant increase in robbery when ambient light decreases at sunset hours. We also discuss possible short-term displacement in criminal activity that can be associated with the DST policy. This is an important issue since evidence of substantive time-displacement may limit the scope for action of policies oriented to reduce crime through the use of artificial light in the city. Although we cannot fully reject any possible dimension of crime displacement, we find no large nor consistent response for some

particular periods of the day.

We focus the attention in a single and large urban area which allows us to extend the evidence of the effect of ambient light on crime in two important dimensions. Regarding the interpretation of the reduced-form coefficients, we highlight that our main estimates can be interpreted as responses associated with the interaction between supply and demand for offenses. Supply-side responses are related to potential offenders' actions and in particular, to the extent that more (less) hours of ambient light during a certain period of time deter (stimulate) them to offend. On the other hand, a demand-side response refers to the behavior of victims, who can subsequently alter the set of criminal opportunities available precisely because of the variation in ambient light. We can expect that a variation in ambient light induced by DST policy may potentially affect both agents. Without specific information describing both agents we cannot be certain about the actual mechanism that is driving our results. For instance, an extension of sunlight during "sunset hours" can encourage people to spend more time outdoors, which may also potentially alter the protection measures victims adopt, which in turn can be assimilated by offenders. We study a possible adaptive response associated with the shock in ambient light such as the extent to which DST policy causes a substantial change in the time-commuting pattern of the population. We use Metro ridership data at the same frequency level of our previous estimates for the same period of analysis, and we detect no significant variation at any hour of day. Although Metro ridership is a broad measure of victim's behavior, this finding suggests that at least the major portion of the crime variation is unlikely to be driven by an endogenous reaction in the commuting pattern which arguably is a key indicator of victim's behavior.

Finally, we analyze an additional source of heterogeneity, namely the extent to which our findings differ by land use activity. We find that our coefficients are driven by what takes place in residential and, to some degree, educational areas. By contrast, commercial and service area seems to be less impacted by the variations in ambient light imposed by DST policy. We highlight the relevance of an environmental component such as streetlights that could presumably mediate the relationship between ambient light and crime. We also observe that any short-term temporal reaction of potential offenders compensating the reduction in crime at sunset towards night hours is likely to take place in commercial and service areas that are presumably less affected by variations in ambient light induced by DST policy. Overall, our findings suggest that ambient light is a crucial factor in criminal activity.

References

Angrist, J. D., Pischke, J.-S., 2008. Mostly harmless econometrics: An empiricist's companion. Princeton university press.

Becker, G. S., 1968. Crime and punishment: An economic approach. Journal of political economy 76, 169–217.

Camerer, C., Babcock, L., Loewenstein, G., Thaler, R., 1997. Labor supply of new york city cabdrivers: One day at a time. The Quarterly Journal of Economics 112, 407–441.

Chalfin, A., Hansen, B., Lerner, J., Parker, L., 2019. Reducing crime through environmental design: Evidence from a randomized experiment of street lighting in new york city. Tech. rep., National Bureau of Economic Research.

Cook, P. J., Ludwig, J., McCrary, J., 2011. Controlling Crime. University of Chicago Press.

Cornish, D. B., Clarke, R. V., 1987. Understanding crime displacement: An application of rational choice theory. Criminology 25, 933–948.

Doleac, J. L., Sanders, N. J., 2015. Under the cover of darkness: How ambient light influences criminal activity. Review of Economics and Statistics 97, 1093–1103.

Domínguez, P., 2017. How offenders and victims interact: A case-study from a public transport reform .

Glaeser, E. L., 2008. Cities, agglomeration, and spatial equilibrium. Oxford University Press.

Glaeser, E. L., Sacerdote, B., 1999. Why is there more crime in cities? Journal of political economy 107, S225–S258.

Grasmick, H. G., Bursik Jr, R. J., 1990. Conscience, significant others, and rational choice: Extending the deterrence model. Law and society review pp. 837–861.

Grogger, J., Willis, M., 2000. The emergence of crack cocaine and the rise in urban crime rates. Review of Economics and Statistics 82, 519–529.

Hechter, M., Kanazawa, S., 1997. Sociological rational choice theory. Annual review of sociology 23, 191–214.

Imbens, G. W., Lemieux, T., 2008. Regression discontinuity designs: A guide to practice. Journal of econometrics 142, 615–635.

Jacob, B., Lefgren, L., Moretti, E., 2007. The dynamics of criminal behavior evidence from weather shocks. Journal of Human resources 42, 489–527.

Nagin, D. S., 2013. Deterrence: A review of the evidence by a criminologist for economists. Annu. Rev. Econ. 5, 83–105.

Sekhon, J. S., 2008. The neyman-rubin model of causal inference and estimation via matching methods. The Oxford handbook of political methodology 2.

Van Koppen, P. J., Jansen, R. W., 1999. The time to rob: variations in time of number of commercial robberies. Journal of Research in Crime and Delinquency 36, 7–29.

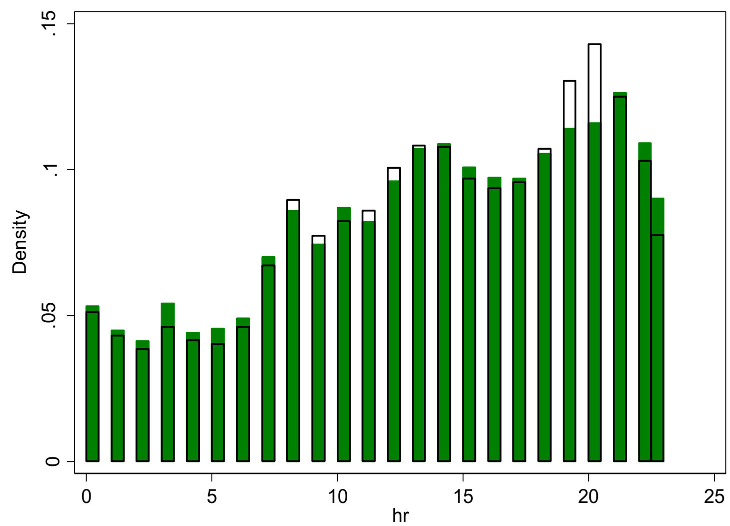
Williams, K. R., Hawkins, R., 1989. The meaning of arrest for wife assault. Criminology 27, 163–182.

Wolff, H., Makino, M., 2012. Extending becker's time allocation theory to model continuous time blocks: Evidence from daylight saving time .

7. Online Appendix

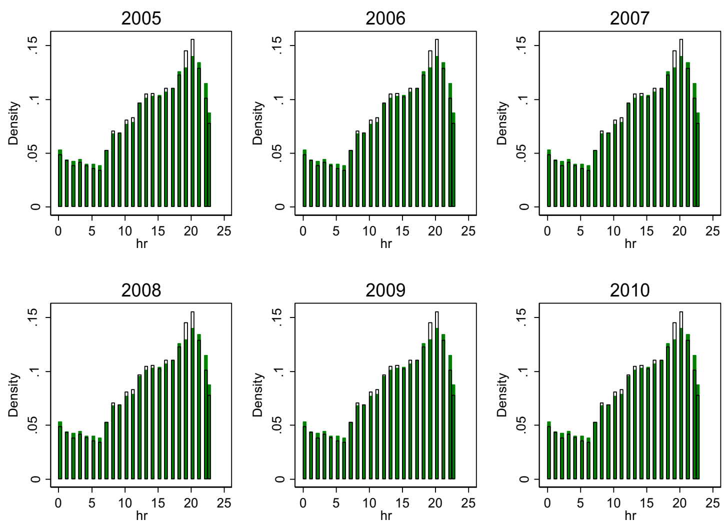
7.1. Figures

Figure 14. Distribution of Crime by Hour of Day, Fall DST Transition



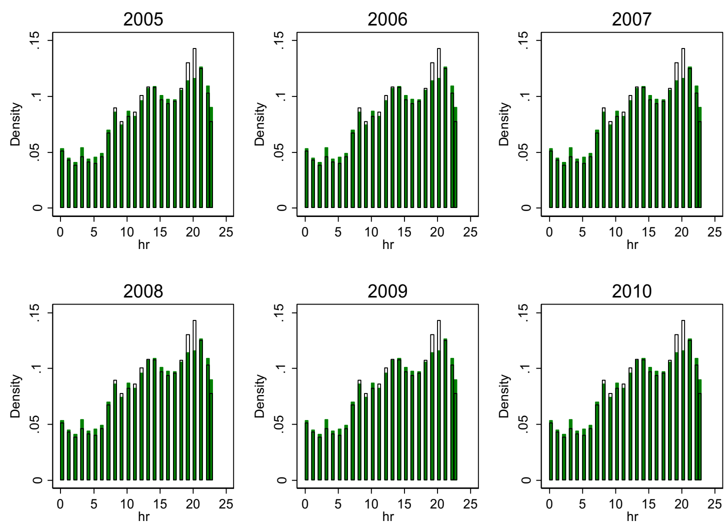
Notes: Histogram of crime reports by hours of the day. It considers robbery, larceny, theft, vehicle theft, burglary, murder, and rape incidents. Summer and winter refer to the DST schedule,e which usually takes place after the second Saturday of March, except for the years 2008 and 2010, when the implementation of DST transition was delayed. Sample considers a window of three weeks after (summer) and before (winter) the DST transition.

Figure 15. Distribution of Crime by Hour of Day, Spring DST Transition



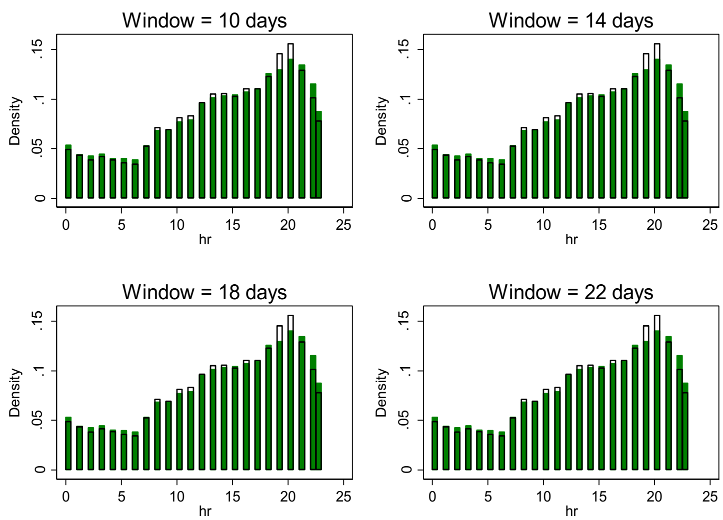
Notes: Histogram of crime reports by hours of the day. It considers robbery, larceny, theft, vehicle theft, burglary, murder, and rape incidents. Summer and winter refer to the DST schedule, which usually takes place after the second Saturday of October. Sample considers a window of three weeks after (summer) and before (winter) the DST transition.

Figure 16. Distribution of Crime by Hour of Day, Fall DST Transition



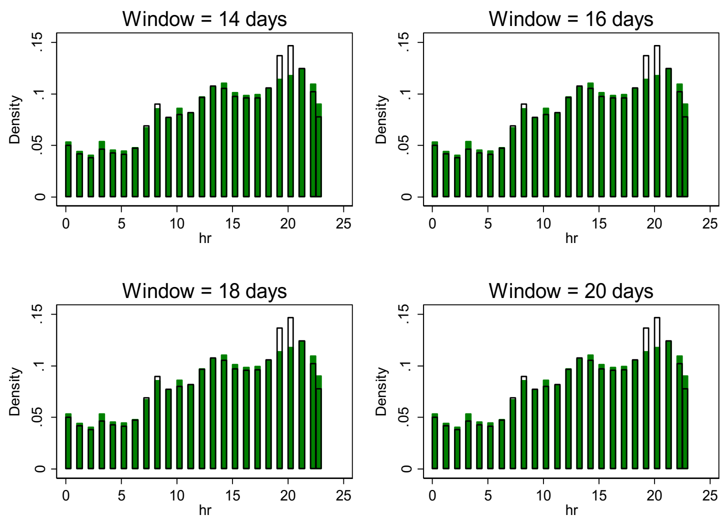
Notes: Histogram of crime reports by hours of the day. It considers robbery, larceny, theft, vehicle theft, burglary, murder, and rape incidents. Summer and winter refer to the DST schedule, which usually takes place after the second Saturday of March, except for the years 2008 and 2010, when the implementation of DST transition was delayed. Sample considers a window of three weeks after (summer) and before (winter) the DST transition.

Figure 17. Distribution of Crime by Hour of Day, Spring DST Transition



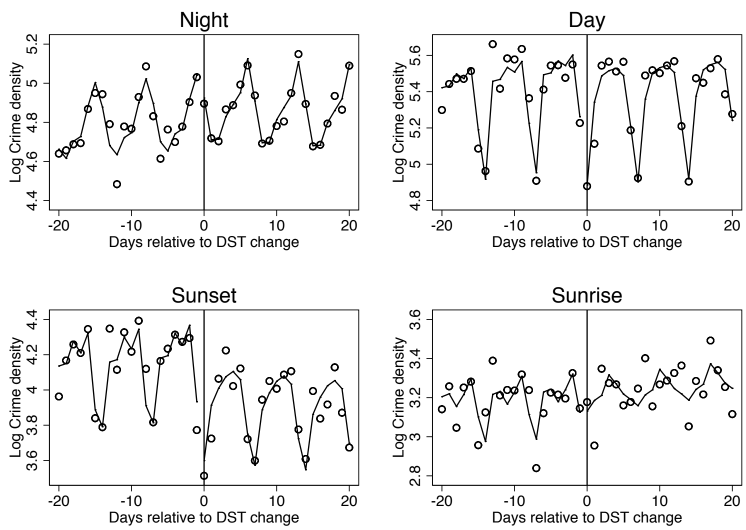
Notes: Histogram of crime reports by hours of the day. It considers robbery, larceny, theft, vehicle theft, burglary, murder, and rape incidents. Summer and winter refer to the DST schedule, which usually takes place after the second Saturday of October. Sample considers different number of days around the DST transition.

Figure 18. Distribution of Crime by Hour of Day, Fall DST Transition



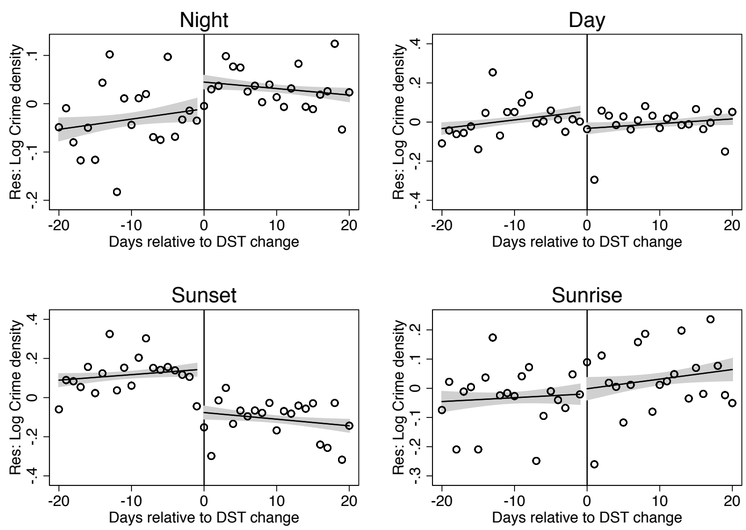
Notes: Histogram of crime reports by hours of the day. It considers robbery, larceny, theft, vehicle theft, burglary, murder, and rape incidents. Summer and winter refer to the DST schedule, which usually takes place after the second Saturday of March, except for the years 2008 and 2010, when the implementation of DST transition was delayed. Sample considers different number of days around the DST transition.

Figure 19. Crime Incidents during Spring DST Transition by Daytime Period: 2005-2010



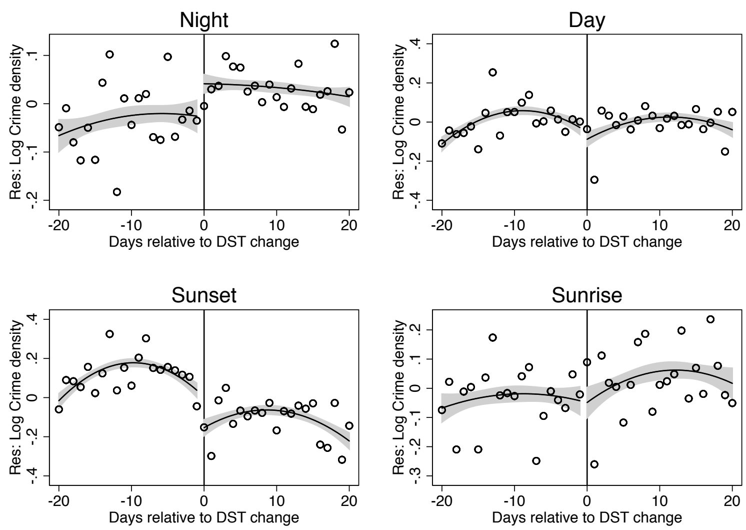
Notes: Each figure corresponds to a scatterplot of the average log-crime and day relative to the DST transition. Black lines connect predicted values estimated from a regression for each period of time and at each side of the threshold. We used log of crime incidents and consider controls as specified in equation 4. Cutoff is defined as the actual DST, and sample is restricted to 21 days on both sides of the threshold.

Figure 20. Crime Variation during Spring DST Transition by Daytime Period: 2005-2010



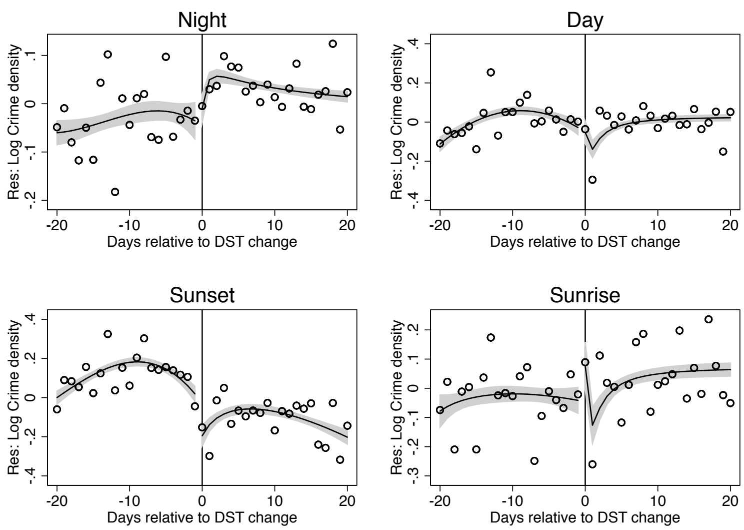
Notes: Linear adjustments at each side of the threshold at different periods of the days using residuals from separate regression that controls for year and day-of-week fixed effects. Shadowed areas represent 95% confidence intervals. Horizontal axis is the number of days away from DST transition, and the sample is restricted to 21 days on both sides of the threshold.

Figure 21. Crime Variation during Spring DST Transition by Daytime Period: 2005-2010



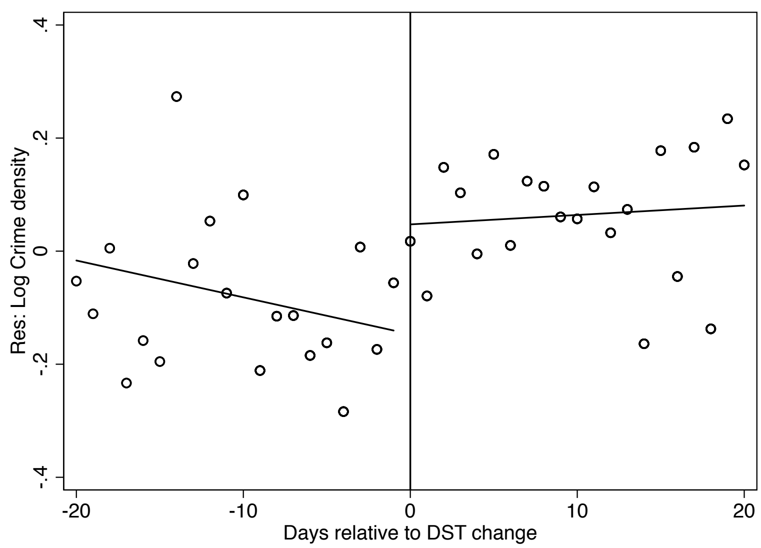
Notes: Quadratic adjustments on each side of the threshold at different periods of days using residuals from separate regression that controls for year and day-of-week fixed effects. Shadowed areas represent 95% confidence intervals. Horizontal axis is the number of days away from DST transition, and the sample is restricted to 21 days on both sides of the threshold.

Figure 22. Crime Variation during Spring DST Transition by Daytime Period: 2005-2010



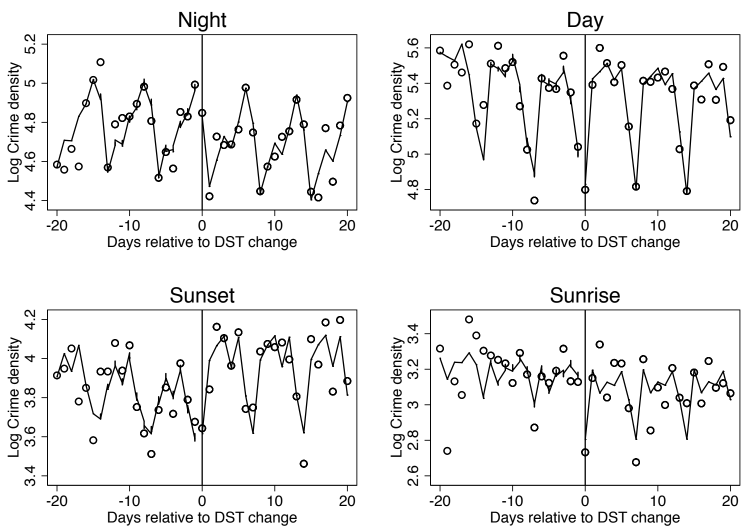
Notes: Fractional polynomial adjustments on each side of the threshold at different periods of days using residuals from separate regression that controls for year and day-of-the-week fixed effects. Shadowed areas represent 95% confidence intervals. Horizontal axis is the number of days away from DST transition, and the sample is restricted to 21 days on both sides of the threshold.

Figure 23. Crime Variation during Fall DST Transition: Sunset Hours, 2005-2010



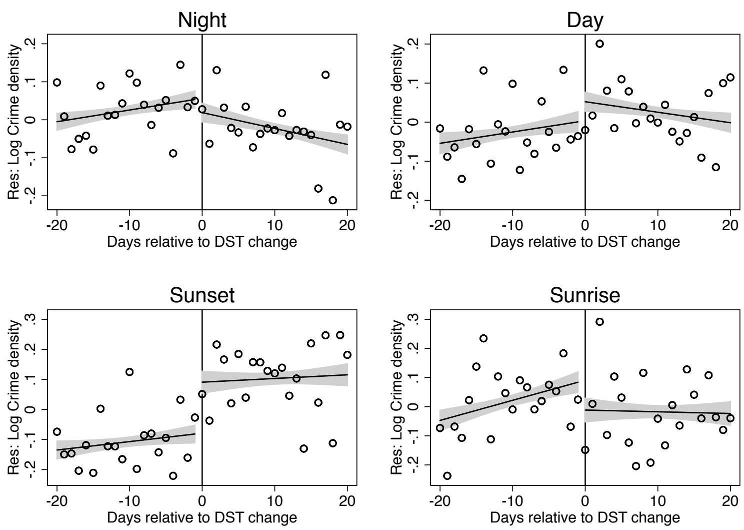
Notes: Linear adjustments at each side of the threshold at sunset hours using residuals from a regression that controls for year and day-of-week fixed effects. Horizontal axis is the number of days away from DST transition, and the sample is restricted to 21 days on both sides of the threshold.

Figure 24. Crime Incidents during Fall DST Transition by Daytime Period: 2005-2010



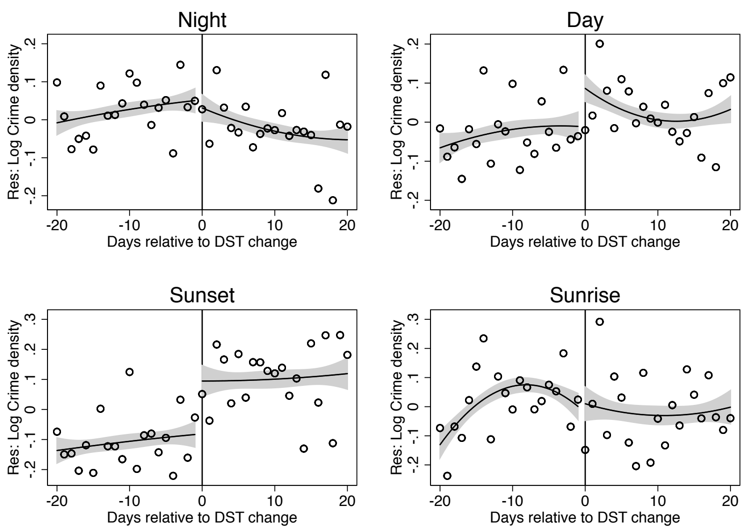
Notes: Each figure corresponds to a scatterplot of the average log-crime and day relative to the DST transition. Black lines connect predicted values estimated from a regression for each period of time and at each side of the threshold. We used log of crime incidents and consider controls as specified in equation 4. Cutoff is defined as the actual DST, and sample is restricted to 21 days on both sides of the threshold.

Figure 25. Crime Variation during Fall DST Transition by Daytime Period



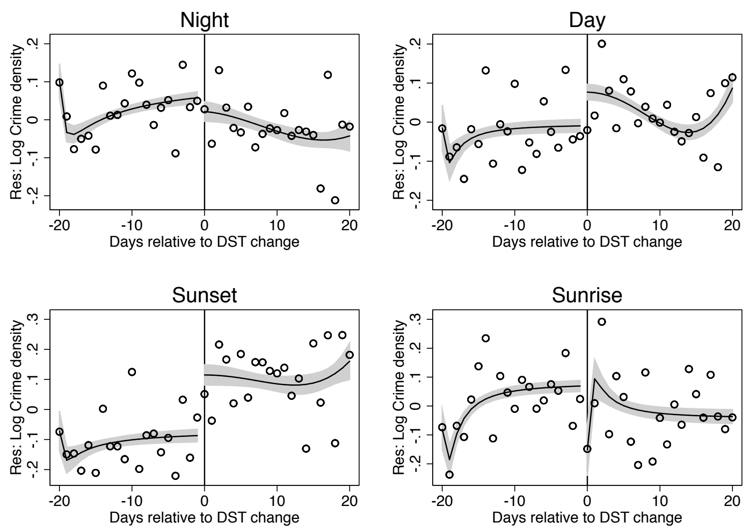
Notes: Linear adjustments at each side of the threshold at different periods of days using residuals from separate regression that controls for year and day-of-the-week fixed effects. Shadowed areas represent 95% confidence intervals. Horizontal axis is the number of days away from DST transition, and the sample is restricted to 21 days on both sides of the threshold.

Figure 26. Crime Variation during Fall DST Transition by Daytime Period



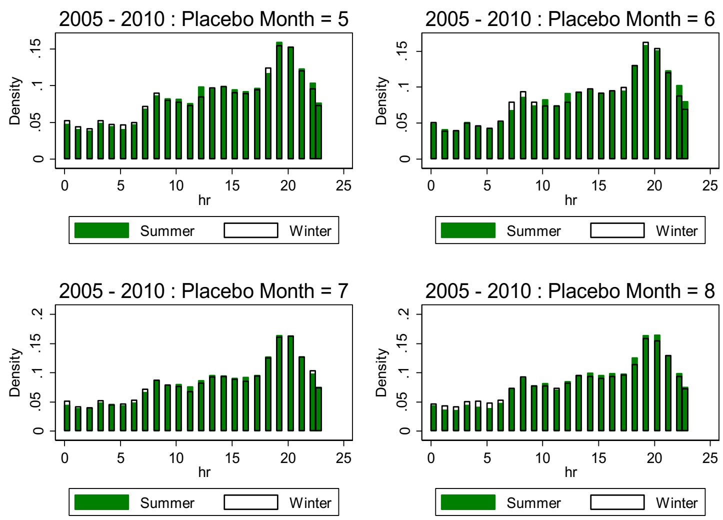
Notes: Quadratic adjustments at each side of the threshold at different periods of the days using residuals from separate regression that controls for year and day-of-week fixed effects. Shadowed areas represent 95% confidence intervals. Horizontal axis is the number of days away from DST transition, and the sample is restricted to 21 days on both sides of the threshold.

Figure 27. Crime Variation during Fall DST Transition by Daytime Period



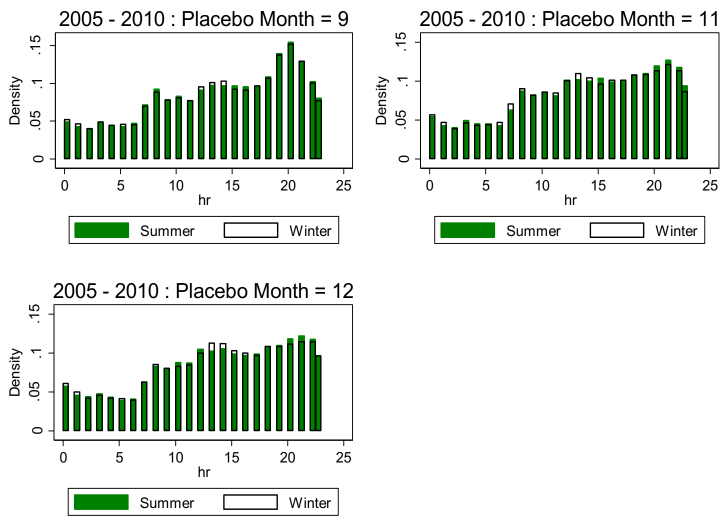
Notes: Fractional polynomial adjustments at each side of the threshold at different periods of the days using residuals from separate regression that controls for year and day-of-the-week fixed effects. Shadowed areas represent 95% confidence intervals. Horizontal axis is the number of days away from DST transition, and the sample is restricted to 21 days on both sides of the threshold.

Figure 28. Distribution of Crime by Hour of Day around False DST Transition



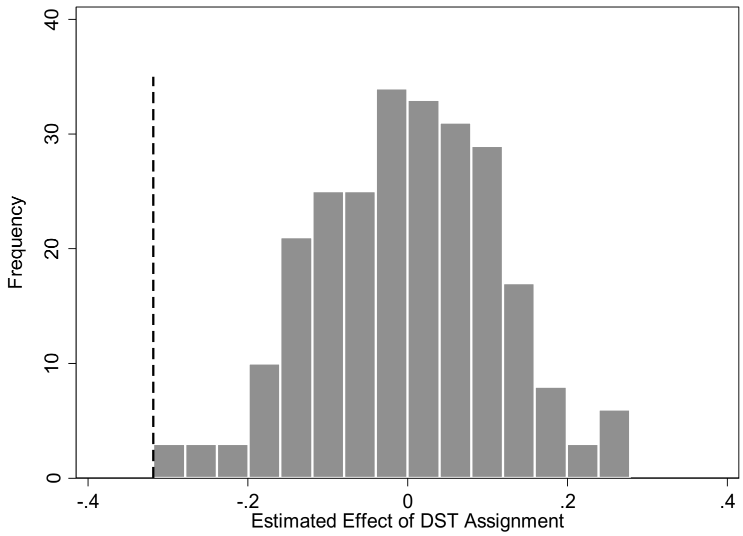
Notes: Histogram of crime reports by hours of the day. It considers robbery, larceny, theft, vehicle theft, burglary, murder, and rape incidents. Summer and winter refer to a false DST schedule, which is set to begin after the second Saturday of May. Sample considers a window of three weeks after (summer) and before (winter) the false DST transition during the month indicated above each figure.

Figure 29. Distribution of Crime by Hour of Day around False DST Transition



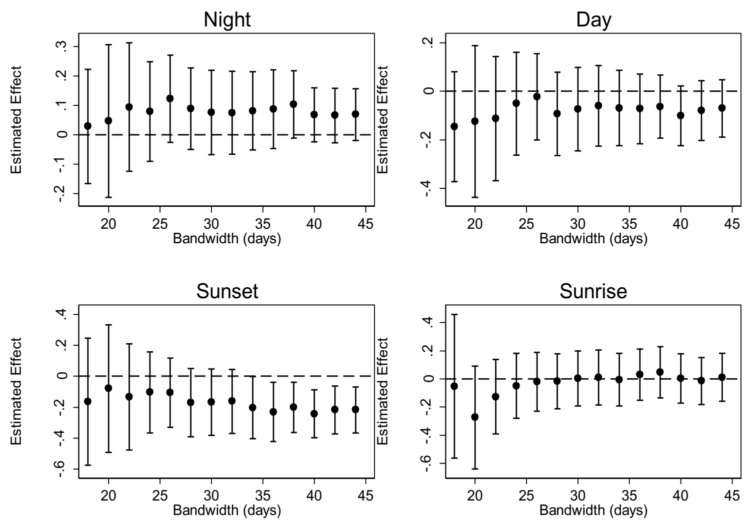
Notes: Histogram of crime reports by hours of the day. It considers robbery, larceny, theft, vehicle theft, burglary, murder, and rape incidents. Summer and winter refer to a false DST schedule which is set to begin after the second Saturday of May. Sample considers a window of three weeks after (summer) and before (winter) the false DST transition during the month indicated above each figure.

Figure 30. Histogram of RD Sunset Estimates by Day of Year: Robbery



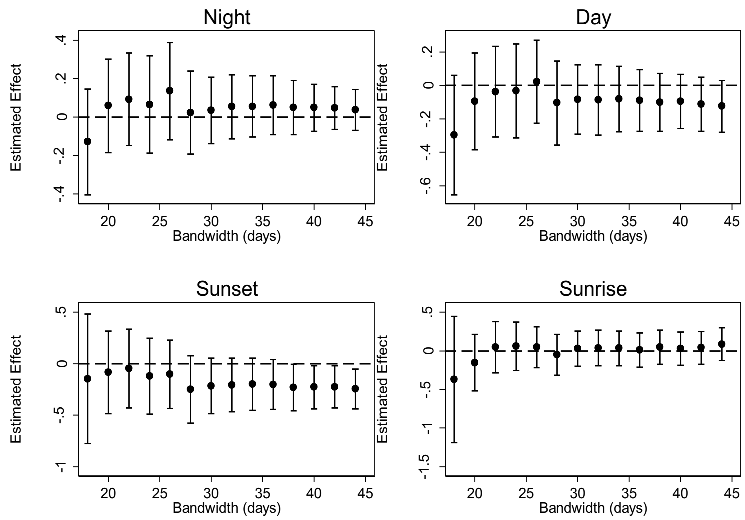
Notes: Histogram of RD coefficients estimates using equation (4) at sunset hours for every day of the year. We exclude days after December 15 and before April 15 to avoid both strong seasonality effects during the calendar year. All regressions consider robbery incidents during a window of three weeks after (summer) and before (winter) the false DST transition. Dashed line represents the value of our true DST transition in spring.

Figure 31. RD Spring Coefficients Sensitivity to Bandwidth Size by Daytime Period: Quadratic



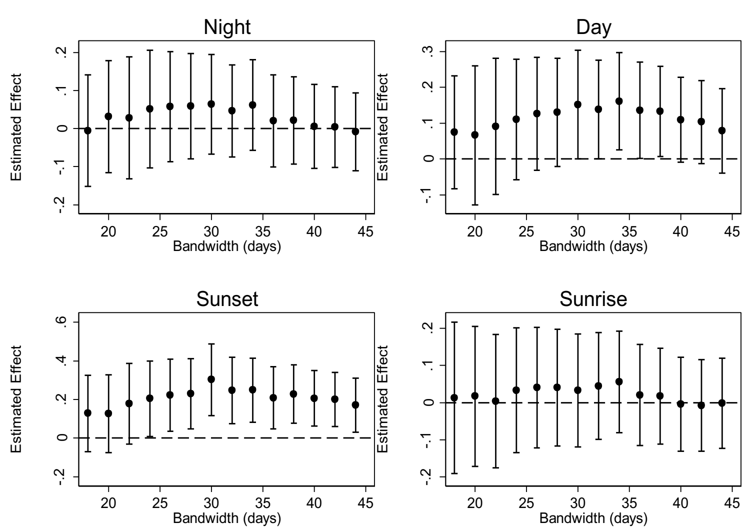
Notes: Each point represents RD estimates of summer coefficient using a sample of days indicated on x-axis. It includes 95% confidence intervals for each estimate using robust standard errors. Regressions consider log of crime incidents as dependent variable as specified in equation (4), considering a quadratic specification of the running variable.

Figure 32. RD Spring Coefficients Sensitivity to Bandwidth Size by Daytime Period: Cubic



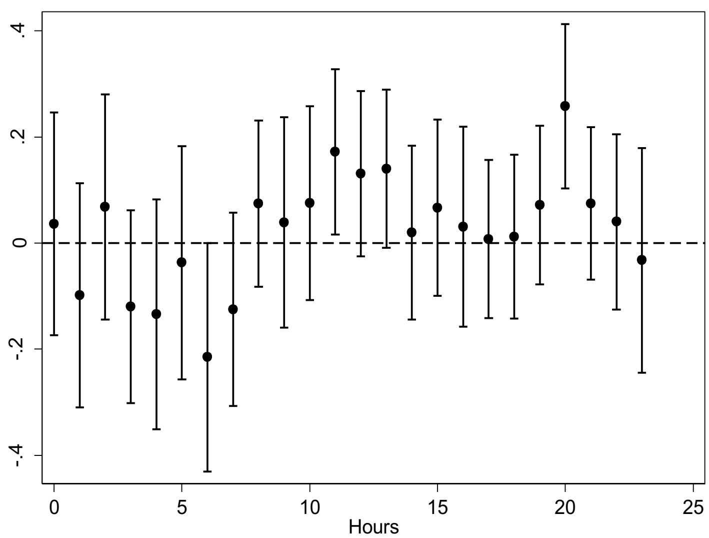
Notes: Each point represents RD estimates of summer coefficient using a sample of days indicated on x-axis. It includes 95% confidence intervals for each estimate using robust standard errors. Regressions consider log of crime incidents as dependent variable as specified in equation (4), considering a cubic specification of the running variable.

Figure 33. RD Fall Coefficients Sensitivity to Bandwidth Size by Daytime Period: Linear



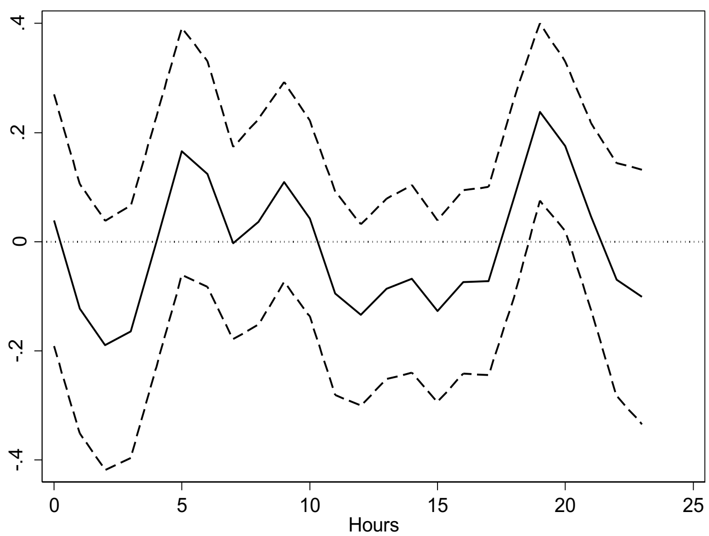
Notes: Each point represents RD estimates of winter coefficient using a sample of days indicated on x-axis. It includes 95% confidence intervals for each estimate using robust standard errors. Regressions consider log of crime incidents as dependent variable as specified in equation (4), considering a linear specification of the running variable.

Figure 34. RD Estimates by Hour during Fall DST Transition



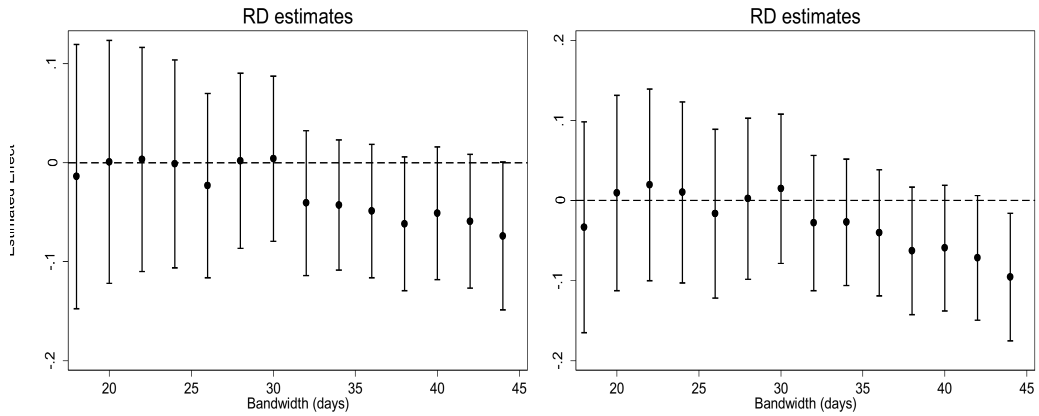
Notes: Each point represents the RD estimate of a regression using a sample restricted to the hour indicated on x-axis as specified in equation (4). It includes 95% confidence intervals for each estimate using robust standard errors. Summer refers to the DST schedule, which takes place after the second Saturday of March. Sample is restricted to three weeks before and after the DST transition in fall.

Figure 35. Difference-in-Differences Estimates by Hour of Day: Valparaíso



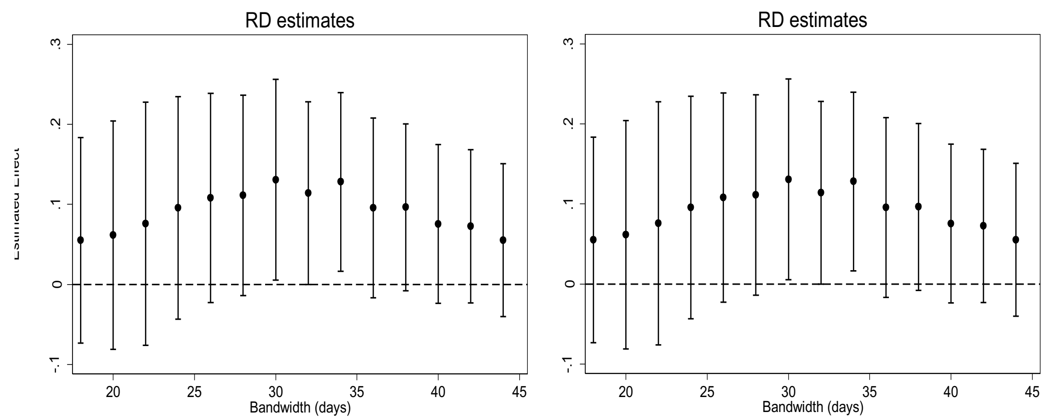
Notes: Figure represents hourly estimates of 24 difference in differences regressions as defined by equation (5) and using data from Valparaiso city. Each regression is estimated using a two-hour window period and the coefficient is plotted at the initial hour of the period. Sample is restricted to the period between the earliest DST March transition between the treatment (March 8) and control groups (March 29).

Figure 36. RD Spring Coefficients Sensitivity to Bandwidth Size: Overall Daily Effect, All Crimes (left) versus Robbery (right)



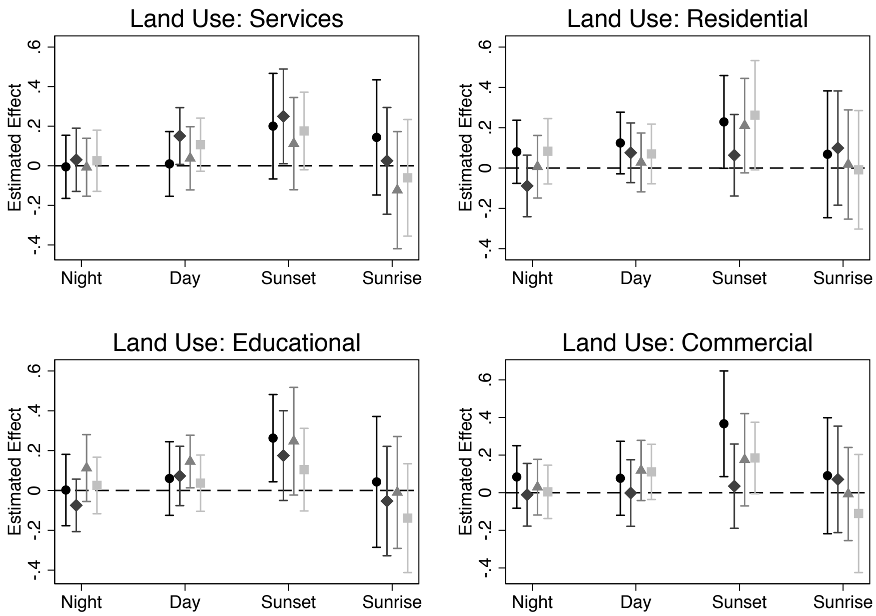
Notes: Figures show RD estimates using different bandwidth sizes according to equation (4). Left and right figures show estimates for property crime and robbery respectively. All coefficients are estimates for Winter using days before (winter) and after (summer) DST spring transition.

Figure 37. RD Fall Coefficients Sensitivity to Bandwidth Size: Overall Daily Effect, All Crimes (left) versus Robbery (right)



Notes: Figures show RD estimates using different bandwidth sizes according to equation (4). Left and right figures show estimates for property crime and robbery, respectively. All coefficients are estimates for Winter using days before (winter) and after (summer) DST fall transition.

Figure 38. RD Coefficients by Land Use around Fall DST Transition



Notes: RD coefficients by land-use using equation (4). Coefficients represents the effect of DST transition using different samples. For each period of the day, coefficients are estimated using separate samples, sorted by quartiles of land use intensity. Circles coefficients are estimated using a sample of the bottom quarter of *Estraus* zones, whereas squared coefficients are estimated using a sample of the top quarter of *Estraus* zones. Each coefficient includes a 95% confidence interval.

7.2. Tables

Table 8: RD Estimates by Daytime Period during Spring DST Transition

	Night	**Night**	**Night**	**Day**	**Day**	**Day**	**Sunrise**	**Sunrise**	**Sunrise**
Summer (D)	0.059	0.059	0.098	-0.0811	-0.0811*	-0.0441	0.0154	0.0154	0.0166
	(0.04)	(0.04)	(0.09)	(0.05)	(0.05)	(0.09)	(0.07)	(0.07)	(0.10)
Days	Y	Y	Y	Y	Y	Y	Y	Y	Y
Days^2	N	N	Y	N	N	Y	N	N	Y
Summer*Days	Y	Y	Y	Y	Y	Y	Y	Y	Y
Summer*Days^2	N	N	Y	N	N	Y	N	N	Y
DoWeek FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	Y	Y	N	Y	Y	N	Y	Y
N	210	210	210	210	210	210	210	210	210
R2	0.264	0.307	0.309	0.51	0.573	0.584	0.092	0.141	0.141

Notes: Coefficients using equation (4) by daytime period. Running variable is days before and after spring DST transition. Summer captures the discontinuity imposed by the DST schedule which usually takes place after the second Saturday of October. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: RD Estimates by Daytime Period during Fall DST Transition

	Night	**Night**	**Night**	**Day**	**Day**	**Day**	**Sunrise**	**Sunrise**	**Sunrise**
Winter (D)	-0.0225	-0.00819	0.0466	0.0905	0.0783	0.158	0.0131	-0.00193	0.0425
	(0.05)	(0.05)	(0.08)	(0.06)	(0.06)	(0.10)	(0.06)	(0.06)	(0.10)
Days	Y	Y	Y	Y	Y	Y	Y	Y	Y
Days^2	N	N	Y	N	N	Y	N	N	Y
Summer*Days	Y	Y	Y	Y	Y	Y	Y	Y	Y
Summer*Days^2	N	N	Y	N	N	Y	N	N	Y
DoWeek FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	Y	Y	N	Y	Y	N	Y	Y
N	221	221	221	221	221	221	221	221	221
R2	0.317	0.348	0.351	0.436	0.49	0.496	0.412	0.492	0.494

Notes: Coefficients using equation (4) by daytime period. Running variable is days before and after spring DST transition. Winter captures the discontinuity imposed by the DST schedule, which usually takes place after the second Saturday of March; see text for exceptions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: RD Estimates by Offense and Daytime Period: Fall DST Transition

	Night	**Day**	**Sunset**	**Sunrise**
All Crimes	0.0199	0.135*	0.209*	0.0204
	(0.06)	(0.07)	(0.08)	(0.07)
Robbery	0.103	0.137	0.317**	-0.113
	(0.08)	(0.08)	(0.11)	(0.13)
Larceny	0.245	0.113	0.236	-0.0479
	(0.15)	(0.11)	(0.17)	(0.18)
Vehicle Theft	-0.168	0.13	0.11	0.221
	(0.11)	(0.12)	(0.17)	(0.18)
Theft from vehicles	0.0495	0.0501	0.198	0.0718
	(0.08)	(0.08)	(0.12)	(0.16)
Burglary w/People	-0.149	0.0343	0.26	-0.107
	(0.12)	(0.09)	(0.19)	(0.13)
Burglary w/o People	-0.0449	0.0143	0.131	0.0304
	(0.12)	(0.12)	(0.19)	(0.16)
Other robbery	-0.0565	0.0682	-0.109	-0.165
	(0.20)	(0.17)	(0.18)	(0.20)
Theft	0.129	0.239*	0.217	0.312
	(0.15)	(0.10)	(0.14)	(0.17)

Notes: Estimates from 36 regressions using equation (4) by crime category and daytime period. Sample size considers three weeks before and after DST transition and excluding days in February as in Table 3. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: RD Estimates by Offenses and Two-Hour Period: Spring DST Transition

	All	**Rob**	**Larc**	**VehTh**	**ThfVeh**	**BwP**	**Bw/oP**	**ORob**	**Thef**
[1-2]	-0.0125	-0.104	-0.235	0.0116	0.167	-0.118	-0.11	-0.344*	-0.0116
	(0.08)	(0.11)	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)	(0.16)	(0.13)
[3-4]	0.0251	-0.0611	-0.0731	0.107	-0.0981	-0.0573	0.114	0.0274	0.0523
	(0.09)	(0.12)	(0.15)	(0.12)	(0.11)	(0.11)	(0.12)	(0.16)	(0.13)
[5-6]	0.108	0.286**	0.0201	0.087	-0.0308	0.0192	-0.0198	0.063	0.158
	(0.09)	(0.11)	(0.15)	(0.11)	(0.13)	(0.13)	(0.11)	(0.14)	(0.12)
[7-8]	-0.0783	0.0604	0.0463	-0.0785	-0.00681	-0.228	0.089	-0.146	-0.234
	(0.07)	(0.12)	(0.11)	(0.12)	(0.12)	(0.13)	(0.13)	(0.18)	(0.14)
[9-10]	-0.0815	-0.162	0.0182	0.244	-0.235*	0.0451	-0.0248	-0.146	-0.328*
	(0.07)	(0.12)	(0.12)	(0.13)	(0.11)	(0.12)	(0.13)	(0.16)	(0.13)
[11-12]	-0.11	-0.109	-0.115	0.0224	-0.0504	-0.0816	0.124	-0.243	-0.0884
	(0.06)	(0.12)	(0.13)	(0.11)	(0.11)	(0.12)	(0.11)	(0.13)	(0.10)
[13-14]	-0.105	0.00422	-0.19	-0.101	0.0392	-0.237	-0.089	0.201	-0.131
	(0.06)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)	(0.11)	(0.12)	(0.11)
[15-16]	-0.046	0.0291	-0.319**	-0.062	0.113	-0.0388	0.0907	-0.058	-0.166
	(0.06)	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)	(0.11)	(0.15)	(0.09)
[17-18]	0.0141	-0.0506	0.0661	-0.145	0.0269	0.179	0.126	-0.367**	0.0684
	(0.05)	(0.11)	(0.12)	(0.11)	(0.12)	(0.12)	(0.12)	(0.13)	(0.10)
[19-20]	-0.181***	-0.354***	0.0697	-0.164	-0.260*	-0.231	-0.0858	-0.145	-0.239*
	(0.05)	(0.10)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.14)	(0.11)
[21-22]	0.0684	0.129	-0.143	0.0134	0.0724	-0.0182	0.0243	0.132	0.156
	(0.05)	(0.10)	(0.13)	(0.12)	(0.10)	(0.12)	(0.11)	(0.15)	(0.11)
[23-0]	0.0766	0.0734	-0.0723	0.274*	0.0992	0.056	0.182	0.0171	-0.126
	(0.10)	(0.12)	(0.15)	(0.13)	(0.13)	(0.13)	(0.13)	(0.16)	(0.14)

Notes: Estimates from 108 regressions using equation (4) by crime category and hour of the day. Sample size considers 17 days before and after DST transition as in Table 2. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 12: RD Estimates by Offenses and Two-Hour Period: Fall DST Transition

	All	**Rob**	**Larc**	**VehTh**	**ThfVeh**	**BwP**	**Bw/oP**	**ORob**	**Thef**
[1-2]	0.012	0.0626	0.0686	0.0337	-0.0173	-0.0224	0.172	-0.131	-0.0465
	(0.09)	(0.12)	(0.17)	(0.13)	(0.14)	(0.13)	(0.11)	(0.19)	(0.12)
[3-4]	-0.11	-0.0847	0.11	0.131	-0.0862	-0.168	0.0723	0.0269	-0.0913
	(0.08)	(0.13)	(0.14)	(0.12)	(0.12)	(0.13)	(0.12)	(0.22)	(0.13)
[5-6]	-0.0606	-0.0443	0.122	-0.0967	0.0817	-0.254*	-0.0569	0.102	0.0607
	(0.10)	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)	(0.12)	(0.10)	(0.14)
[7-8]	0.0133	0.11	0.00435	0.141	0.0524	-0.146	0.0112	-0.232	0.259
	(0.07)	(0.13)	(0.12)	(0.13)	(0.14)	(0.12)	(0.12)	(0.19)	(0.14)
[9-10]	0.0892	-0.0235	0.0821	0.000636	0.0432	0.158	-0.0828	-0.0554	0.101
	(0.08)	(0.12)	(0.12)	(0.13)	(0.13)	(0.13)	(0.13)	(0.21)	(0.14)
[11-12]	0.220**	0.17	0.155	0.141	0.0238	0.105	-0.0744	-0.137	0.366**
	(0.07)	(0.13)	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.18)	(0.12)
[13-14]	0.125	0.148	0.02	0.331**	-0.118	0.162	-0.0568	-0.232*	0.236*
	(0.06)	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)	(0.12)	(0.10)	(0.11)
[15-16]	0.11	0.0391	0.163	-0.0172	0.0533	0.0209	-0.232	-0.154	0.237
	(0.08)	(0.11)	(0.12)	(0.13)	(0.13)	(0.13)	(0.12)	(0.09)	(0.13)
[17-18]	0.0926	-0.0196	0.0998	0.0745	0.126	-0.159	0.156	0.137	0.113
	(0.06)	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)	(0.11)	(0.13)	(0.11)
[19-20]	0.203**	0.365**	0.0373	0.0761	0.281*	0.175	0.149	-0.0656	0.199
	(0.07)	(0.11)	(0.13)	(0.13)	(0.12)	(0.14)	(0.13)	(0.09)	(0.13)
[21-22]	0.105	0.288**	0.129	-0.192	0.16	0.0764	0.00406	-0.038	0.227
	(0.07)	(0.11)	(0.13)	(0.13)	(0.12)	(0.12)	(0.14)	(0.13)	(0.14)
[23-0]	0.0291	0.11	0.0463	-0.1	0.0209	-0.225	-0.0442	-0.141	-0.146
	(0.10)	(0.13)	(0.14)	(0.14)	(0.14)	(0.13)	(0.15)	(0.17)	(0.14)

Notes: Estimates from 108 regressions using equation (4) by crime category and hour of the day. Sample size considers three weeks before and after DST transition and excluding days in February as in Table 3. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 13: RD Estimates of Metro Ridership during Fall DST Transition: Santiago, 2005-2010

	Night	Night	Day	Day	Sunset	Sunset	Sunrise	Sunrise
Winter (D)	-0.017	0.231	0.0763	0.142	0.0708	0.132	0.372*	0.369
	(0.089)	(0.143)	(0.058)	(0.095)	(0.054)	(0.087)	(0.178)	(0.307)
Days	Y	Y	Y	Y	Y	Y	Y	Y
Days^2	N	Y	N	Y	N	Y	N	Y
Winter x Days	Y	Y	Y	Y	Y	Y	Y	Y
Winter x Days^2	N	Y	N	Y	N	Y	N	Y
DoWeek FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	221	221	221	221	221	221	221	221
R2	0.821	0.83	0.893	0.895	0.854	0.856	0.891	0.892

Notes: Regressions coefficients using equation (6). Dependent variable is log of metro ridership in each daytime period. Summer and winter refer to the DST schedule, which switches in fall and spring. Sample size considers 21 days before and after (winter) DST transition as in Table 2. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Crime Distribution by Land Use Zones

	Other-uses	Services	Industrial	Residential	Educational	Commercial
Panel B: Crime Distribution. Spring DST Transition						
p1	0.006	0.000	0.000	0.006	0.000	0.002
p25	0.056	0.007	0.001	0.426	0.013	0.023
p50	0.133	0.031	0.007	0.652	0.029	0.051
p75	0.201	0.083	0.055	0.836	0.050	0.109
p99	0.646	0.482	0.368	0.971	0.224	0.358
Panel C: Crime Distribution. Fall DST Transition						
	Other-uses	Services	Industrial	Residential	Educational	Commercial
p1	0.006	0.000	0.000	0.006	0.000	0.002
p25	0.057	0.008	0.001	0.424	0.013	0.024
p50	0.137	0.032	0.007	0.644	0.029	0.052
p75	0.204	0.084	0.055	0.832	0.050	0.110
p99	0.647	0.482	0.357	0.971	0.206	0.358

Notes: Columns show land distribution by different uses identified at the top. Rows indicate percentiles of the sample when sample of zones is sorted by each particular use. Values indicate the proportion of the land devoted to each particular use for each percentile of the sample. Panel B and C are calculated using the sample of crime incidents used around spring and fall DST transition, respectively.

Table 15: RD Coefficients by Land Use: Spring DST Transition

	Land Use < Median	Land Use > Median	Difference	Difference
Panel E: Industrial	(1)	(2)	(1) - (2)	P-Value
Night	0.113	0.020	-0.093	0.071
	(0.052)	(0.043)		
Day	-0.107	-0.065	0.042	0.340
	(0.053)	(0.047)		
Sunset	-0.154	-0.255	-0.101	0.195
	(0.076)	(0.065)		
Sunrise	0.014	0.031	0.017	0.893
	(0.106)	(0.089)		
Panel E: Other				
Night	0.049	0.065	0.016	0.759
	(0.049)	(0.044)		
Day	-0.077	-0.082	-0.005	0.906
	(0.047)	(0.052)		
Sunset	-0.210	-0.203	0.006	0.936
	(0.077)	(0.068)		
Sunrise	0.150	-0.096	-0.245	0.036
	(0.093)	(0.092)		

Notes: Coefficients represents the effect of spring DST transition using different samples. Coefficients are estimated using equation (4) by daytime period and considering crimes that take place in zones identified by each column and panel. Column (1) and (2) considers crimes that take place in areas where land use of the zone indicated in the respective panel is below (above) the median of Santiago. The hypothesis tests are Wald chi-square tests of the type $H_0 : \beta_{below}$- $\beta_{above} = 0$ on SUR models including the respective above and below median regressions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 16: RD Coefficients by Land Use: Fall DST Transition

	Land Use < Median	Land Use > Median	Difference	Difference
Panel A: Services	(1)	(2)	(1) - (2)	P-Value
Night	0.015	-0.024	0.039	0.491
	(0.062)	(0.057)		
Day	0.084	0.081	0.003	0.941
	(0.060)	(0.062)		
Sunset	0.245	0.177	0.068	0.449
	(0.095)	(0.077)		
Sunrise	0.058	-0.149	0.207	0.113
	(0.117)	(0.095)		
Panel B: Residential				
Night	-0.004	-0.004	0.001	0.989
	(0.064)	(0.057)		
Day	0.106	0.048	0.058	0.218
	(0.070)	(0.055)		
Sunset	0.128	0.190	-0.062	0.446
	(0.086)	(0.089)		
Sunrise	-0.015	-0.108	0.093	0.496
	(0.134)	(0.086)		
Panel C: Educational				
Night	-0.038	0.016	-0.054	0.367
	(0.060)	(0.061)		
Day	0.077	0.069	0.008	0.864
	(0.069)	(0.056)		
Sunset	0.214	0.152	0.061	0.462
	(0.082)	(0.083)		
Sunrise	-0.010	-0.111	0.101	0.428
	(0.122)	(0.089)		
Panel D: Commercial				
Night	0.025	-0.012	0.038	0.543
	(0.064)	(0.057)		
Day	0.024	0.088	-0.065	0.243
	(0.070)	(0.062)		
Sunset	0.148	0.191	-0.043	0.672
	(0.099)	(0.077)		
Sunrise	0.010	-0.138	0.148	0.305
	(0.126)	(0.095)		

Notes: Coefficients represents the effect of fall DST transition using different samples. Coefficients are estimated using equation (4) by daytime period and considering crimes that take place in zones identified by each column and panel. Column (1) and (2) considers crimes that take place in areas where land-use of the zone indicated in the respective panel is below (above) the median of Santiago. The hypothesis tests are Wald chi-square tests of the type H_0 : β_{below}- β_{above} = 0 on SUR models including the respective above and below median regressions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 17: RD Coefficients by Land Use: Fall DST Transition

	Land Use < Median	Land Use > Median	Difference	Difference
Panel E: Industrial	(1)	(2)	(1) - (2)	P-Value
Night	(0.033)	-(0.038)	0.070	0.187
	0.063	0.055		
Day	0.123	0.047	0.076	0.104
	(0.066)	(0.060)		
Sunset	0.165	0.183	-0.018	0.815
	0.079	0.082		
Sunrise	(0.022)	-(0.099)	0.120	0.345
	0.110	0.093		
Panel E: Other				
Night	0.064	-0.023	0.087	0.151
	(0.063)	(0.059)		
Day	0.047	0.093	-0.047	0.320
	0.058	0.064		
Sunset	(0.210)	(0.178)	0.032	0.711
	0.097	0.075		
Sunrise	-0.084	-0.075	-0.009	0.928
	(0.102)	(0.098)		

Notes: Coefficients represents the effect of fall DST transition using different samples. Coefficients are estimated using equation (4) by daytime period and considering crimes that take place in zones identified by each column and panel. Column (1) and (2) considers crimes that take place in areas where land-use of the zone indicated in the respective panel is below (above) the median of Santiago. The hypothesis tests are Wald chi-square tests of the type $H_0 : \beta_{below}$- $\beta_{above} = 0$ on SUR models including the respective above and below median regressions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.