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# The Unequal Impact of Natural Light on Crime

EMILIANO TEALDE\*

This paper studies the relationship between ambient light and criminal activity. A Becker-style crime model is developed where it is shown that in areas with less public lighting a sudden increase in ambient light produces a higher reduction in crime. The Daylight Saving Time, the natural experiment used, induces a sharp increase in natural light during crime-intense hours. Using geolocated data on crime and public lighting for the city of Montevideo in Uruguay, regression discontinuity estimates identify a strong and statistically significant decrease in robbery of 17-percent. The decrease is larger in poorly lit areas. Computing the level of public lighting at which DST has no effect on crime reduction, we identify the minimum level of public lighting that an area should target.

*JEL: K42*

*Keywords: DST, property crime, public lighting, heterogeneous effects*

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## I. Introduction

The Becker model of crime (Becker, 1968) states that a potential offender weighs costs against benefits before committing a crime. Taking the Becker model as a starting point, a vast empirical literature studies the influence of different factors on criminal activity. In this paper, we follow this tradition and evaluate how natural light affects crime.

Among the factors that have been proposed and studied as determinants of crime, we can find the probability of capture and the cost of finding a potential victim. Natural light is related to both. On the one hand, more light eases the task of identifying a criminal, which in turn increases the probability of capture and therefore the cost of crime. Yet, it also increases outdoor activities, which diminish the cost of finding a potential victim and, thus, the cost of crime. In this paper, we empirically evaluate the causal net effect of ambient light on crime.

Daylight Summer Time (DST) delays sunset one hour. It exogenously improves natural light available at one hour of late afternoon. DST "moves" one hour of natural light from the sunrise to the sunset. A pattern of crime is that it is not evenly spread throughout the day. Crime is very low around sunrise, increases during "working hours" and peaks around sunset. Thus, by taking one hour from the morning and placing it in the late afternoon, DST gives an additional hour of natural light to a crime-intense period of the day.

The change in ambient light provoked by a change in natural light is not the same throughout a city. When DST is implemented and clocks are moved forward one hour, the change from nighttime to daytime yields different changes in ambient light according to different levels of public lighting availability. In a poorly lit area, the implementation of DST causes a larger increase in ambient light availability than in a well lit area.

In this work, the causal impact of DST on criminal activity is measured for the city of Montevideo, Uruguay, where DST was observed from 2004 to 2014. During this period, on the second Sunday of October, the beginning of Spring in the Southern Hemisphere, clocks were shifted ahead one hour and were set back one hour on the second Sunday of March, near to the end of the Summer. The discontinuity in natural light during working hours provoked by this natural experiment is used to recover the causal effect of natural light on crime. With georeferenced data on crime and public lighting, we measure the heterogeneous impact across the city.

The most important contribution of this work is that we find a heterogeneous impact of DST on criminal activity. We split the city into quartiles of public lighting. In the first quartile, the reduction in robbery reaches the 33.1-percent. In the second quartile, the reduction is of 25.6-percent. These results are statistically significant at standard levels. In the third and fourth quartiles the magnitude of the effect estimated is not only much lower, 3.9 and 2-percent, respectively, but also non-significant statistically. To the best of our knowledge, no work has addressed previously

the heterogeneous effect of natural light on crime, according to differences in public lighting.

It is worth noting that no effects are found in the third and fourth quartiles of public lighting, for any of the forms of crime analyzed: robbery, theft, murder and rape. Above a certain threshold, more public lighting does not reduce crime. The point at which DST has no effect on crime is the minimum level of public lighting that an area should target to minimize crime. For this point and above, in terms of crime reduction, DST does not provoke an increase in ambient light. In this regard, the threshold is the minimum point at which public lighting is "as good as natural light". We also present descriptive evidence that shows that there is a negative correlation between public lighting and economic conditions across the city.

We find that DST reduces total property crime in the city. In our preferred specification, daily robbery decreases by a magnitude of 17-percent. During sunset hours, the decrease reaches the 22.9-percent. The effect on theft, murder and rape are also evaluated. Some estimates indicate a negative effect of DST on theft; however, the results are not robust to different specifications. The policy does not seem to have any effect on murder and rape. This is not a surprising result: while robberies and thefts are commonly committed outdoors and victims are unknown to offenders, murders and rapes are usually either committed indoors, or the criminal knows the victim beforehand, or both. This makes murder and rape forms of crime that are less prone to respond to changes in ambient light. Moreover, personal crime is less likely to respond to economic incentives than property crime.

To recover the causal effect of DST on criminal rates this paper uses a Regression Discontinuity Design. In an interval of days close enough to the first Sunday that DST is observed, the environmental variables affecting crime other than natural light in late afternoon remain stable. We test the robustness of the results to different bandwidths and different specifications.

We use three datasets to put together the dataset used to compute the estimates. First, we use georeferenced data on criminal activity for the city of Montevideo, provided by the Ministry of Interior. This dataset contains each complaint filled in the city, discriminated by offense, with the exact date, hour and minute of occurrence. For each offense, the dataset contains the exact coordinates where it occurred. To estimate the impact for different areas of the city, we use georeferenced data on street lighting. The dataset indicates the availability of street lighting at the block level for the entire city. The dataset is provided by the National Statistics Institute (NSI). From the Continuous Household Surveys (CHS), also conducted by the NSI, we obtain data on home income, unemployment and family composition, used as controls in some specifications and to explore the relationship between socioeconomic variables and public lighting.

The most innovative result of this paper is that the impact of natural light on crime depends on the public lighting available, a result that has not been found before in the literature. The effect is heterogeneous across the city, with poorly lit, poorest areas of the city, the most favored in terms of

crime reduction. Well lit areas do not witness a change in crime trends after the implementation of DST. These results provide relevant inputs for the design of the urban landscape, as they show that additional lighting in already well lit areas are not useful while improvements in poorly lit areas yield large drops in crime.

This work is closely related to previous works that have exploited the discontinuity of natural light during working hours provided by DST to evaluate the effect of luminosity on criminal activity. Doleac and Sanders (2015) are the first to use DST as a source of exogenous variation to causally identify the effect of natural light on criminal activity. They use a sample of 582 counties that report to the National Incident-Based Reporting System in the US to measure the impact of DST on criminal activity, and find that daily robbery rates fall 7-percent with a decrease of 27-percent during sunset hours. Dominguez and Asahi (2017) evaluate the effect of DST in the Chilean cities of Santiago de Chile and Valparaíso and find a reduction in daily property crime rates of 20-percent, a reduction that reaches 33-percent for robberies during sunset hours.

Munyo (2018) evaluates the effect of the implementation of DST on crime in Montevideo. Although exploiting the same policy, the author uses a different research design. In this work, we follow Doleac and Sanders (2015) and Dominguez and Asahi (2017) and exploit a discontinuity of natural light during working hours to evaluate the effect of natural light on crime. We use days as the running variable and evaluate the effect on daily crime. Munyo (2018) exploits the potential sleep deprivation caused by DST on criminals to evaluate its effect on crime during the hours immediately after the implementation of the policy. He uses hours as the running variable and evaluates the effect of DST only on hourly crime. He finds a decrease in hourly rates of robbery and theft of 24 and 11-percent, respectively.

The mechanism through which DST reduces criminal activity is that it increases the probability of being captured. In this regard, this paper is related to a large literature that evaluates the impact of policies aimed to increase the probability of capture. A work closely related is Chalfin, Hansen, Lerner and Parker (2019). The authors provide experimental evidence, for New York City, that street lighting reduces crime, in particular violent outdoor crimes that occur during nighttime. In this work, we provide an estimate of the minimum level of public lighting that an area should target to minimize crime. The installment of security cameras is also a manner of increasing the probability of capture. Priks (2015) for Stockholm and Munyo and Rossi (2019) for Montevideo, using quasi-experimental designs, find that security cameras diminish criminal activity. The causal effect of police deployment on crime has received a lot of attention in the literature. The results are mixed, with some findings indicating that more police results in less criminal activity (Draca, Machin and Witt, 2011; Klick and Tabarrok, 2005; Di Tella and Schagrodsky, 2004) and others suggesting that crime is only displaced to adjacent areas (Blattman, Green, Ortega and Tobón,

2018; Donohue, Ho and Leahy, 2013).<sup>1</sup>

Recent literature studies the distributional effects of security measures, a point addressed in this work. Galiani, López and Torrens (2018) study the relationship between police deployment, welfare, and inequality. The authors find that when the police concentrate protection on some neighborhoods, instead of providing dispersed protection across the city, welfare is maximized but social disparities are exacerbated.<sup>2</sup>

This work is structured as follows. The next section presents a model that extends the Becker model of crime to study the effect of natural and artificial light on criminal behavior. The third section provides a brief background on DST in Uruguay. Section IV presents the empirical strategy and Section V the data used. Section VI presents the main results, provides some robustness checks and a placebo test. Section VII concludes the document.

## II. The Model

### A. The General Setup

We develop a Becker-style crime model that studies the relationship between ambient light, the sum of natural light and public lighting, and criminal activity. In this simple model a homogeneous agent must choose to offend among two areas that differ only in the amount of ambient light available. During daytime ambient light is natural light, which is equal for all areas. During nighttime ambient light is given by public lighting, which varies by area. The model makes explicit under which conditions an increase in ambient light provokes a reduction in crime. A crime-ambient light elasticity is derived, and it is shown that the elasticity is higher in absolute value, given similar crime levels, for areas with less ambient light.

In this paper I model the Becker model of crime in a similar way to Draca, Machin and Witt (2015), Machin and Meghir (2004) and Freeman (1999). A rational offender commits a crime as long as the following inequality holds:

$$P(1 - \pi) - \pi S - D \geq W \quad (1)$$

where  $P$  is the value of the loot derived from the sell of the only good of the economy;  $\pi$  is the probability of apprehension faced by the individual  $i$ ;  $S$  is the legal sanction the criminal faces if captured;  $D$  is the direct cost of committing a crime; and  $W$  is the wage the individual could receive in the legal labor market.

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<sup>1</sup>Chalfin and McCrary (2017) provide a comprehensive review of the literature that studies the relationship between crime and police presence.

<sup>2</sup>A revision of the vast literature that addresses the relationship between inequality and crime is beyond the scope of this paper. It is worth mention, however, that Kang (2016) provides a recent review of the literature.

The individual can choose between two areas to offend: area 1 and area 2. The areas can differ in the amount of ambient light availability and crime levels. Ambient light affects  $\pi$  through the following equation:

$$\pi_a = kA_aC_a \quad (2)$$

The subindex  $a$  indicates an area and can take two values: 1 and 2. The parameter  $k$ , equal for both areas, belongs to the  $(0, 1]$  interval. Equation (2) reflects the positive relationship of ambient light and the likelihood of capture. With more ambient light, it is easier for a witness to spot a criminal, and therefore  $\pi$  increases. It also highlights the positive relationship between the criminal level in the area and the likelihood of capture. As crime in the area increases, it is less likely that additional criminal activities remain unseen. As criminal activity goes up, there are fewer criminal opportunities left, which yields a higher likelihood of capture in the area.

Ambient light affects the decision of offending although through its incidence on the direct cost of committing a crime. The relationship between ambient light and the direct cost is represented by the following equation:

$$D_a = \frac{q}{A_a} \quad (3)$$

that holds for  $a=1, 2$ , where  $q \in (0, 1]$ . Equation (3) reflects a negative relationship between ambient light and the cost of committing a crime. More ambient light impulses outdoor activities, thus reducing the cost of finding a victim outdoors for a given criminal level. To ensure that criminal activity related to the only good of this economy is attractive,  $P$ , the value of the loot, is larger than the sum of the opportunity cost of crime,  $W$ , and the direct cost of crime,  $\frac{q}{A_a}$ :

$$P > W + \frac{q}{A_a} \quad (4)$$

for  $a = 1, 2$ .

The individual will offend in area 1 rather than in area 2 as long as:

$$P(1 - CA_1k(P + S)) - \frac{q}{A_1} > P(1 - CA_2k(P + S)) - \frac{q}{A_2} \quad (5)$$

If the above inequality holds, crime in area 1 will increase. The level of criminal activity in area 1 will increase until the expected return to crime in the area equals the expected return to crime in area 2. In equilibrium, the expected return to crime in both areas equal  $W$ , the value of the outside option:

$$P(1 - CA_ak(P + S)) - \frac{q}{A_a} = W \quad (6)$$

for every  $a$ . The number of criminal offenses in area 1 can be found by equalizing the expected return to crime with the wage offered in the labor market:

$$C_1 = \frac{P - W - \frac{q}{A_1}}{A_1 k(P + S)} \quad (7)$$

From (6) it is possible to find the crime-ambient light elasticity, by deriving the equation with respect to  $A_1$  and multiplying by  $\frac{A_1}{C_1}$ :

$$\epsilon_{C_1, A_1} = \frac{(W - P + \frac{2q}{A_1})}{A_1 k(P + S) C_1} \quad (8)$$

The restriction imposed by equation (4) ensures that the above elasticity is negative for both areas. It is worth noting that equation (8) implies that, given similar crime levels, a one-percent change in ambient light yields a larger reduction in criminal activity in the area with a smaller amount of initial ambient light.

## B. The Expected Effect of DST

Ambient light is the addition of natural light (N) and public lighting (L):

$$A = N + L \quad (9)$$

Natural light is equal to the positive constant  $n$  for both areas, during daytime. During nighttime, natural light equals 0. Public lighting equals 0 during daytime, and a positive constant  $l_1$  and  $l_2$ , during nighttime, for areas 1 and 2, respectively. Area 1 has better public lighting than area 2,  $l_1 > l_2$ , and no public lighting is as good as natural light,  $n > l_1$ .

DST delays sunset by one hour.<sup>3</sup> Sunset, that is the time of the day when criminal rates peak, is suddenly moved ahead one hour with the implementation of DST. This produces a change in ambient light during one hour that before-DST is nighttime, and therefore ambient light equals the amount of public lighting disposable in the area, and after-DST is daytime, and as a consequence ambient light equals natural light.

The change in ambient light available, due to DST, differs depending on the amount of public lighting available in the area. In area 1, the percentage change is:

$$\frac{\Delta A_1}{A_1} = \frac{A_{1,DST} - A_{1,preDST}}{A_{1,preDST}} = \frac{n - l_1}{l_1} \quad (10)$$

The analogous equation for area 2 is:

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<sup>3</sup>Early morning is a low-intense-crime time of the day. Changes in ambient light during sunrise hours are not expected to provoke perceivable changes in criminal activity. Previous empirical literature corroborates this intuition (Doleac and Sanders, 2015).



$$\frac{\Delta A_2}{A_2} = \frac{n - l_2}{l_2} \quad (11)$$

Naturally, the percentage change provoked by the DST implementation is higher in area 2 than in area 1. According to equation (8), each percent-point change in ambient light in area 2 produces a larger reduction in crime than in area 1. These two effects combined imply that DST implementation is expected to produce a larger drop in crime in the area with the worst public lighting.

### III. DST

Uruguay observed DST during many periods along the 20th Century: 1923–1926, 1933–1943, 1959–1960, 1965–1970, 1972, 1974–1980 and 1987–1993. In the spring of 2004 DST was implemented again, with the Government defending the measure on the same grounds as when it was previously observed: a saving energy action. From the spring of 2004 to the spring of 2014 clocks shift ahead one hour until the end of the summer, to be set back one hour during autumn and winter. It is for this period that we have geo-referenced data on criminal activity, and therefore it is the period we are focusing on.

When DST was implemented in 2004, it lasted from the third Sunday of September to the fourth Saturday of March 2005. DST was implemented again the following spring but covered a shorter period, from the second Sunday of October 2005 to the second Saturday of March 2006. From the Spring of 2006 until the Spring of 2014, DST was introduced always the second Sunday of October and lasted until the second Saturday of the following March. In 2015 DST was discontinued and has not been observed again in Uruguay. The Government mentioned concerns of the tourism sector regarding DST, as many visitors preferred to enjoy outdoor activities rather than to consume at bars and restaurants.

Montevideo is populated by more than 1,5 million inhabitants and social life is very dynamic during evenings and nights. The lack of extreme weather conditions contributes to the enjoyment of outdoor activities. Daily mean temperatures range from 11.1 °C (53.1 °F) in July, the coldest month of the year, to 23.2 °C (73.8 °F) in January, the warmest one.<sup>4</sup> Even without a subway, public transportation is efficient in relative terms, which contributes as well to the movement of people around the city until late hours. In 2019, the average commute time was 40 minutes in Montevideo, less than in any other South American capital. Bogotá, for instance, had an average commute time of 67 minutes, Sao Paulo 62 and Buenos Aires, 53.<sup>5</sup> For a city of its size, Montevideo is secure in relative terms. In 2016, its murder rate per 100,000 inhabitants was 10.6. If we compare it with

<sup>4</sup>Source: *Dirección Nacional de Meteorología*. The data covers the period 1980-2009.

<sup>5</sup>The average commute time data is taken from the Moovit Public Transport Index.

some US cities, in the same year, Chicago, Miami and New York City presented a murder rate per 100,000 inhabitants of 12.2, 27.7 and 3.4, respectively.

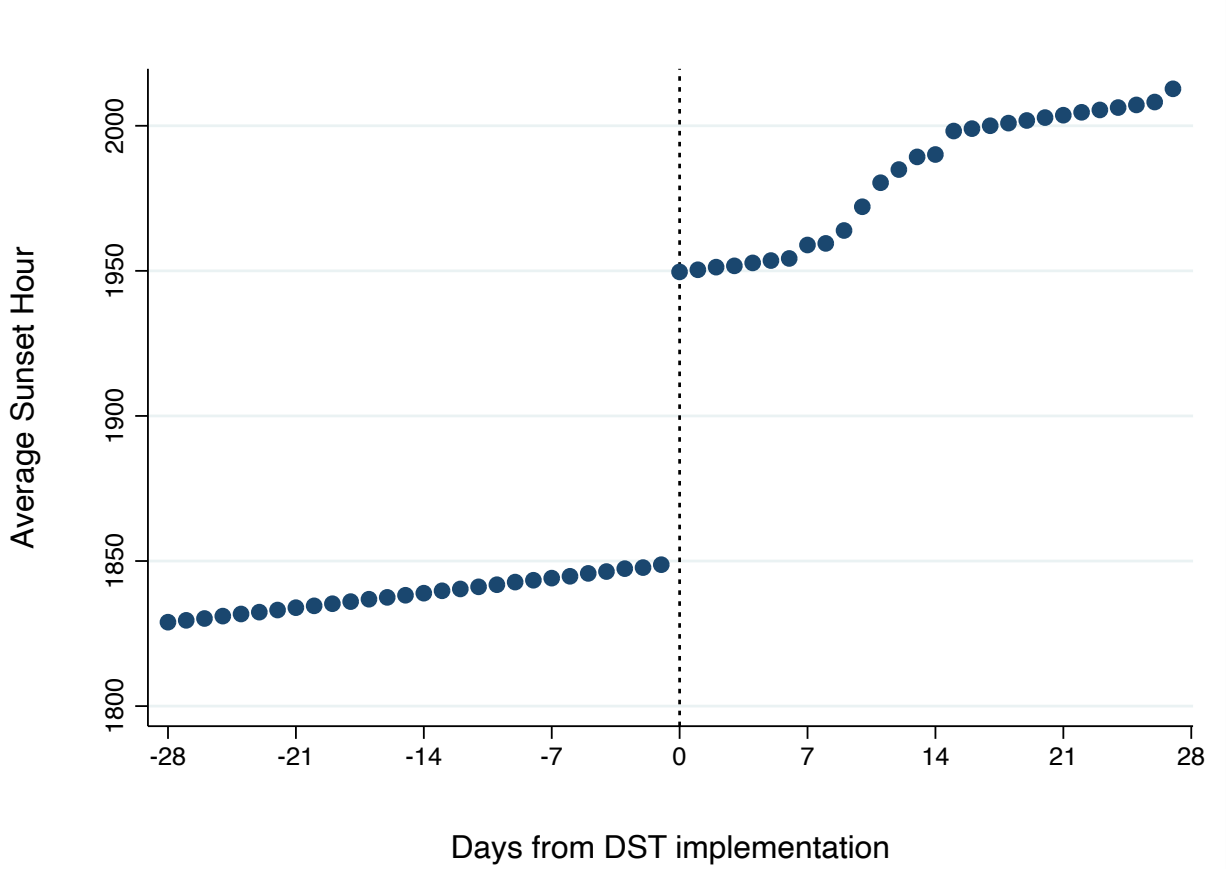
In a city like Montevideo, the delay in the sunset is not likely to change habits sharply. We would expect larger changes in habits in cities where social life drops significantly during nighttime, due to crime, inefficient public transportation, or bad weather. This feature of the city reinforces the validity of our empirical strategy. In a window of time around the implementation of DST, it is not likely that urban dynamics will change drastically.

#### **IV. Empirical Strategy**

In this paper, the causal effect of natural light on crime is recovered by exploiting the discontinuity of natural light during key hours provided by the DST. From one day to the next sunset is delayed one hour, which gives an additional hour of sunlight during the late afternoon. Using a Regression Discontinuity Design, we can identify the impact of natural light on criminal activity.

We compute estimates for property crime with and without violence, robbery and theft, respectively. As these crimes are usually committed outdoors, it is reasonable to expect that they will be affected by changes in natural light. We also compute estimates for two types of personal crime, homicide and rape. These types of crime are many times committed indoors or the offender knows the victim in advance, which makes murders and rapists less likely to respond to changes in luminosity. Thus, we should expect a larger effect on property than on personal crime.

Figure 1: Sunset



Notes: the figure depicts the average sunset hour around the threshold for the period 2004-2014. The horizontal axis measures the distance in days from the threshold. The average sunset hour is depicted for an 8-weeks bandwidth.

The baseline estimate is the following:

$$crime_i = \alpha + \beta_1 days_i + \beta_2 DST_i + \beta_3 DST_i * days_i \quad (12)$$

where  $DST$  is a dummy variable that takes the value 1 if the day  $i$  is under DST. The variable  $days$  is the running variable; it takes the value 0 for the threshold, the day that DST begins. The running variable for the day  $i$  takes the value of the distance in days of the day  $i$  to the threshold. The specification of equation (12) allows for different linear trends of the RD polynomial, below and above the cutoff.

Figure 1 depicts the discontinuity in the average sunset hour, for an 8-weeks bandwidth, around the threshold. The sunset hour is averaged across the 2004-2014 period.<sup>6</sup>

<sup>6</sup>In our empirical design, we will only consider the starting date of DST implementation, in the springs, and not

## V. Data

### A. Data on Crime

The dataset used to evaluate the effect of DST on criminal activity is constructed using three datasets as inputs. The input datasets are about criminal activity, population and public lighting, all for the city of Montevideo.

The dataset on criminal activity is a rich, detailed dataset provided by the Ministry of Interior, that centralizes all the complaints filled in the city. For each complaint, we have the date, hour and minute of occurrence. The data is geo-referenced which allows locating the exact place where the offense occurred. To construct criminal rates, we use data on population provided by the NSI. For statistical purposes, the NSI splits the city into 62 geographical areas, that closely resemble neighborhoods, but many areas contain more than one.

Table 1 presents descriptive statistics for an 8-weeks bandwidth around the starting day of the DST. With 62 areas, 11 DST starting dates and 56 days per DST period, the sample is a balanced panel of 38,192 observations. The table presents data on crime rates and the probability of occurrence for four different types of crime: robbery, theft, murder, and rape. Daily data is presented in the first four columns and sunset hours data in the last four.

Daily data consider criminal activity occurred at any moment of the day, whilst sunset data considers only criminal activity during sunset hours. To construct sunset hours the procedure is the following. For each Saturday before the Sunday where DST is implemented, we take the exact hour and minute of the sunset. To this exact time, we add two hours. These 120 minutes are the sunset hours for each DST period that goes from Spring to the following Summer.

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the ending date of DST, in the following summers. The reason is that around the ending date of DST each year, that was the second Saturday of March for all the years but 2005, it is not reasonable to assume that environmental variables affecting crime others than natural light at working hours remain stable after DST goes off. Each year, the first weeks of March are the moment where the academic year begins. As primary schools, secondary schools and college students return to classes, a large part of the population of Montevideo returns to the city after vacations. The number of persons in the city varies significantly around the first days of March, which invalids the RD strategy around the ending date of DST.

Table 1: Descriptive Statistics

|         | All Day            |                    |                  |                  | Sunset           |                  |                  |                  |
|---------|--------------------|--------------------|------------------|------------------|------------------|------------------|------------------|------------------|
|         | Rates              |                    | Probability      |                  | Rates            |                  | Probability      |                  |
|         | Pre DST            | Post DST           | Pre DST          | Post DST         | Pre DST          | Post DST         | Pre DST          | Post DST         |
| Robbery | 1.960<br>(3.444)   | 2.011<br>(3.555)   | 0.321<br>(0.467) | 0.319<br>(0.466) | 0.288<br>(1.248) | 0.203<br>(1.060) | 0.061<br>(0.239) | 0.043<br>(0.203) |
| Theft   | 10.910<br>(10.336) | 10.627<br>(10.101) | 0.806<br>(0.395) | 0.801<br>(0.399) | 1.342<br>(2.904) | 1.122<br>(2.672) | 0.230<br>(0.421) | 0.195<br>(0.397) |
| Murder  | 0.022<br>(0.317)   | 0.026<br>(0.353)   | 0.005<br>(0.072) | 0.006<br>(0.078) | 0.001<br>(0.070) | 0.003<br>(0.118) | 0.000<br>(0.019) | 0.001<br>(0.025) |
| Rape    | 0.021<br>(0.319)   | 0.019<br>(0.302)   | 0.005<br>(0.069) | 0.004<br>(0.067) | 0.002<br>(0.111) | 0.003<br>(0.128) | 0.001<br>(0.023) | 0.001<br>(0.024) |

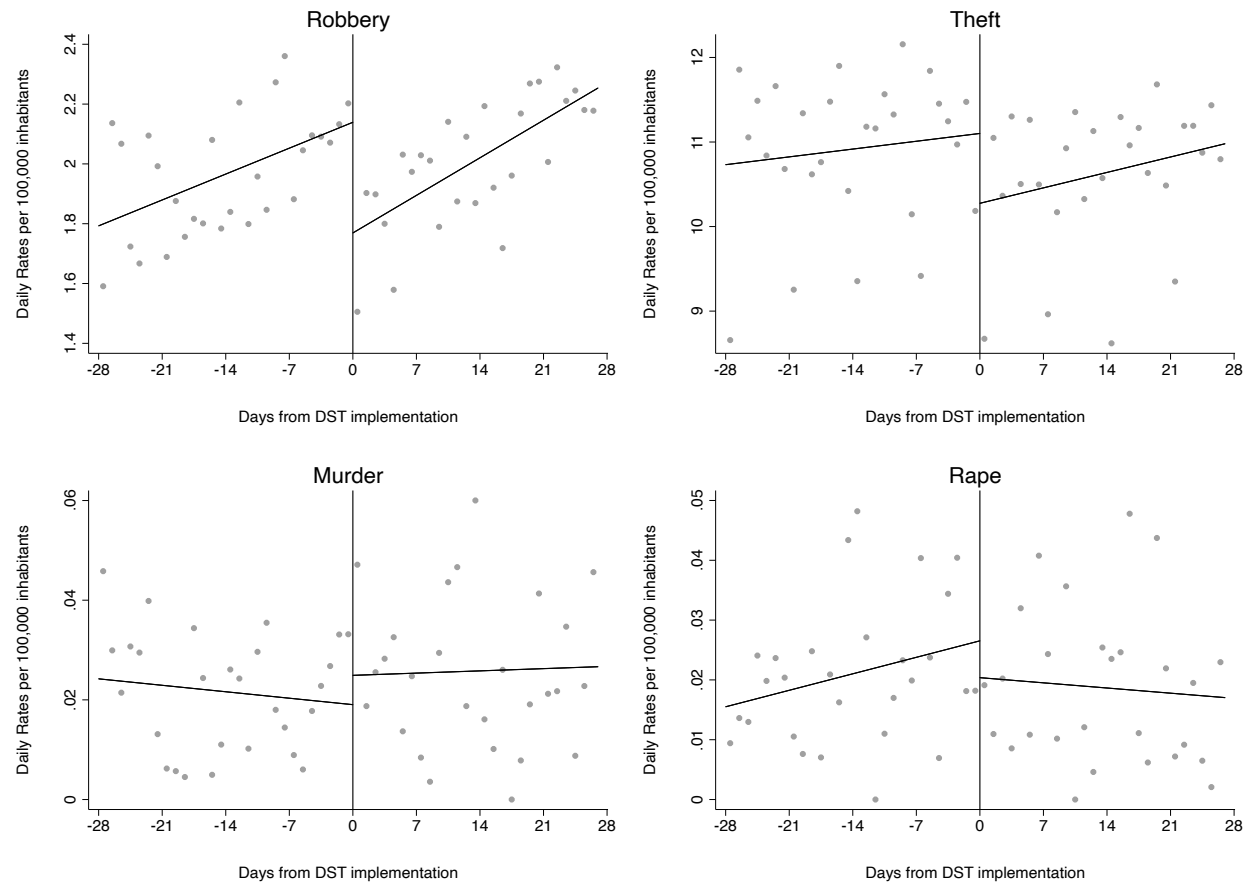
*Notes:* the table presents data on criminal activity for the city of Montevideo. The second column of the table contains the average daily rates per 100,000 inhabitants for four types of crime: robbery, theft, murder and rape. The data are the average for the 62 statistical areas of the city during the period 2004-2014 and for the four weeks previous to the DST implementation. The third column contains the same data, but for the first four weeks under DST. Fourth and fifth columns present data analogous to what is included in the second and third columns, respectively, but instead of rates per 100,000 inhabitants the daily probability of an incident is presented. From the sixth to the ninth column, only data on criminal activity during sunset hours, instead of daily data, is presented. Standard deviations in parentheses.

Figure 2 provides a visual analysis of the effect of DST on criminal rates, using a Regression Discontinuity Design, for robbery, theft, murder and rape. For each graph, data for four weeks at both sides of the threshold is included. A total of 56 bins are presented per graph so that each bin represents a day. Daily rates are averaged over the 2004 - 2014 period. In Figure 2, aggregate data for the entire city is presented. In the Appendix, figures AI.1, AI.2, AI.3, and AI.4, we present data by quartile for each type of crime.

Robbery rates present a sharp drop following DST implementation. Linear trends before and after DST do not change clearly. For theft rates, a more nuanced drop is visible. Before and after DST implementation, a series of bins are clearly below the others, showing average daily rates per 100,000 inhabitants of approximately 9. These bins are Sundays, when commercial activity in the city is restricted to basic services, such as supermarkets and pharmacies.

The effect on personal crimes is evident. Murder rates seem to increase and rape rates seem to decrease, both in small magnitudes and with trends changing after the threshold.

Figure 2: Daily rates before and during DST

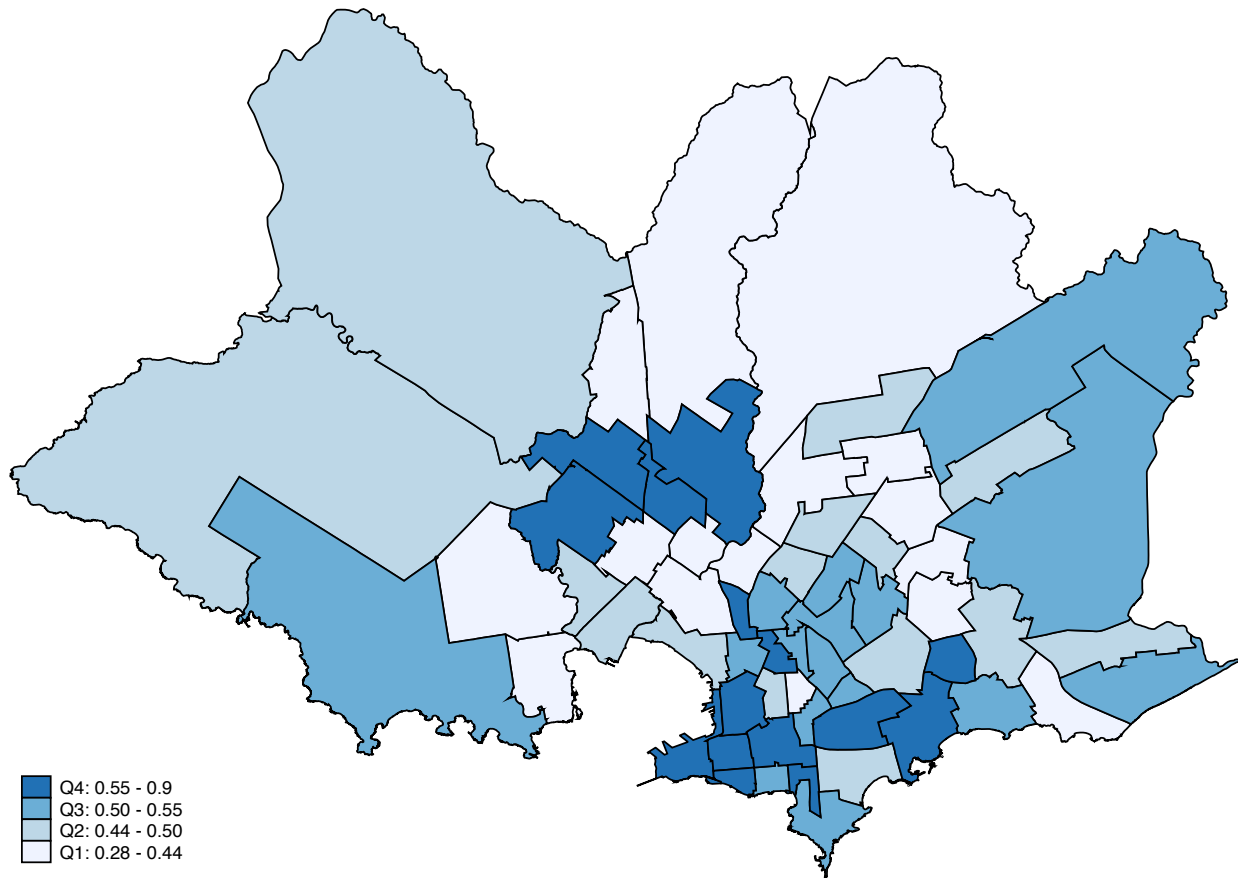


*Notes:* the figure presents average daily rates per 100,000 inhabitants during the period 2004-2014 for four types of crime: robbery, theft, murder and rape. The day DST is implemented is represented by the value 0. Data on eight-weeks bandwidths are included. Each figure contains 56 bins, that is to say, one bin per day of the bandwidth.

## B. Data on Public Lighting

Figure 3 presents a map of the city of Montevideo, with the 62 areas defined by the NSI depicted.

Figure 3: Map of Montevideo



*Notes:* the figure represents the map of the city of Montevideo. The map is divided into 62 statistical areas, according to the division of the National Statistics Institute. The areas are shadowed with blues of different intensity, to highlight to which quartile of public lighting they belong to. At the bottom left of the figure, is presented the range of the values of the Public Lighting Index for each quartile. The Public Lighting Index is constructed as the quotient of the number of blocks with public lighting in the area over the total number of blocks in the area.

This paper uses geo-referenced data on public lighting to study the differential effect of DST implementation. This data is taken from a Census in Urban Environment, conducted by the NSI in 2011. For each block of the city, the Census indicates whether it has public lighting. This dataset allows us to compute, for each area, the quotient of the number of blocks with public lighting in the area over the total number of blocks in the area. We call the quotient the Public Lighting Index (PLI). Quartiles of public lighting availability are constructed based on the PLI.



Table 2: Crime by Quartiles

|         | Q1               |                  | Q2               |                  | Q3                |                   | Q4                 |                    |
|---------|------------------|------------------|------------------|------------------|-------------------|-------------------|--------------------|--------------------|
|         | Pre DST          | Post DST         | Pre DST          | Post DST         | Pre DST           | Post DST          | Pre DST            | Post DST           |
| Robbery | 2.120<br>(3.363) | 2.162<br>(3.553) | 1.835<br>(3.295) | 1.868<br>(3.346) | 1.668<br>(3.294)  | 1.783<br>(3.399)  | 2.209<br>(3.763)   | 2.228<br>(3.870)   |
| Theft   | 7.831<br>(8.555) | 7.315<br>(7.803) | 9.770<br>(8.870) | 9.403<br>(8.554) | 11.192<br>(9.637) | 11.028<br>(9.232) | 14.672<br>(12.460) | 14.581<br>(12.557) |
| Murder  | 0.044<br>(0.410) | 0.039<br>(0.376) | 0.018<br>(0.306) | 0.034<br>(0.409) | 0.016<br>(0.315)  | 0.017<br>(0.280)  | 0.009<br>(0.213)   | 0.013<br>(0.327)   |
| Rape    | 0.031<br>(0.365) | 0.022<br>(0.277) | 0.022<br>(0.338) | 0.022<br>(0.337) | 0.012<br>(0.245)  | 0.015<br>(0.308)  | 0.019<br>(0.316)   | 0.016<br>(0.282)   |

*Notes:* the table presents data on criminal activity for the city of Montevideo by public lighting quartile. For each statistical area of the city, is computed the quotient of the number of blocks with public lighting in the area over the total number of blocks in the area. Quartiles of public lighting availability are constructed based on this quotient. The second column of the table contains the average daily rates per 100,000 inhabitants for four types of crime: robbery, theft, murder and rape. The data are the average of the statistical areas that belong to the first quartile, during the period 2004-2014, and for the four weeks previous to the DST implementation. The third column contains the same data, but for the first four weeks under DST. The fourth and fifth, sixth and seventh, eighth and ninth columns, present data analogous to what is included in the second and third columns, but for the statistical areas that belong to the second, third and fourth quartiles, respectively. Standard deviations in parentheses.

Table 2 contains data on criminal activity by quartile. Average criminal rates at the area level for robbery, theft, murder and rape are presented. Table 2 replicates what is presented in Table 1, but for each quartile.<sup>7</sup> If we read Table 2 from left to right, we can appreciate that crime rates change for different quartiles. In the case of theft, it is clear that crime rates and public lighting show a positive correlation. In the case of Robbery, the largest rates are found for the first and fourth quartiles.

In figures A1, A2, A3 and A4 of Appendix, for robbery, theft, murder and rape, respectively, a visual analysis of the effect of DST implementation is provided. The figures replicate what is depicted in Figure 2, but a graph for each pair of crime-quartile is presented. Figure A1, for instance, includes for each quartile a visual analysis of the discontinuity in criminal rates at the moment of DST implementation. We can see clearly how the first two quartiles are the ones where DST seems to have a larger impact. Figure A2, that shows criminal rates for theft, indicates that the larger effect appears to happen in the second quartile. The visual analysis for murder and rape do not suggest clear effects of the policy.

### **C. Data on Socioeconomic Variables**

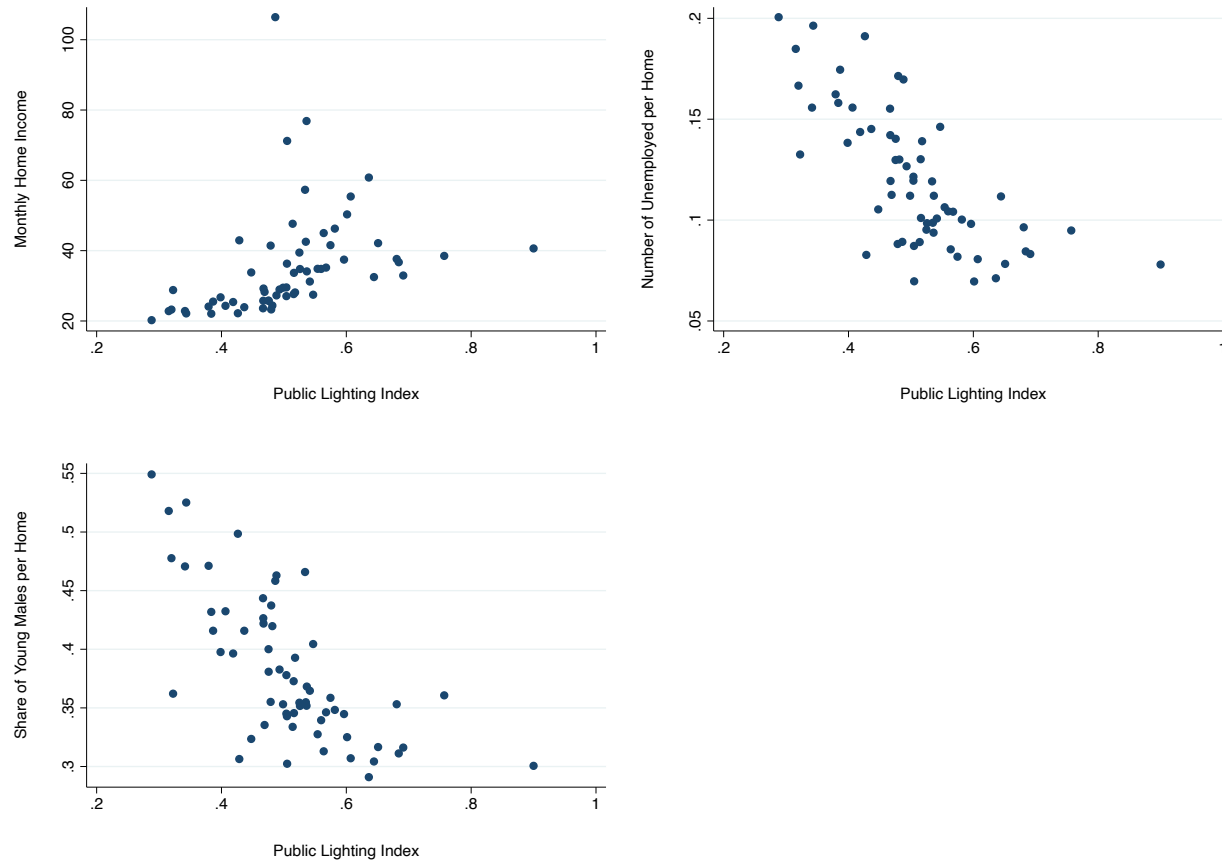
To evaluate the causal effect of DST on criminal activity, the identifying assumption of the Regression Discontinuity Design requires socioeconomic variables that may affect crime to remain stable around the threshold. It is reasonable to assume that the assumption is satisfied, as we are using an 8-weeks bandwidth, a short period to relatively stable socioeconomic conditions.

However, in this work address the differential impact of DST on criminal activity, for different levels of public lighting. We find that the effect of the increase in natural light has a heterogeneous impact across the city, that is a contribution in itself. Naturally, it is of interest to evaluate if the result is robust if we control for variables that may be correlated with public lighting provision at the area level, as the differential effect could be attributed to variables such as income, unemployment, or the gender-age profile of the population. Figure 4 provides a visual analysis of the correlation between these variables and public lighting provision. Monthly Home Income is the average income of homes at the area level, Unemployment is the average number of unemployed per home at the area level, and Share of Young Males is the average share of young males per home at the area level. The data on income, unemployment, and the share of young males is obtained from the Continuous Household Survey (CHS) conducted by the NSI. The data is available at the area and year level. In Figure 4, we present the data averaged for the period 2004-2014.

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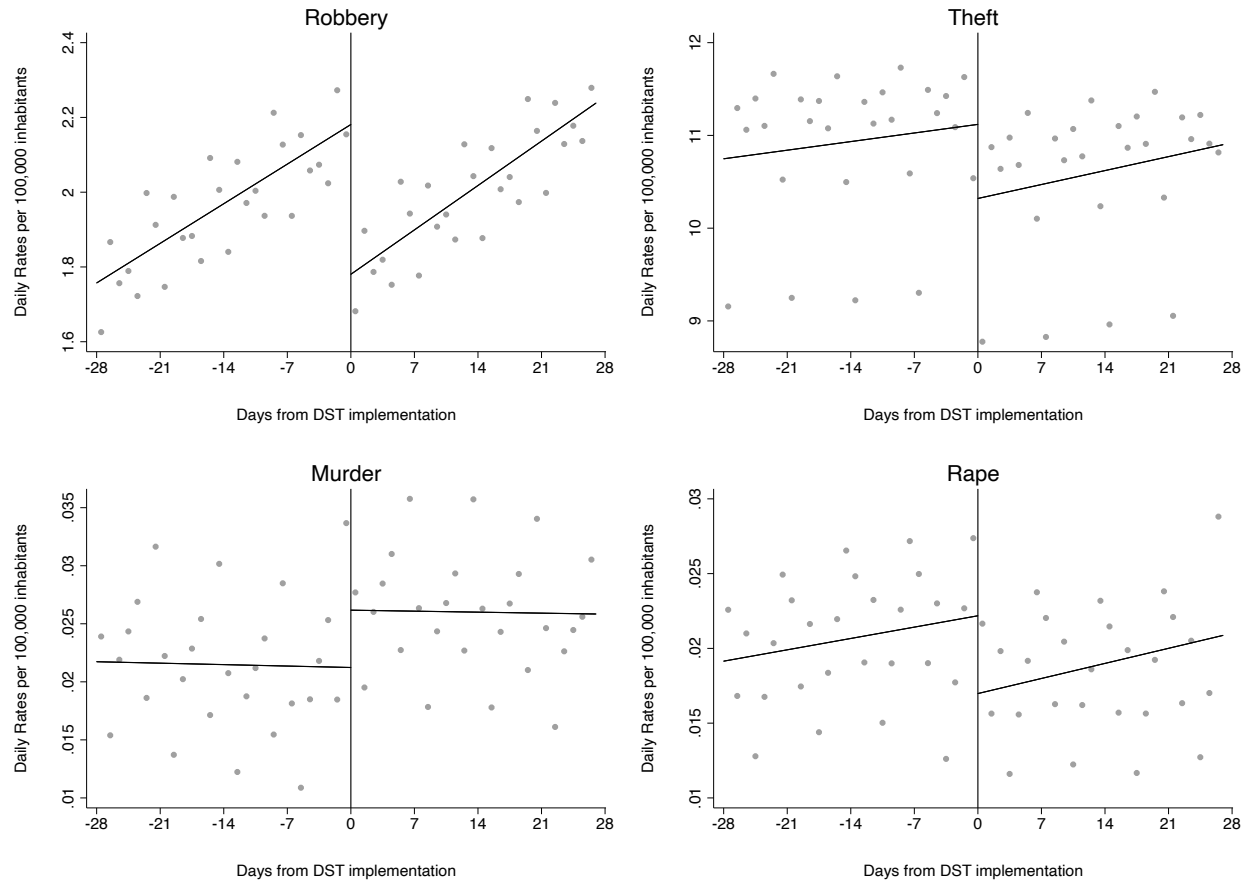
<sup>7</sup>In Table 2 the likelihood of occurrence of an incident is not included for the sake of clarity.

Figure 4: Socioeconomic Outcomes and Public Lighting



*Notes:* for each subfigure, the horizontal axis represents the number of blocks with public lighting over the number of total blocks in the area. Monthly home income is the average monthly home income, measured in thousands of 2004 Uruguayan Pesos; Unemployment is computed as the average number of unemployed per home; and Share of Young Males is the average share of males aged 15 to 34 per home.

Figure 5: Daily rates before and during DST  
Adjusted by Socioeconomic Controls



*Notes:* the figure presents average daily rates per 100,000 inhabitants during the period 2004-2014 for four types of crime: robbery, theft, murder and rape. The day DST is implemented is represented by the value 0. Data on eight-weeks bandwidths are included. Each figure contains 56 bins, that is to say, one bin per day of the bandwidth. The plots are adjusted by yearly data, at the area level, on home income, unemployment and the share of young males.

The statistical correlation between public lighting provision and home income is positive; areas with better artificial lighting are wealthier. In the same line, as expected, unemployment is more prevalent in areas with less public lighting provision. The correlation with the average share of young males per home is also negative; more artificial light in areas with a lesser share of young males per home.

In Figure 5, a visual analysis of the effect of the DST implementation on criminal rates controlling for covariates is presented. The figure is analogous to Figure 3, with the only difference that in Figure 5 the plots are adjusted by monthly home income, unemployment, and the share of young males. The data on socioeconomic controls vary by area and year. As can be seen, figures 3 and 5 are similar: robbery is the form of crime that appears to suffer the largest impact in both. Theft shows a negative impact in both figures. The figures suggest that the differential effect is being driven by differences in public lighting, and not by differences in socioeconomic conditions that may be associated with its provision. This point will be reinforced with the Regression Discontinuity estimates, that do not suffer any significant modification when socioeconomic variables are included as controls.

## VI. Results

### A. Aggregate Impact

In this section we present the estimates of the aggregate effect of DST on crime in Montevideo. We estimate the following equation:

$$crime_i = \alpha + \beta_1 day_i + \beta_2 DST_i + \beta_3 DST_i * day_i + A_a + DoW_{dow} + T_t \quad (13)$$

where DST is a dummy variable that represents the DST period. The running variable, *days*, for the day *i* takes the value of the distance in days of the day *i* to the threshold.  $A_a$  represents area fixed effects,  $DoW_{dow}$  day-of-the-week effects, and  $T_t$  stands for month-year effects. We use criminal rates and the probability of occurrence as dependent variables, for robbery, theft, murder, and rape. The average effect of DST on criminal activity for the different forms of crime is estimated using an eight-weeks bandwidth and a data-driven bandwidth. As we have 62 areas, data for 11 years and a bandwidth of 56 days per year, the sample has 38,192 observations. The results are presented in Table 3.

Table 3: The Effect of DST on Crime

|               | Robbery              |                      | Theft                |                     | Murder             |                   | Rape              |                   |
|---------------|----------------------|----------------------|----------------------|---------------------|--------------------|-------------------|-------------------|-------------------|
|               | Rate                 | Probability          | Rate                 | Probability         | Rate               | Probability       | Rate              | Probability       |
| All Day       | -0.334***<br>(0.082) | -0.050***<br>(0.013) | -0.355*<br>(0.198)   | -0.011<br>(0.008)   | 0.003<br>(0.008)   | 0.000<br>(0.002)  | -0.003<br>(0.007) | -0.001<br>(0.002) |
| Pre-DST share | 0.170                | 0.156                | 0.033                | 0.014               | 0.157              | 0.072             | 0.149             | 0.129             |
| Sunset        | -0.066***<br>(0.020) | -0.018***<br>(0.005) | -0.144***<br>(0.050) | -0.021**<br>(0.009) | 0.004**<br>(0.002) | 0.001*<br>(0.000) | 0.001<br>(0.004)  | -0.000<br>(0.001) |
| Pre-DST share | 0.229                | 0.300                | 0.107                | 0.093               | 2.674              | 2.079             | 0.223             | 0.216             |

*Notes:* every model controls for area fixed effects, day-of-the-week effects, and month-year effects. The observations are weighted by area population. Every specification uses data from an 8-weeks bandwidth. Every estimate uses a sample of 38,192 observations: 56 days for 62 statistical areas by year, for 11 years. Models for four types of crime are included: robbery, theft, murder and rape. For each type of crime, the results for two models are presented. The results presented under the Rate headers belong to models where the dependent variable is the crime rate per 100,000 inhabitants; the results presented under the Probability headers belong to models that use as the dependent variable the probability of occurrence of an incident of that type of crime. Standard errors clustered at the area level in parentheses. \*\*\* Significant at the 1-percent, significant at the \*\* 5-percent, \* significant at the 10-percent.

The top panel of Table 3 contains the results for daily crime models, and the bottom panel the results for sunset hours crime models. The results indicate that robbery decreased drastically with DST implementation. The model with daily robbery rates per 100,000 inhabitants as the dependent variable has a -0.334 coefficient, that represents the 17-percent of the pre-DST average daily rate. The probability of occurrence of at least one robbery incidence also decreased remarkably, a 5-percent decrease in the probability that represents the 15.6-percent of the pre-DST average daily probability, which suggests that the decrease in crime is mostly in the extensive margin. As expected, the effect during sunset hours is stronger than the effect when we consider daily rates. The results indicate that DST caused a 22.9-percent and a 30-percent decrease in sunset hours rates and probability of occurrence, respectively. The coefficients of the four models are significant at the 1-percent level.

Table 3 shows that DST has a negative impact also on theft, the other form of property crime studied in this work. The daily theft rate decreased in a magnitude that represents the 3.3-percent of the pre-DST mean; the coefficient is significant at the 10-percent level. The model of the daily probability of occurrence also has a negative coefficient but is not significant even at the 10-percent level. However, the decrease in theft during sunset hours is robust: a 10.7-percent decrease in theft rates and a 9.3-percent decrease in the probability of occurrence significant at the 1 and 5-percent level, respectively.

The estimates for murder models do not provide evidence of a robust impact of DST on this form of personal crime. DST did not have a significant effect on daily rates or the daily probability of occurrence of murders. During sunset hours there is a significant- at the 5-percent level- increase in murder rates, but not in the probability of occurrence. Contrary to what is found in crimes against property, the coefficients for murder models are all positive.

The lack of significant results in murder models must be read with caution, as this is a rare event and the statistical power of the models is low. Capturing a 10-percent change in the average pre-DST murder rate requires a sample size of 78,942 observations -more than double the size of the sample used in the estimates- in a one-sided test with a Type-I error of 0.05 and a statistical power of 0.8. With 38,192 observations, a statistical power of 0.8 and a Type-I error of 0.05, in a one-sided test statistical significance only would be achieved for effects of at least a 13.04-percent of the average pre-DST rate.

Regarding rape models, those with daily data present negative and not significant coefficients. During sunset hours, the rate model has a positive coefficient and the probability model a negative one, but neither of them is significant. As in murder models, the statistical power of the estimates is low. In a one-sided test, under a Type-I error of 0.05 and a statistical power of 0.8, capturing a 10-percent change in the pre-DST rate requires a sample size of 73,509 observations. With 18,192 observations, under the same conditions, statistical significance requires an effect of at least 13-8

percent of the pre-DST rate.

## **B. Unequal Impact**

The estimates of the aggregate effect of DST implementation on criminal activity shows that crime property is negatively affected by natural light. Is this effect homogeneous for all areas of the city? Lighting provision in an area is not random. Figure 4 shows the link between public lighting and income, unemployment and demographics. Moreover, lighting provision could be associated to the provision of other public services, like security and attention from law enforcement. Thus, in this section we are not looking for a causal effect of public lighting on crime. We are presenting a statistical analysis that highlights the correlation between public lighting and the magnitude of the impact on criminal rates.

To analyze this point the sample is split into quartiles constructed based upon the value of the quotient of total blocks with public lighting in the area over total blocks in the area, the PLI, which ranges from 0.28 to 0.9 for the 62 areas of the city. Table 4 contains the results of the estimates of equation (13) for each quartile, with daily data as dependent variables.

The first two columns provide evidence that the effect on robberies fades away as we go from the first to the fourth quartile. The effect in the first quartile is a decrease in robbery rates of 33.1-percent, and a decrease in the probability of robbery of 25.4-percent. In the second quartile, these magnitudes reach 25.6 and 20.4-percent, respectively. Coefficients in the first quartile are significant at the 1-percent level, and coefficients at the second quartile are significant at the 5-percent level; at the third and fourth quartile, coefficients are not significant even at the 10-percent level.

The relationship between public lighting and the effect of DST is less stable when we consider theft. For the first, second and fourth quartile, the causal effect of DST on theft, either for crime rates and for the probability of occurrence, is negative, whilst for the third quartile is positive. At standard levels of significance, the only significant coefficients among theft models are the second quartiles'; the 10.3-percent decrease in daily crime rates is significant at the 1-percent and the 3.4-percent decrease in the probability of occurrence is significant at the 10-percent.

For the models of murder, the sign of coefficients is negative for the first and fourth quartiles and positive for the second and third quartiles. The only significant coefficient is the model of the probability of occurrence for the second quartile, which implies a huge effect: a 114.9-percent increase in the probability of occurrence of a murder in an area of the second quartile. Regarding the models of rape, none of the coefficients are significant.



Table 4: Impact by Quartile of Public Lighting

|               | Robbery              |                      | Theft                |                     | Murder            |                   | Rape              |                   |
|---------------|----------------------|----------------------|----------------------|---------------------|-------------------|-------------------|-------------------|-------------------|
|               | Rate                 | Probability          | Rate                 | Probability         | Rate              | Probability       | Rate              | Probability       |
| Q1            | -0.701***<br>(0.154) | -0.097***<br>(0.033) | -0.377<br>(0.376)    | -0.018<br>(0.022)   | -0.002<br>(0.021) | -0.000<br>(0.005) | -0.011<br>(0.017) | -0.001<br>(0.005) |
| Pre-DST share | 0.331                | 0.254                | 0.048                | 0.023               | 0.046             | 0.037             | 0.359             | 0.165             |
| Q2            | -0.469**<br>(0.168)  | -0.059<br>(0.024)    | -1.008***<br>(0.345) | -0.028**<br>(0.016) | 0.020<br>(0.012)  | 0.004*<br>(0.002) | 0.000<br>(0.012)  | -0.000<br>(0.002) |
| Pre-DST share | 0.256                | 0.204                | 0.103                | 0.034               | 1.071             | 1.149             | 0.003             | 0.020             |
| Q3            | -0.066<br>(0.137)    | -0.006<br>(0.018)    | 0.067<br>(0.575)     | 0.022<br>(0.013)    | 0.017<br>(0.019)  | 0.005<br>(0.006)  | 0.001<br>(0.018)  | -0.001<br>(0.005) |
| Pre-DST share | 0.039                | 0.022                | 0.006                | 0.028               | 1.044             | 1.495             | 0.111             | 0.295             |
| Q4            | -0.045<br>(0.110)    | -0.028<br>(0.019)    | -0.093<br>(0.303)    | -0.016<br>(0.010)   | -0.016<br>(0.012) | -0.006<br>(0.003) | -0.001<br>(0.015) | -0.000<br>(0.003) |
| Pre-DST share | 0.020                | 0.080                | 0.006                | 0.019               | 1.650             | 2.519             | 0.059             | 0.060             |

*Notes:* every model controls for area fixed effects, day-of-the-week effects, and month-year effects. The observations are weighted by area population. Every specification uses data from an 8-weeks bandwidth. The estimates are computed by quartile. Quartiles are based on the Public Lighting Index. This index takes the value of the quotient of the number of blocks with public lighting in the area over the number of total blocks in the area. Models for four types of crime are included: robbery, theft, murder and rape. For each type of crime, the results for two models are presented. The results presented under the Rate headers belong to models where the dependent variable is the crime rate per 100,000 inhabitants; the results presented under the Probability headers belong to models that use as the dependent variable the probability of occurrence of an incident of that type of crime. Standard errors clustered at the area level in parentheses. \*\*\* Significant at the 1-percent, significant at the \*\* 5-percent, \* significant at the 10-percent.

Do the results presented in Table 4 change if we include socioeconomic variables as controls? To answer this question we estimate the following equation:

$$crime_i = \alpha + \beta_1 day_i + \beta_2 DST_i + \beta_3 DST_i * day_i + X_i + A_a + DoW_{dow} + T_t \quad (14)$$

where  $X_i$  is a vector of socioeconomic controls that includes the average monthly home income, the average number of unemployed per home, and the average share of males aged between 15 and 34 per home. The variables vary by month and area.

Table 5 presents the results of the estimates of equation (14) for crime rates and the probability of occurrence for robbery, theft, murder, and rape. The estimates are replicated for each quartile constructed based on the PLI.

For robbery models, in the first and second quartiles, the effect of DST on criminal activity is slightly smaller and less robust after the inclusion of the additional controls. The effect of the policy on crime rates in the first quartile is a 31.6-percent decrease, still significant at the 1-percent level, but smaller than the 33.1 decrease found without controls. In this quartile the effect on the likelihood of occurrence, significant at the 5-percent level, is a decrease of the 24.8-percent, 0.6-percentage points smaller than in the specification without controls. For the second quartile the decrease in criminal rates achieves the 25.1-percent, close to the 25.6-percent presented in Table 5; the result is significant at the 10-percent level. The effect on the probability of occurrence is almost unchanged when the econometric specification includes additional controls: a 20.2-percent decrease, significant at the 10-percent level, against a 20.4-percent decrease without controls.

Overall, the effect on robbery over poorly lit areas is weakened with the inclusion of socioeconomic controls, but remain significant and large. For the third and fourth quartiles, the point estimates indicate that the inclusion of controls has almost no effect on the estimates. The effects remain statistically non-significant at standard levels of significance.

For theft models, the results in the first quartile do not suffer any substantial change after the inclusion of socioeconomic controls. The point estimates depict a smaller effect in Table 5, but the impacts are non-significant at standard levels of significance. For the second quartile, with the inclusion of controls, the results are almost unchanged. The impact on crime rates is very similar: a 10.8-percent decrease with controls, significant at the 1-percent level, against a 10.3 decrease without controls. For the probability of occurrence, a 3.2-percent decrease with controls, significant at the 10-percent level, against a 3.4-percent decrease without controls. For the third quartile, the effect on crime rates remains non-significant. The effect on the probability of occurrence is significant at the 10-percent level and shows a 2.2-percent increase in crime. Without controls, the impact on the probability of occurrence is also positive, but the results are not significant. In the fourth quartile, the results are unchanged with respect to what is found when no controls are considered: the estimates are negative and not significant.

Table 5: Impact by Quartile of Public Lighting  
Additional Controls

|               | Robbery              |                     | Theft                |                    | Murder            |                   | Rape              |                   |
|---------------|----------------------|---------------------|----------------------|--------------------|-------------------|-------------------|-------------------|-------------------|
|               | Rate                 | Probability         | Rate                 | Probability        | Rate              | Probability       | Rate              | Probability       |
| Q1            | -0.670***<br>(0.147) | -0.095**<br>(0.032) | -0.343<br>(0.385)    | -0.016<br>(0.020)  | -0.001<br>(0.020) | -0.000<br>(0.005) | -0.014<br>(0.017) | -0.002<br>(0.005) |
| Pre-DST share | 0.316                | 0.248               | 0.044                | 0.021              | 0.014             | 0.006             | 0.451             | 0.273             |
| Q2            | -0.460**<br>(0.168)  | -0.059**<br>(0.024) | -1.056***<br>(0.347) | -0.032*<br>(0.015) | 0.019<br>(0.012)  | 0.004*<br>(0.002) | 0.003<br>(0.011)  | 0.001<br>(0.002)  |
| Pre-DST share | 0.251                | 0.202               | 0.108                | 0.039              | 1.031             | 1.095             | 0.137             | 0.124             |
| Q3            | -0.058<br>(0.133)    | -0.004<br>(0.019)   | 0.004<br>(0.580)     | 0.022*<br>(0.013)  | 0.016<br>(0.019)  | 0.004<br>(0.006)  | -0.002<br>(0.019) | -0.001<br>(0.005) |
| Pre-DST share | 0.035                | 0.016               | 0.000                | 0.028              | 0.999             | 1.361             | 0.158             | 0.573             |
| Q4            | -0.055<br>(0.111)    | -0.028<br>(0.019)   | -0.019<br>(0.284)    | -0.016<br>(0.009)  | -0.016<br>(0.012) | -0.006<br>(0.003) | -0.003<br>(0.014) | -0.001<br>(0.003) |
| Pre-DST share | 0.025                | 0.080               | 0.001                | 0.018              | 1.727             | 2.602             | 0.145             | 0.141             |

*Notes:* every model controls for area fixed effects, day-of-the-week effects, month-year effects, the average monthly home income, the average number of unemployed per household, and the average share of males aged between 15 and 34 per household. These variables change by month and area. The observations are weighted by area population. Every specification uses data from an 8-weeks bandwidth. The estimates are computed by quartile. Quartiles are based on the Public Lighting Index. This index takes the value of the quotient of the number of blocks with public lighting in the area over the number of total blocks in the area. Models for four types of crime are included: robbery, theft, murder, and rape. For each type of crime, the results for two models are presented. The results presented under the Rate headers belong to models where the dependent variable is the crime rate per 100,000 inhabitants; the results presented under the Probability headers belong to models that use as the dependent variable the probability of occurrence of an incident of that type of crime. Standard errors clustered at the area level in parentheses. \*\*\* Significant at the 1-percent, significant at the \*\* 5-percent, \* significant at the 10-percent.

The inclusion of controls does not change the results of theft models substantially. The estimates remain imprecise and without a clear link between public lighting and criminal activity.

For murder models, the sign of the point estimates does not change after the inclusion of controls. All the estimates remain non-significant at standard levels of significance. For rape models, some point estimates change their sign, but all remain non-significant as well.

### C. Urban Design

The results found in this work denote a large impact on robbery, concentrated on the poorly lit areas of the city. In this section we explore these results further. First, we estimate the effect of DST on crime, but with a variation: we allow the treatment to vary by area, as the treatment variable used is the interaction between DST and PLI. Second, we estimate the effect of DST interacted with PLI on crime, but evaluate whether this effect changes for different levels of PLI by using a linear and a quadratic interaction in the same specification. We estimate the following equations:

$$crime_i = \alpha + \beta_1 day_i + (\beta_2 DST_i + \beta_3 DST_i * day_i) * PLI_a + A_a + DoW_{dow} + T_t \quad (15)$$

$$crime_i = \delta + \gamma_1 day_i + (\gamma_2 DST_i + \gamma_3 DST_i * day_i) * PLI_a + \quad (16)$$

$$(\gamma_4 DST_i + \gamma_5 DST_i * day_i) * PLI_a^2 + A_a + DoW_{dow} + T_t$$

where  $PLI_a$  is the Public Lighting Index for area  $a$ . Equation (15) allows us to recover the causal effect of DST weighted by public lighting on criminal activity. The coefficient of interest is  $\beta_2$ , that gives a constant effect for the entire range of values of PLI. Equation (16) allows us to analyze if the effect varies for different values of PLI. The coefficients of interest are  $\gamma_2$  and  $\gamma_4$ . Table 6 presents the results, side by side, of the estimates of both equations.

We include the results for the four types of crime studied in this paper: robbery, theft, murder, and rape. For each type of crime, we present the estimates of equation (15) and (16) for four specifications. The dependent variables used are rates and probabilities of occurrence, both with daily data and with sunset hours data.

Table 6: The Effect of DST on Crime Weighted by Public Lighting

|         |               | Robbery              |                      |                      |                     | Theft                |                     |                      |                    |
|---------|---------------|----------------------|----------------------|----------------------|---------------------|----------------------|---------------------|----------------------|--------------------|
|         |               | Rate                 |                      | Probability          |                     | Rate                 |                     | Probability          |                    |
| All Day | DST*PLI       | -0.602***<br>(0.162) | -1.854***<br>(0.523) | -0.080***<br>(0.023) | -0.228**<br>(0.088) | -0.256<br>(0.367)    | -2.767**<br>(1.073) | -0.007<br>(0.013)    | -0.085*<br>(0.051) |
|         | $DST * PLI^2$ |                      | 2.277***<br>(0.843)  |                      | 0.259*<br>(0.140)   |                      | 3.848**<br>(1.570)  |                      | 0.125*<br>(0.070)  |
|         |               |                      |                      |                      |                     |                      |                     |                      |                    |
| Sunset  | DST*PLI       | -0.095**<br>(0.040)  | -0.464***<br>(0.121) | -0.031**<br>(0.013)  | -0.109**<br>(0.042) | -0.327***<br>(0.091) | -0.626<br>(0.475)   | -0.052***<br>(0.016) | -0.047<br>(0.067)  |
|         | $DST * PLI^2$ |                      | 0.627***<br>(0.192)  |                      | 0.135*<br>(0.078)   |                      | 0.588<br>(0.837)    |                      | 0.009<br>(0.115)   |
|         |               |                      |                      |                      |                     |                      |                     |                      |                    |
|         |               | Murder               |                      |                      |                     | Rape                 |                     |                      |                    |
|         |               | Rate                 |                      | Probability          |                     | Rate                 |                     | Probability          |                    |
| All Day | DST*PLI       | 0.006<br>(0.016)     | 0.034<br>(0.052)     | 0.001<br>(0.004)     | 0.004<br>(0.014)    | -0.002<br>(0.012)    | 0.032<br>(0.052)    | -0.000<br>(0.003)    | 0.005<br>(0.015)   |
|         | $DST * PLI^2$ |                      | -0.041<br>(0.074)    |                      | -0.004<br>(0.021)   |                      | -0.071<br>(0.085)   |                      | -0.012<br>(0.025)  |
|         |               |                      |                      |                      |                     |                      |                     |                      |                    |
| Sunset  | DST*PLI       | 0.007**<br>(0.003)   | 0.012<br>(0.012)     | 0.002**<br>(0.001)   | 0.003<br>(0.004)    | 0.002<br>(0.007)     | -0.010<br>(0.015)   | -0.000<br>(0.002)    | -0.001<br>(0.004)  |
|         | $DST * PLI^2$ |                      | -0.008***<br>(0.019) |                      | -0.001<br>(0.006)   |                      | 0.018<br>(0.023)    |                      | 0.001<br>(0.006)   |
|         |               |                      |                      |                      |                     |                      |                     |                      |                    |

Notes: every model controls for area fixed effects, day-of-the-week effects, and month-year effects. The observations are weighted by area population. Every specification uses data from an 8-weeks bandwidth. PLI is the quotient of the number of blocks with public lighting in the area over the number of total blocks in the area. Models for four types of crime are included: robbery, theft, murder, and rape. The results presented under the Rate headers belong to models where the dependent variable is the crime rate per 100,000 inhabitants; the results presented under the Probability headers belong to models that use as the dependent variable the probability of occurrence of an incident of that type of crime. Standard errors clustered at the area level in parentheses. \*\*\* Significant at the 1-percent, significant at the \*\* 5-percent, \* significant at the 10-percent.

The results for robbery models are presented at the top left of Table 6. In the third column, we can see that the estimates of equation (15) using robbery daily rates as the dependent give an estimate of  $\beta_2$  of -0.602, significant at the 1-percent level. In absolute value, this coefficient is larger than the one found when the treatment does not interact with the PLI, a -0.334 shown in Table 3; the coefficient represents the 30.9-percent of the pre-DST average robbery rate. The estimates of equation (16) provide a point estimate of  $\gamma_2$  and  $\gamma_4$  of -1.854 and 2.277, respectively.

Robbery daily rates are a convex function of the interaction of DST with PLI. According to the point estimates of  $\gamma_2$  and  $\gamma_4$ , the function reaches its minimum at a PLI value of 0.407. The values of the PLI range from 0.28 to 0.9; within this interval, the only root of the function is at 0.81. For an area with a PLI of 0.81, the treatment does not provoke a reduction in robbery rates. This suggests that this is the minimum level of PLI an area should aim to, as it is the level that is "as good as natural light" in terms of crime deterrence. The results do not change substantially if we take a look at the robbery models using sunset hours data. The largest reduction in robberies is achieved at a PLI of 0.37, and PLI does not have an effect at approximately 0.74. The models that study the effect on the probability of robberies, both with daily and with sunset hours data, provide a similar picture as well. With daily data, the largest reduction is achieved when PLI equals 0.44 and the point of PLI as good as natural light is 0.88; with sunset hours data, these figures are 0.40 and 0.8, respectively.

The results for theft models are more imprecise. With daily data, the estimates of equation (15) do not provide significant results. The estimates for equation (16) indicate that the treatment yields the largest reduction in daily theft rates when PLI equals 0.36, and public lighting is as good as natural light when the index achieves a value of 0.72; for the model with the daily probability of thefts as the dependent variable, these values are 0.34 and 0.68, respectively. In the models with sunset hours data, the estimates of equation (16) do not provide significant results; the estimates of equation (15) provide significant estimates of  $\beta_2$ , with the expected sign of the coefficients.

The estimates for models of murder and rape are not significant, except estimates of the equation (15) with sunset hours data for murder, that are significant at the 95-percent level.

The results presented in Table 6 indicate that robbery is the crime most affected by DST. Estimates for theft are imprecise and not robust to different specifications. If we take into account the effects on daily robbery activity, the largest reductions are found when PLI is around 0.4 and 0.44, and public lighting is as good as natural light when PLI is in the interval 0.8 to 0.88.

#### **D. The Effect Across the Day**

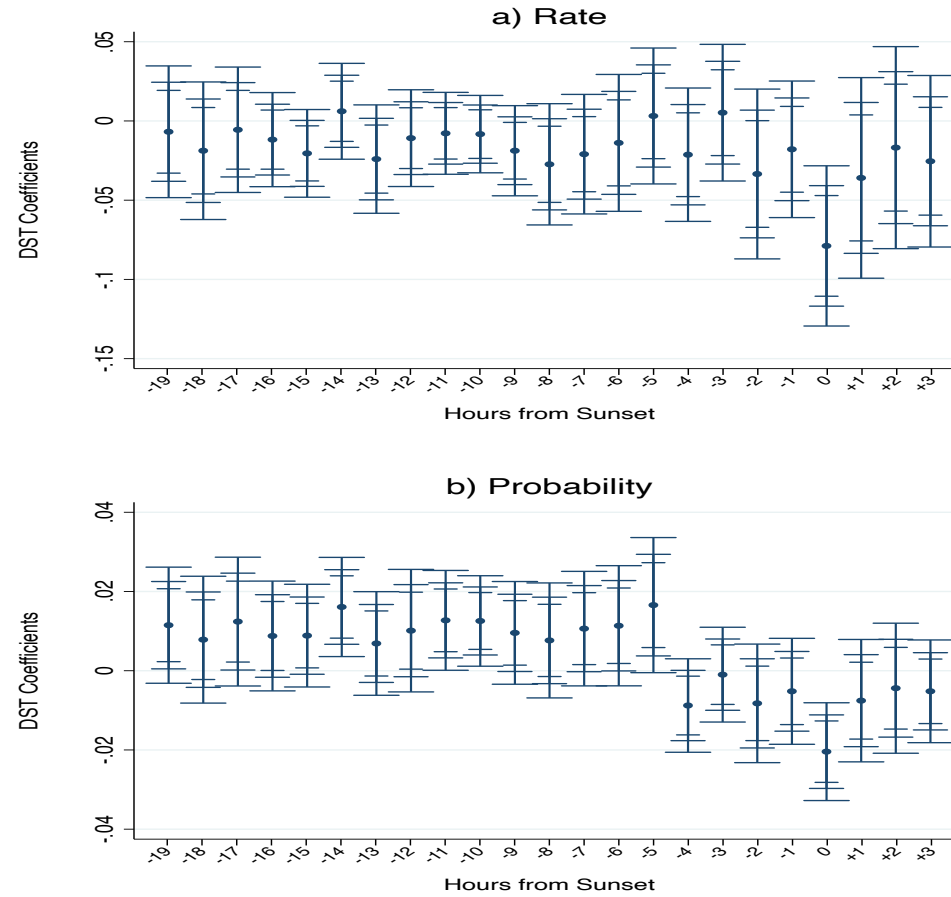
We compute estimates to evaluate the effect of DST across the day. We estimate equation (13), using hourly data as dependent variables, for robbery and theft models. Figure 6(a) presents the results for hourly robbery rates models. Remarkably, the only significant effect is for sunset hours.

No significant effects are found before or after. The point estimates of the effect of DST around sunset hours are lower than the point estimates for hours further away from sunset. However, none of them are significantly different from zero at standard levels of significance.

We estimate equation (13) using the hourly probability of robbery and present the results in Figure 6(b). Again, the only significant result is for sunset hours, except the (-4) model, where the results are significant at the 90-percent level. The point estimates depicted in Figure 6(b) show that the probability of robbery decreased around sunset, but increased during the rest of the day. This suggests that criminal activity was more concentrated around sunset, and more dispersed geographically during the rest of the day.

In Figure 7 we present the results of estimates of equation (13) for theft models. In Figure 7(a) we observe that the only significant reduction in theft rates is at sunset hours, consistent with a deterrence effect. In Figure 7(b), we see that no significant reductions in the probability of theft are found for any hour of the day.

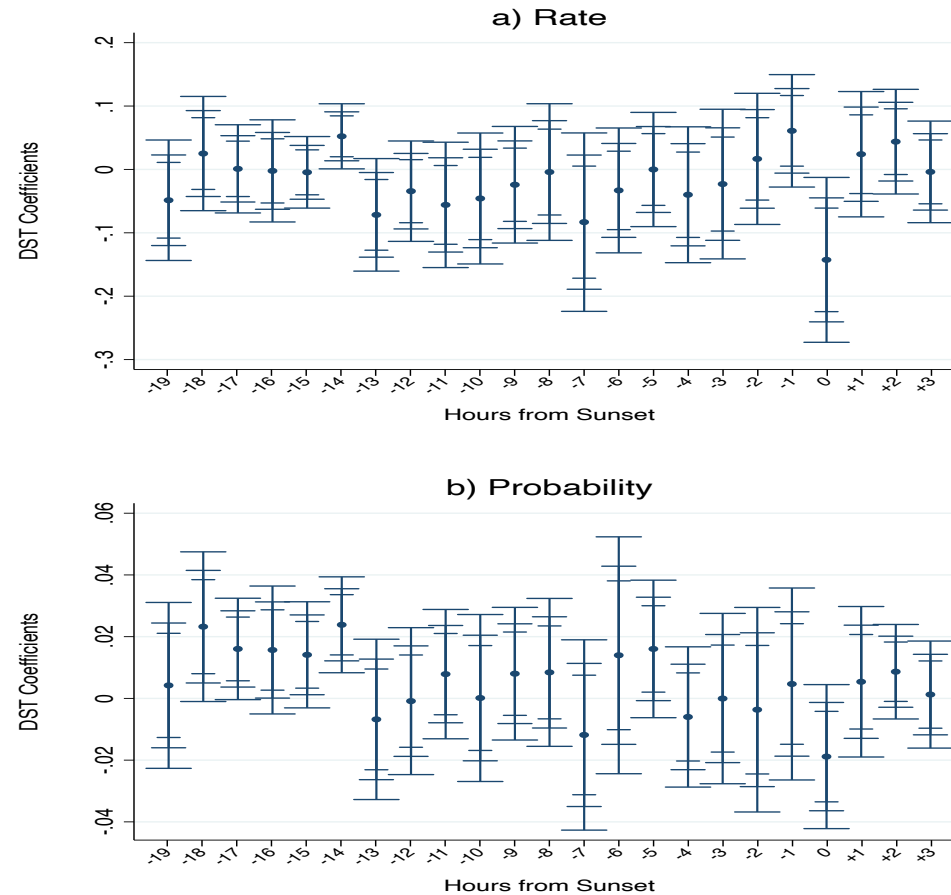
Figure 6: The Effect of DST on Robbery by Hours from Sunset



*Notes:* the spikes represent the 99, 95 and 90-percent confidence intervals for the effect of DST for estimates with an 8-weeks bandwidth. The dependent variables in Figure 6(a) are hourly robbery rates. The dependent variables in Figure 6(b) are hourly probability of robbery. Every model controls for area fixed effects, day-of-the-week effects, and month-year effects. The observations are weighted by area population. Standard errors clustered at the area level.



Figure 7: The Effect of DST on Theft by Hours from Sunset



*Notes:* the spikes represent the 99, 95 and 90-percent confidence intervals for the effect of DST for estimates with an 8-weeks bandwidth. The dependent variables in Figure 6(a) are hourly theft rates. The dependent variables in Figure 6(b) are hourly probability of theft. Every model controls for area fixed effects, day-of-the-week effects, and month-year effects. The observations are weighted by area population. Standard errors clustered at the area level.

## E. Robustness Checks and Placebo Test

The results found in this work indicate that the exogenous increase in natural light has an impact on property crime, whereas personal crime seems unaffected. The estimates presented so far indicate a strong effect of DST on robbery; the effect on theft is more imprecise and unstable across different specifications. This section presents robustness checks to assess whether the results are sensitive to different bandwidths, to different specifications of the RD polynomial, and the inclusion of trends by year. We also present the results of a placebo test: we simulate that DST was implemented in 2003, 2015 and 2016 to analyze if there was an effect in years when the policy was not applied.

Table 7 presents estimates of equation (12) following a data-driven bandwidth selection. The paper follows Calonico, Cattaneo and Titiunik (2014) to select the optimal bandwidth and to construct bias-corrected confidence intervals. At the top panel of Table 7 results for models with daily data are included, and at the bottom panel results for models with sunset hours data are presented.

The estimates of the effect of DST on robbery with daily data indicate a decrease in criminal activity. The coefficient recovered,  $-0.477$ , is larger than the  $-0.334$  found with an 8-weeks bandwidth. The probability of occurrence model presents a coefficient larger in magnitude as well:  $-0.074$  against a  $-0.05$  in Table 3. The results are significant at the 99-percent level. For sunset hours, the decrease in robbery rates is significant at the 95-percent level. The point estimate is larger in absolute value for the estimates with the data-driven bandwidth:  $-0.136$  in comparison to the  $-0.066$  found with an 8-weeks bandwidth. For the model of the probability of occurrence the point estimate indicates a decrease after DST implementation, but the results are not significant for standard levels of significance.

For theft, murder and rape models, either with daily or sunset hours data, the effects found are not significant at standard levels of significance. Thus, theft models, with a data-driven bandwidth cannot identify a statistically significant effect, a difference with the results presented in Table 3. Murder and rape models not only remain non-significant, as point estimates change with different bandwidths as well.

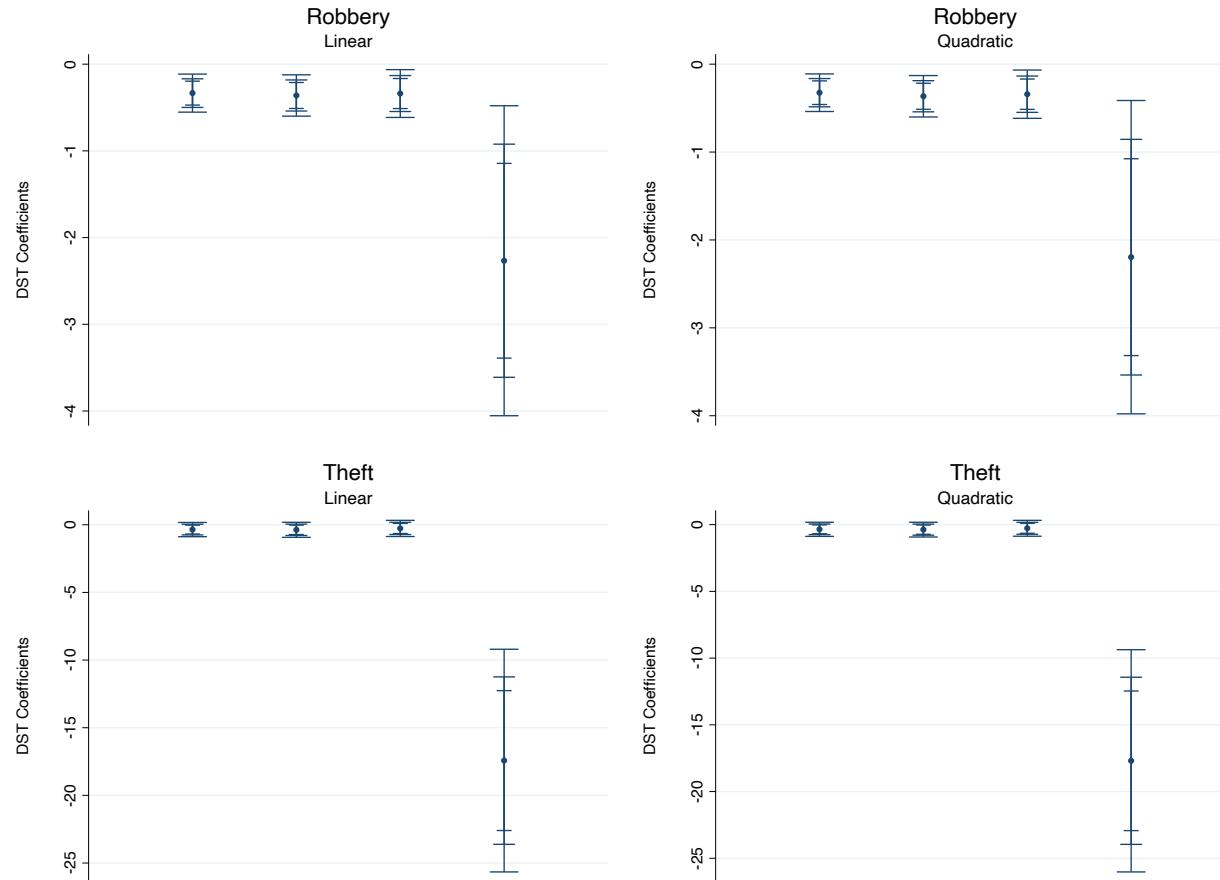
Overall, the negative effect of DST on criminal activity related to robbery is robust to a data-driven bandwidth selection procedure. Results for theft are less robust to the choice of different bandwidths, and the effect on personal crime remains non-significant.

Table 7: The Effect of DST on Crime

|                | Rate                 |               |                | Probability         |               |                |
|----------------|----------------------|---------------|----------------|---------------------|---------------|----------------|
|                | Coefficient          | Observations  |                | Coefficient         | Observations  |                |
|                |                      | (to the left) | (to the right) |                     | (to the left) | (to the right) |
| <b>All Day</b> |                      |               |                |                     |               |                |
| Robbery        | -0.477***<br>(0.179) | 7502          | 8184           | -0.074**<br>(0.033) | 8866          | 9548           |
| Theft          | -0.657<br>(1.059)    | 4774          | 5456           | -0.000<br>(0.036)   | 4774          | 5456           |
| Murder         | -0.015<br>(0.026)    | 4092          | 4774           | -0.008<br>(0.009)   | 3410          | 4092           |
| Rape           | -0.000<br>(0.017)    | 4092          | 4774           | 0.002<br>(0.006)    | 4092          | 4774           |
| <b>Sunset</b>  |                      |               |                |                     |               |                |
| Robbery        | -0.137***<br>(0.053) | 4092          | 4774           | -0.024*<br>(0.015)  | 3410          | 4092           |
| Theft          | -0.112<br>(0.180)    | 5456          | 6138           | -0.014<br>(0.042)   | 4092          | 4774           |
| Murder         | 0.000<br>(0.004)     | 6820          | 7502           | -0.000<br>(0.001)   | 6820          | 7502           |
| Rape           | -0.008<br>(0.012)    | 4092          | 4774           | -0.003<br>(0.004)   | 4092          | 4774           |

*Notes:* the table presents the results of models for four types of crime: robbery, theft, murder, and rape. The observations are weighted by area population. The models at the top left panel use as the dependent variable daily crime rates per 100,000 inhabitants; the models at top right panel use as the dependent variable the daily probability of occurrence of an incident of that type of crime. The models at the bottom left panel use as the dependent variable crime rates per 100,000 inhabitants during sunset hours; the models at the bottom right panel use as the dependent variable the probability of occurrence of an incident of that type of crime during sunset hours. Standard errors clustered at the area level in parentheses. \*\*\* Significant at the 1-percent, significant at the \*\* 5-percent, \* significant at the 10-percent.

Figure 8: Sensitivity of the Results to Different Bandwidths



*Notes:* from left to right, at each graph, the first spikes represent the 99, 95 and 90-percent confidence intervals for the effect of DST ( $\beta_2$ ) for estimates with an 8-weeks bandwidth. The second spikes, the effect of DST for estimates with a 6-weeks bandwidth, the third for a 4-weeks bandwidth, and the fourth with a 2-weeks bandwidth. Every model controls for area fixed effects, day-of-the-week effects, and month-year effects. The observations are weighted by area population. Standard errors clustered at the area level.

Figure 8 presents the results of additional robustness checks. For robbery and theft models, RD estimates are computed with a linear and a quadratic polynomial as controls. The estimates are computed for four different bandwidths: eight, six, four and two weeks. The figure depicts confidence intervals at the 90, 95 and 99-percent for the effect of DST on property crime. At each graph, from left to right, the first vertical line refers to estimates for an 8-weeks bandwidth, the second vertical line refers to estimates for a 6-weeks bandwidth, the third vertical line to estimates with a 4-weeks bandwidth, and the fourth vertical line to estimates with a 2-weeks bandwidth.

For robbery models the results are robust to different specifications. For the linear and the quadratic specifications of the RD polynomial, the estimates with the four different bandwidths used report always a decrease in robbery, even at the upper bound of the confidence intervals. The point estimates for the bandwidths that go from eight weeks to four weeks are negative and similar in magnitude. With just two weeks as the bandwidth, the point estimates are larger in absolute value.

The reason for this drop in the absolute value is because one week at each side of the cutoff is not enough to fully identify day-of-the-week effects. Indeed, when day-of-the-week effects are not included in the estimates with a two-weeks bandwidth, the point estimate is quite similar to the estimates with four, six or eight weeks as bandwidths. The minimum number of days at both sides of the cutoff to fully identify day-of-the-week effects is 8; with a 16-days bandwidth and including day-of-the-week effects, the point estimates are also similar to those found using four, six or eight weeks as bandwidths.<sup>8</sup>

For theft models, it is worth noting that all the point estimates indicate that DST implementation produced a decrease in crime rates. However, the imprecision of the results is considerable. Either with the linear or quadratic specification of the RD polynomial, for bandwidths of at least four weeks it is not possible to reject the null of no effect at the 95-percent level of significance. For bandwidths of eight or six weeks, the effect of DST is significant only at the 90-percent level of significance. For the specifications with bandwidths of two weeks, the upper bounds of any confidence interval lie well below 0.

In the Appendix we include figures AII.1, AII.2, AII.3, and AII.4, that present the results of the robustness check by quartiles. In Figure AII.1 we present results for RD estimates, allowing for different linear trends at both sides of the cutoff, of robbery rates models by public lighting quartile. The results confirm that the stronger effects are found in the first and second quartiles; in the third and fourth quartiles, no significant effects are found. When we look at Figure AII.2, we appreciate that a quadratic specification does not change the results.

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<sup>8</sup>The results of the models with 16-days as the bandwidth and the models with two-weeks bandwidths and no day-of-the-week effects are not included to save space.

Table 8: The Effect of DST on Crime  
Different Trends by Year

|               | Robbery              |                      | Theft                |                     | Murder            |                   | Rape             |                  |
|---------------|----------------------|----------------------|----------------------|---------------------|-------------------|-------------------|------------------|------------------|
|               | Rate                 | Probability          | Rate                 | Probability         | Rate              | Probability       | Rate             | Probability      |
| All Day       | -0.326***<br>(0.082) | -0.049***<br>(0.013) | -0.345*<br>(0.207)   | -0.011<br>(0.011)   | 0.002<br>(0.010)  | -0.000<br>(0.003) | 0.001<br>(0.009) | 0.001<br>(0.003) |
| Pre-DST share | 0.167                | 0.154                | 0.032                | 0.013               | 0.088             | 0.094             | 0.046            | 0.121            |
| Sunset        | -0.060***<br>(0.023) | -0.015***<br>(0.006) | -0.154***<br>(0.055) | -0.022**<br>(0.010) | 0.004*<br>(0.002) | 0.001<br>(0.001)  | 0.002<br>(0.005) | 0.000<br>(0.001) |
| Pre-DST share | 0.208                | 0.254                | 0.115                | 0.098               | 2.971             | 2.511             | 0.999            | 0.740            |

*Notes:* every model controls for area effects, day-of-the-week effects, and month-year effects. The models are fully interacted with a variable that represents years, but the treatment variable DST. Every specification uses data from an 8-weeks bandwidth. Models for four types of crime are included: robbery, theft, murder and rape. For each type of crime, the results for two models are presented. The results presented under the Rate headers belong to models where the dependent variable is the crime rate per 100,000 inhabitants; the results presented under the Probability headers belong to models that use as the dependent variable the probability of occurrence of an incident of that type of crime. Standard errors clustered at the area level in parentheses. \*\*\* Significant at the 1-percent, significant at the \*\* 5-percent, \* significant at the 10-percent.

Figures AII.3 and AII.4 present the results of RD estimates with a linear and a quadratic specification, respectively, for theft rate models. No significant results are found for theft when the sample is split into quartiles, with the only exception of the second quartile where we do find a significant reduction using an 8-weeks bandwidth.

Table 8 presents the results of an additional robustness check. We test the sensitivity of the results when different trends are allowed for each year. We estimate equation (13) fully interacted with a variable that represents years, but the treatment variable DST. The effect on robbery is negative and significant, for all the models. The magnitude of the coefficient is similar to what is presented in Table 3. The -0.326 coefficient of the daily robbery rates model represents the 16.7-percent of the average pre-DST daily robbery rate; in Table 3, the -0.334 coefficient of the analogous model represents the 17-percent of the average pre-DST daily robbery rate. For the remaining robbery models, the results are mostly unchanged as well. Theft, murder and rape models do not suffer any remarkable change in their results after the inclusion of trends by year.

In Table 9 we present the results of the estimates split by public lighting quartile. As Table 8 is analogous to Table 3, Table 9 is analogous to Table 4, but different trends for each year are allowed. The estimates indicate a strong reduction in robbery in the first and second quartiles, and no effects are found in the third and fourth quartiles. For theft, murder and rape models, the results are generally not significant, with the exceptions of theft and murder models for the second quartile. The magnitude of the coefficients of all the models included in Table 9 is quite similar to what is presented in Table 4.

Finally, in Table 10 we present the results of a placebo test. We obtained data on criminal activity for the years 2003, 2015 and 2016, years when DST was not implemented. We simulate that DST was introduced the second Sunday of October, and compute estimates of equation (13) with an 8-weeks bandwidth. The results of a pooled regression are presented in the table. None of the models present a significant effect.

Table 9: Impact by Quartile of Public Lighting  
Different Trends by Year

|               | Robbery              |                     | Theft                |                    | Murder            |                   | Rape              |                   |
|---------------|----------------------|---------------------|----------------------|--------------------|-------------------|-------------------|-------------------|-------------------|
|               | Rate                 | Probability         | Rate                 | Probability        | Rate              | Probability       | Rate              | Probability       |
| Q1            | -0.632***<br>(0.169) | -0.091**<br>(0.032) | -0.223<br>(0.460)    | -0.003<br>(0.028)  | -0.006<br>(0.028) | -0.002<br>(0.007) | 0.002<br>(0.022)  | 0.002<br>(0.007)  |
| Pre-DST share | 0.298                | 0.238               | 0.029                | 0.004              | 0.130             | 0.206             | 0.066             | 0.246             |
| Q2            | -0.453***<br>(0.148) | -0.054**<br>(0.023) | -1.079***<br>(0.355) | -0.043*<br>(0.023) | 0.016<br>(0.013)  | 0.004*<br>(0.003) | 0.005<br>(0.010)  | 0.001<br>(0.002)  |
| Pre-DST share | 0.247                | 0.185               | 0.110                | 0.054              | 0.851             | 1.011             | 0.203             | 0.236             |
| Q3            | -0.168<br>(0.148)    | -0.024<br>(0.017)   | 0.214<br>(0.579)     | 0.019<br>(0.017)   | 0.022<br>(0.020)  | 0.004<br>(0.006)  | 0.003<br>(0.022)  | 0.001<br>(0.007)  |
| Pre-DST share | 0.100                | 0.091               | 0.019                | 0.024              | 1.337             | 1.368             | 0.215             | 0.535             |
| Q4            | -0.022<br>(0.124)    | -0.022<br>(0.019)   | -0.270<br>(0.245)    | -0.013<br>(0.012)  | -0.018<br>(0.013) | -0.006<br>(0.003) | -0.004<br>(0.015) | -0.002<br>(0.004) |
| Pre-DST share | 0.010                | 0.063               | 0.018                | 0.015              | 1.853             | 2.662             | 0.236             | 0.448             |

*Notes:* every model controls for area effects, day-of-the-week effects, and month-year effects. The models are fully interacted with a variable that represents years, but the treatment variable DST. Every specification uses data from an 8-weeks bandwidth. Models for four types of crime are included: robbery, theft, murder and rape. For each type of crime, the results for two models are presented. The results presented under the Rate headers belong to models where the dependent variable is the crime rate per 100,000 inhabitants; the results presented under the Probability headers belong to models that use as the dependent variable the probability of occurrence of an incident of that type of crime. Standard errors clustered at the area level in parentheses. \*\*\* Significant at the 1-percent, \*\* 5-percent, \* significant at the 10-percent.



Table 10: Placebo Years

|               | Robbery           |                   | Theft             |                   | Murder            |                   | Rape              |                   |
|---------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|               | Rate              | Probability       | Rate              | Probability       | Rate              | Probability       | Rate              | Probability       |
| All Day       | -0.164<br>(0.160) | -0.007<br>(0.020) | -0.467<br>(0.303) | 0.005<br>(0.013)  | -0.021<br>(0.015) | -0.006<br>(0.004) | -0.004<br>(0.015) | -0.002<br>(0.004) |
| Pre-DST share | 0.063             | 0.017             | 0.047             | 0.007             | 0.953             | 1.259             | 0.148             | 0.310             |
| Sunset        | -0.036<br>(0.052) | -0.009<br>(0.011) | -0.111<br>(0.090) | -0.028<br>(0.024) | -0.004<br>(0.007) | -0.001<br>(0.002) | 0.004<br>(0.006)  | 0.001<br>(0.002)  |
| Pre-DST share | 0.092             | 0.117             | 0.086             | 0.126             | 0.964             | 1.276             | 0.920             | 1.270             |

*Notes:* every model controls for area fixed effects, day-of-the-week effects, and month-year effects. The observations are weighted by area population. Every specification uses data from an 8-weeks bandwidth. Every estimate uses a sample of 38,192 observations: 56 days for 62 statistical areas by year, for 11 years. Models for four types of crime are included: robbery, theft, murder, and rape. For each type of crime, the results for two models are presented. The results presented under the Rate headers belong to models where the dependent variable is the crime rate per 100,000 inhabitants; the results presented under the Probability headers belong to models that use as the dependent variable the probability of occurrence of an incident of that type of crime. Standard errors clustered at the area level in parentheses. \*\*\* Significant at the 1-percent, significant at the \*\* 5-percent, \* significant at the 10-percent.

## VII. Discussion and Conclusion

The contribution of this paper is that it shows that an increase in natural light has a heterogeneous effect on criminal activity across the city. Poorly lit areas are where an increase in natural light provokes the largest reductions. We show that above a certain level of public lighting, more natural light does not reduce crime.

A Regression Discontinuity Design is used to recover the causal effect of natural light on crime. The implementation of DST provides a sharp discontinuity of natural light in the late afternoon, a period of the day of intense criminal activity, from one day to another. Within a window of time close enough to the beginning of the DST period, it is reasonable to assume that other factors affecting criminal activity remain stable.<sup>9</sup>

Robbery is the form of crime that is affected the most. In our preferred specification, daily robbery rates decrease 17-percent. For the first quartile of public lighting the decrease in robbery reaches 33.1-percent and for the second quartile, 25.6-percent. For the third and four quartiles, the effect is not significant. The largest reductions are found in areas with a PLI - the share of blocks with public lighting over the total number of blocks- of approximately 0.4. For areas with a PLI of 0.8 and above, the treatment does not provoke any reduction in robberies. For the crime of theft, the results are not robust to the different specifications. For murder and rape we do not find significant effects, although the estimates have low statistical power.

The results found in this work are in line with the literature of the field. The large crime reduction is of similar magnitude to what Dominguez and Asahi (2017) find for robberies in Chile. Doleac and Sanders (2015) also find that DST reduces crime in the United States, although the effect is less pronounced: a 7-percent decrease in robberies. Chalfin, Hansen, Lerner, and Parker (2019) run a field experiment in public housing developments in New York City and find a 4-percent decrease in violent outdoor crime following the deployment of lighting towers. All these papers find the largest effects for robberies, while thefts and personal crime remain mostly unaffected by the treatments.

To derive a policy recommendation regarding the implementation of DST is necessary to balance the beneficial consequences in terms of crime reduction with negative consequences that may arise. Some empirical evidence suggests that, through sleep deprivation, DST may negatively affect health outcomes. Jin and Ziebarth (2020) show that hospital admissions decrease in the US after DST finishes because it ends sleep deprivation originated when clocks are set one hour forward; Smith (2016) finds that fatal car accidents increase during DST; Barnes and Wagner (2009) show that DST increases workplace injuries. On the contrary, Wolff and Makino (2012) suggest that DST is beneficial for health, as it promotes outdoor activities and helps to burn calories.

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<sup>9</sup>For instance, Eriksson, Hjalmarsson, Lindquist and Sandberg (2016) show that neighborhood effects can affect local crime rates.

## **Compliance with Ethical Standards**

The author declares that he has no conflict of interest.

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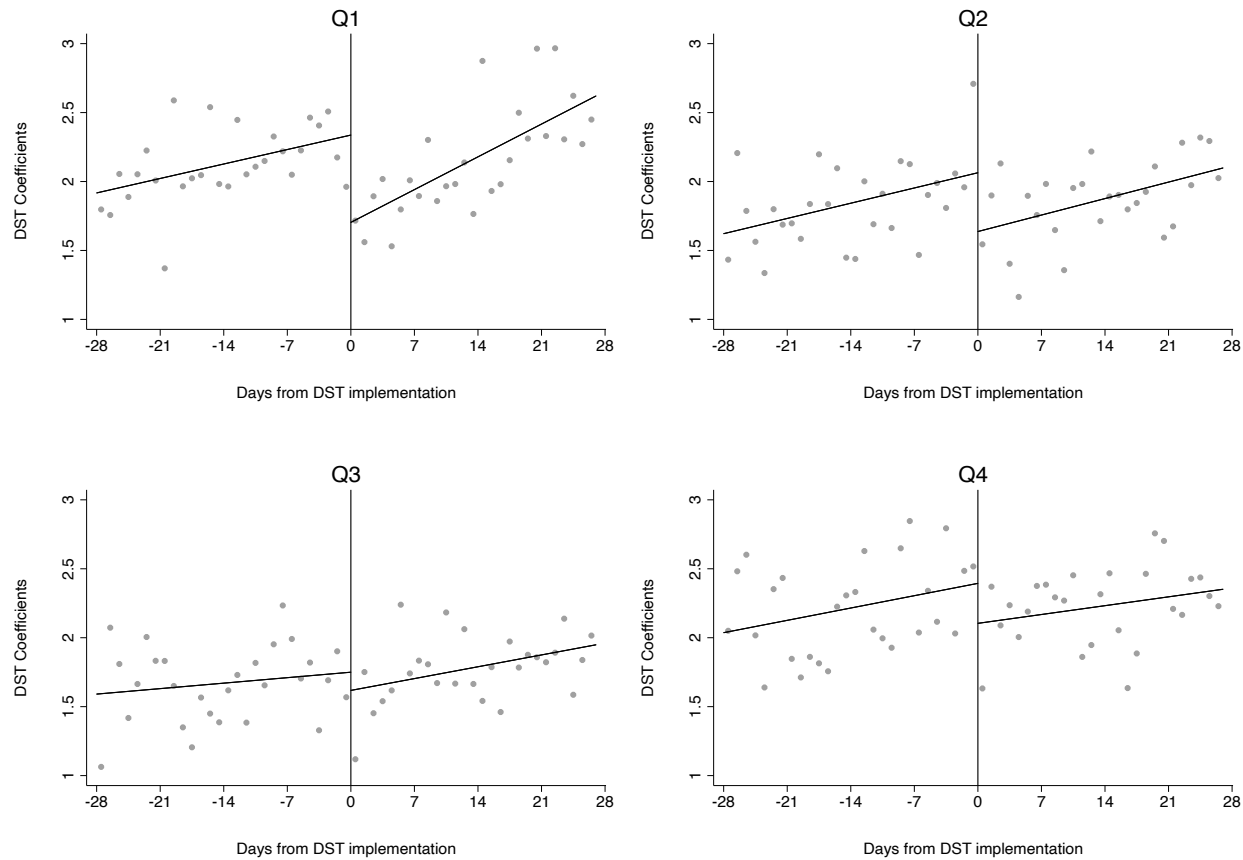
## Appendix

Table A1: Impact by Quartile of Public Lighting  
Additional Controls - Two-way cluster-robust standard errors.

|               | Robbery              |                     | Theft                |                    | Murder            |                   | Rape              |                   |
|---------------|----------------------|---------------------|----------------------|--------------------|-------------------|-------------------|-------------------|-------------------|
|               | Rate                 | Probability         | Rate                 | Probability        | Rate              | Probability       | Rate              | Probability       |
| Q1            | -0.670***<br>(0.166) | -0.095**<br>(0.035) | -0.343<br>(0.425)    | -0.016<br>(0.023)  | -0.001<br>(0.019) | -0.000<br>(0.005) | -0.014<br>(0.021) | -0.002<br>(0.006) |
| Pre-DST share | 0.316                | 0.248               | 0.044                | 0.021              | 0.014             | 0.006             | 0.451             | 0.273             |
| Q2            | -0.460**<br>(0.178)  | -0.059**<br>(0.027) | -1.056***<br>(0.343) | -0.032*<br>(0.017) | 0.019<br>(0.011)  | 0.004*<br>(0.002) | 0.003<br>(0.011)  | 0.001<br>(0.002)  |
| Pre-DST share | 0.251                | 0.202               | 0.108                | 0.039              | 1.031             | 1.095             | 0.137             | 0.124             |
| Q3            | -0.058<br>(0.147)    | -0.004<br>(0.021)   | 0.004<br>(0.610)     | 0.022*<br>(0.014)  | 0.016<br>(0.019)  | 0.004<br>(0.006)  | -0.002<br>(0.019) | -0.001<br>(0.005) |
| Pre-DST share | 0.035                | 0.016               | 0.000                | 0.028              | 0.999             | 1.361             | 0.158             | 0.573             |
| Q4            | -0.055<br>(0.125)    | -0.028<br>(0.021)   | -0.019<br>(0.311)    | -0.016<br>(0.011)  | -0.016<br>(0.012) | -0.006<br>(0.004) | -0.003<br>(0.015) | -0.001<br>(0.003) |
| Pre-DST share | 0.025                | 0.080               | 0.001                | 0.018              | 1.727             | 2.602             | 0.145             | 0.141             |

*Notes:* every model controls for area fixed effects, day-of-the-week effects, month-year effects, the average monthly home income, the average number of unemployed per household, and the average share of males aged between 15 and 34 per household. These variables change by month and area. The observations are weighted by area population. Every specification uses data from an 8-weeks bandwidth. The estimates are computed by quartile. Quartiles are based on the Public Lighting Index. This index takes the value of the quotient of the number of blocks with public lighting in the area over the number of total blocks in the area. Models for four types of crime are included: robbery, theft, murder, and rape. For each type of crime, the results for two models are presented. The results presented under the Rate headers belong to models where the dependent variable is the crime rate per 100,000 inhabitants; the results presented under the Probability headers belong to models that use as the dependent variable the probability of occurrence of an incident of that type of crime. Two-way cluster-robust standard errors, at the area and day level, in parentheses. \*\*\* Significant at the 1-percent, significant at the \*\* 5-percent, \* significant at the 10-percent.

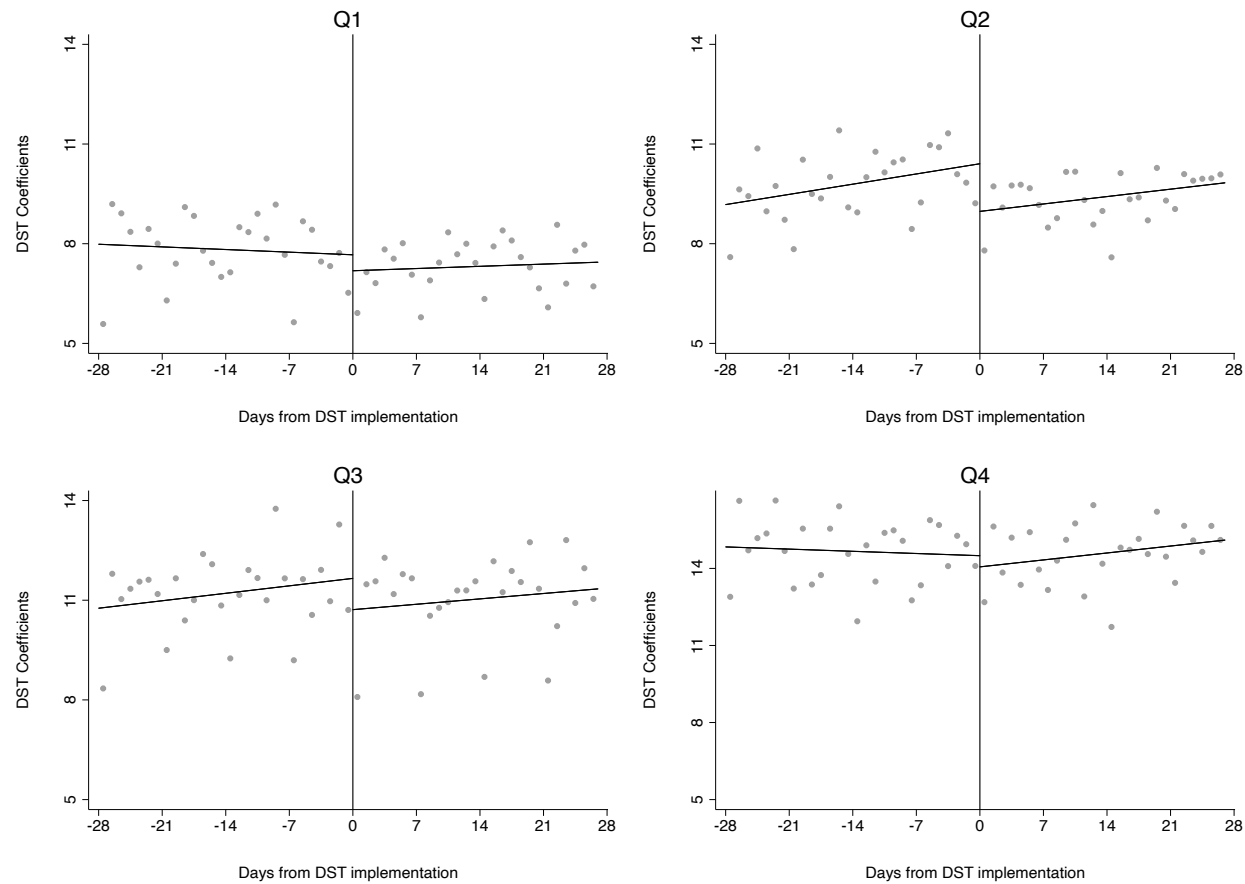
Figure AI.1: Robbery Rates



*Notes:* the figure presents average robbery daily rates per 100,000 inhabitants during the period 2004-2014 by public lighting quartile. To construct the quartiles the index considered is the number of blocks with public lighting over the number of total blocks in the area. The day DST is implemented is represented by the value 0. Data on eight-weeks bandwidths are included. Each subfigure contains 56 bins, that is to say, one bin per day of the bandwidth.

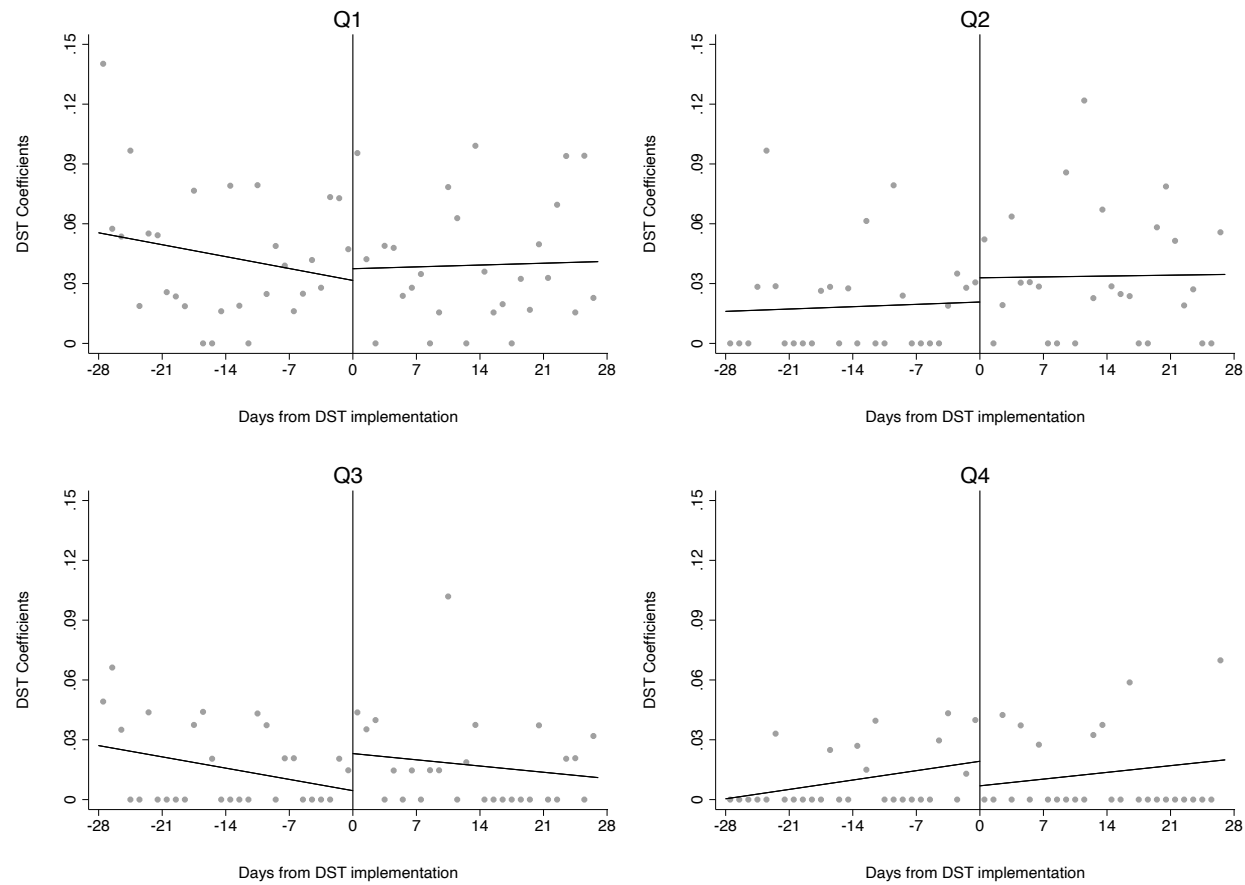


Figure AI.2: Theft Rates



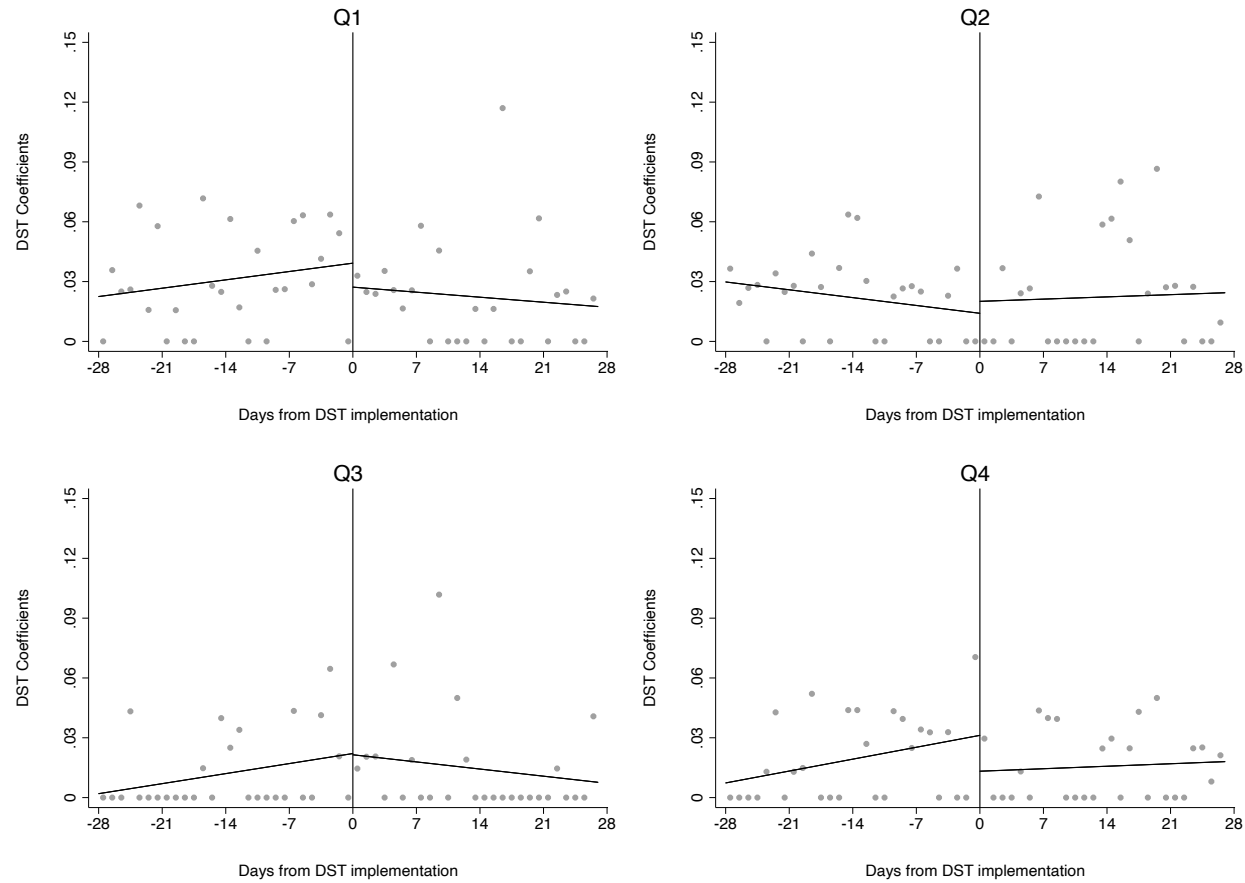
*Notes:* the figure presents average theft daily rates per 100,000 inhabitants during the period 2004-2014 by public lighting quartile. To construct the quartiles the index considered is the number of blocks with public lighting over the number of total blocks in the area. The day DST is implemented is represented by the value 0. Data on eight-weeks bandwidths are included. Each subfigure contains 56 bins, that is to say, one bin per day of the bandwidth.

Figure A1.3: Murder Rates



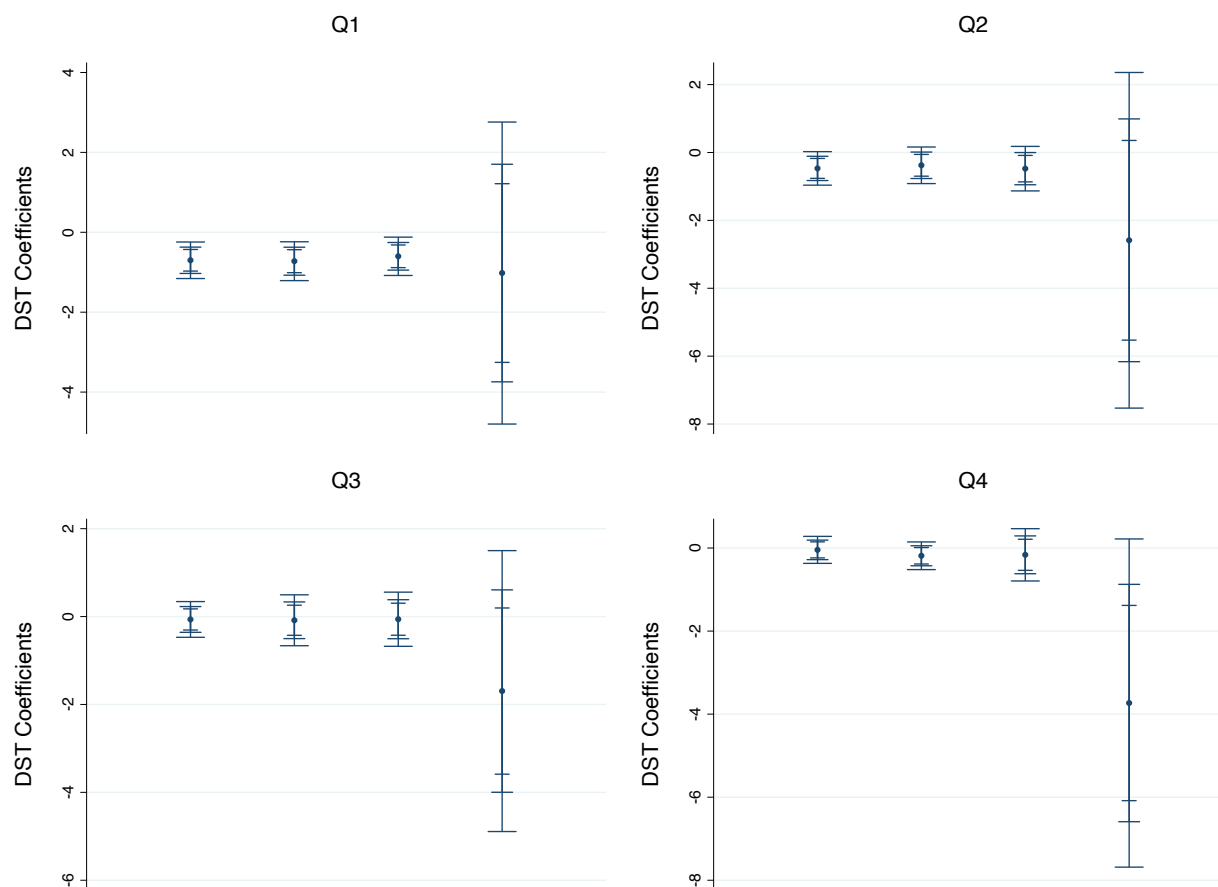
*Notes:* the figure presents average murder daily rates per 100,000 inhabitants during the period 2004-2014 by public lighting quartile. To construct the quartiles the index considered is the number of blocks with public lighting over the number of total blocks in the area. The day DST is implemented is represented by the value 0. Data on eight-weeks bandwidths are included. Each subfigure contains 56 bins, that is to say, one bin per day of the bandwidth.

Figure AI.4: Rape Rates



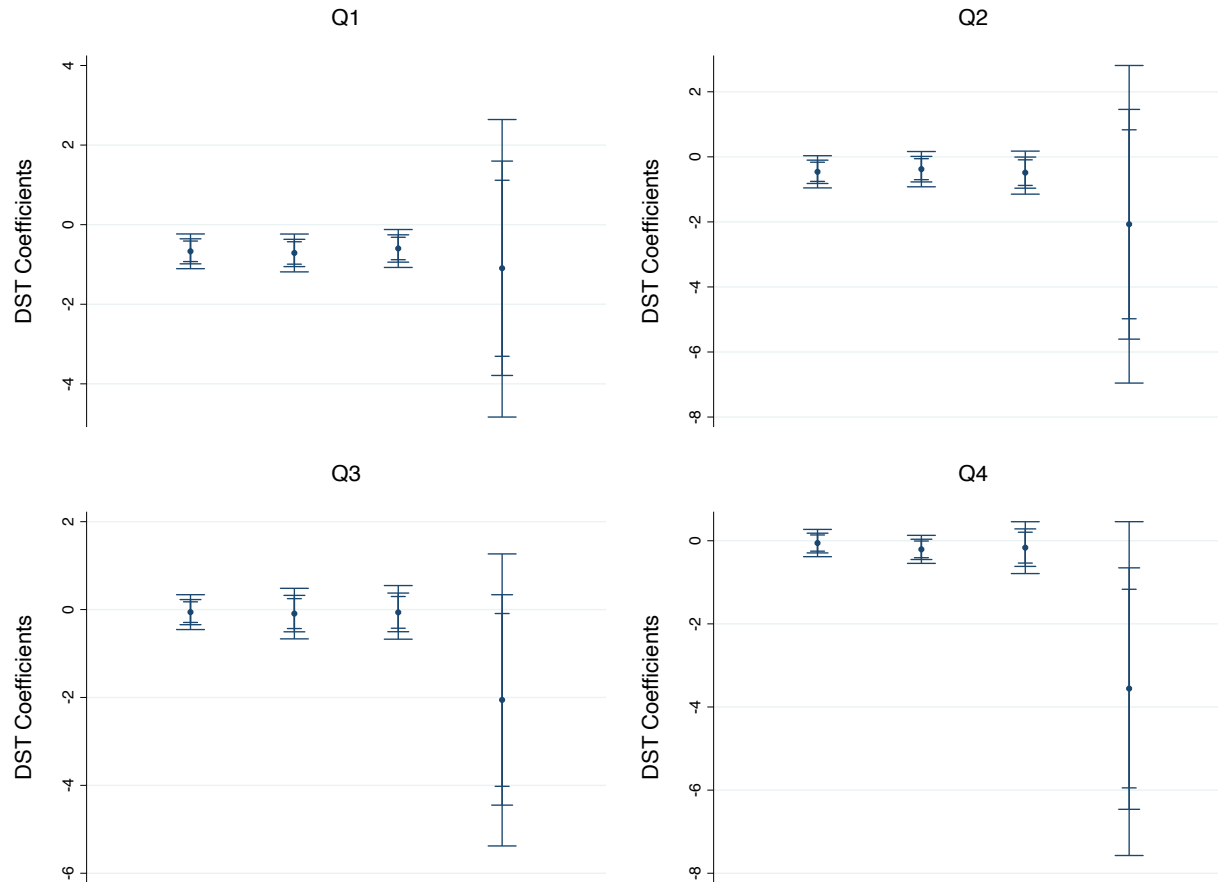
*Notes:* the figure presents average rape daily rates per 100,000 inhabitants during the period 2004-2014 by public lighting quartile. To construct the quartiles the index considered is the number of blocks with public lighting over the number of total blocks in the area. The day DST is implemented is represented by the value 0. Data on eight-weeks bandwidths are included. Each subfigure contains 56 bins, that is to say, one bin per day of the bandwidth.

Figure AII.1: Impact on Robbery Rates by Public Lighting  
Sensitivity of the Results to Different Bandwidths - Linear Polynomial



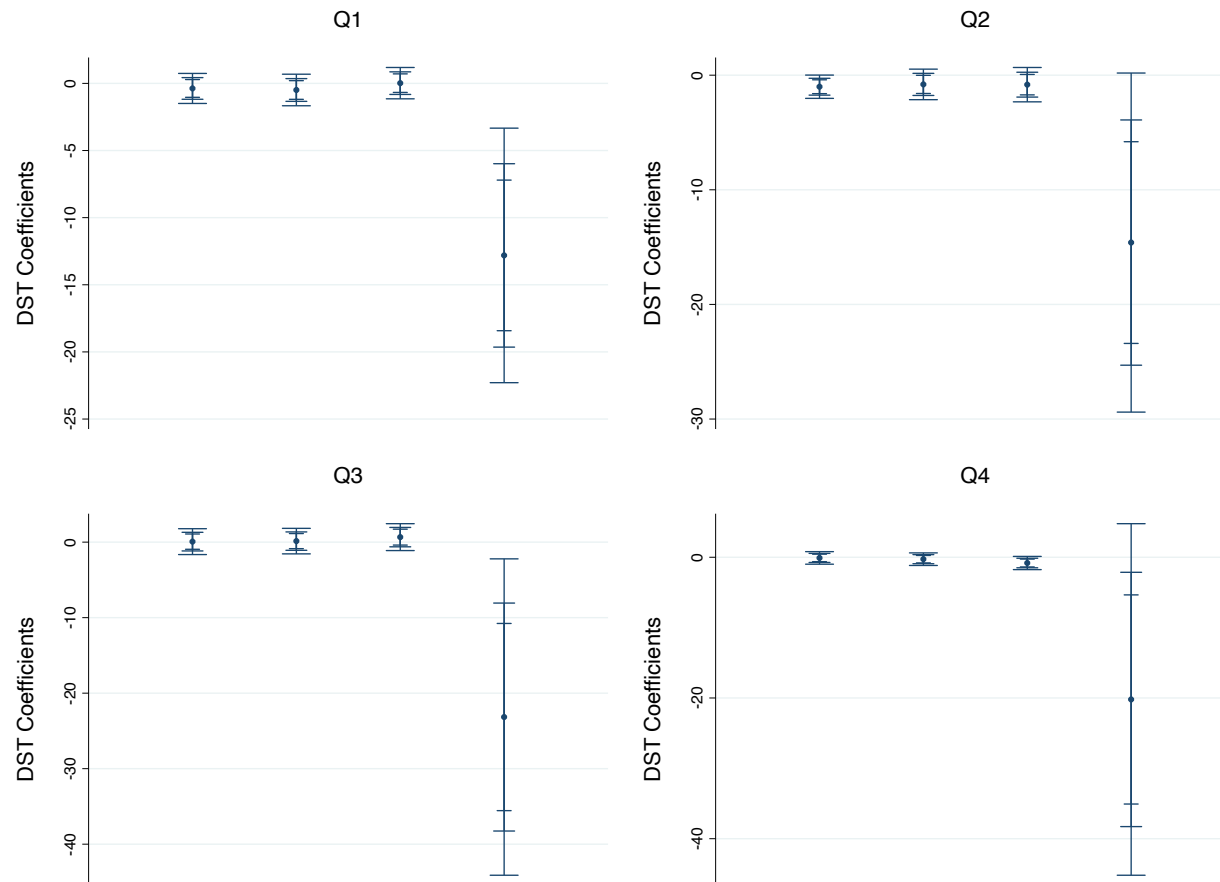
*Notes:* to construct the quartiles the index considered is the number of blocks with public lighting over the number of total blocks in the area. From left to right, at each graph, the first spikes represent the 99, 95 and 90-percent confidence intervals for the effect of DST ( $\beta_2$ ) for estimates with an 8-weeks bandwidth. The second spikes, the effect of DST for estimates with a 6-weeks bandwidth, the third for a 4-weeks bandwidth, and the fourth with a 2-weeks bandwidth. Every model controls for area fixed effects, day-of-the-week effects, and month-year effects. The observations are weighted by area population. Standard errors clustered at the area level.

Figure AII.2: Impact on Robbery Rates by Public Lighting  
Sensitivity of the Results to Different Bandwidths - Quadratic Polynomial



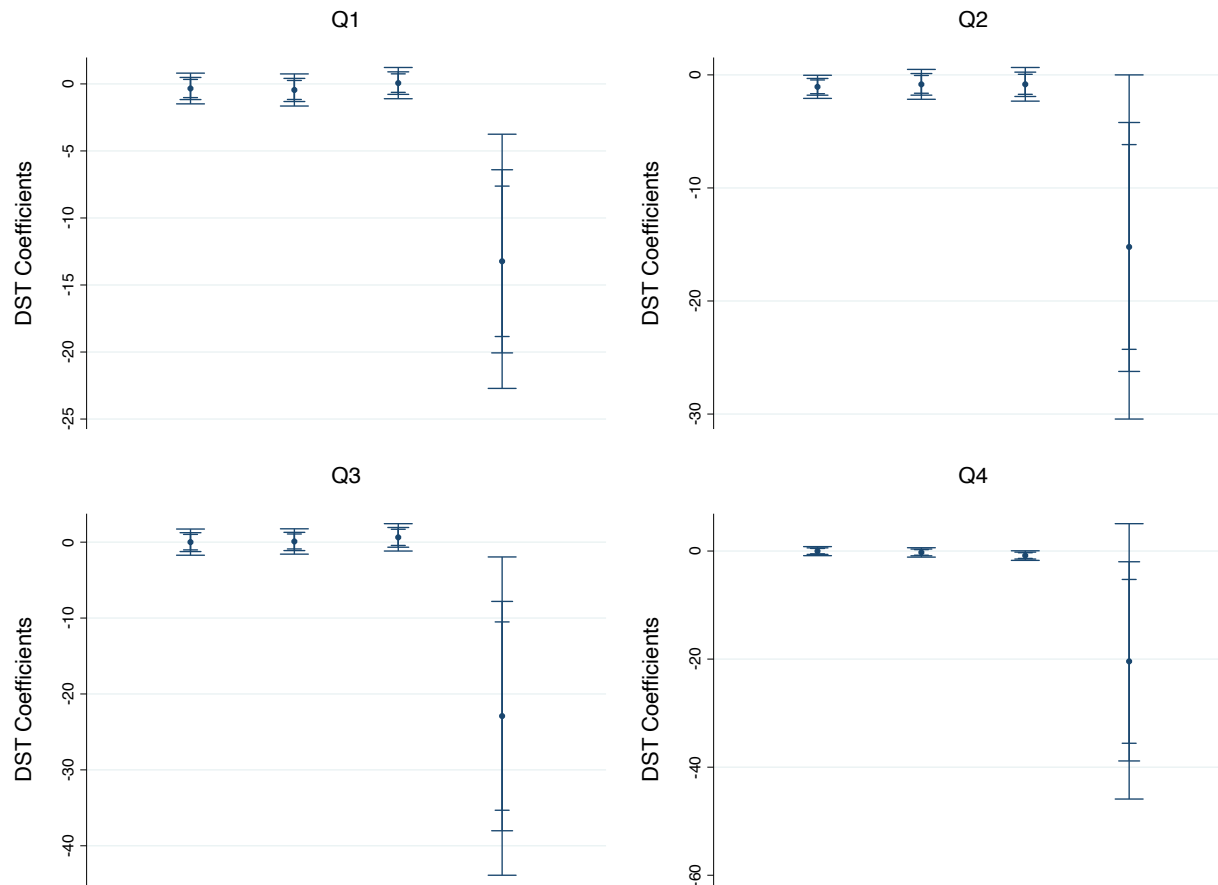
*Notes:* to construct the quartiles the index considered is the number of blocks with public lighting over the number of total blocks in the area. From left to right, at each graph, the first spikes represent the 99, 95 and 90-percent confidence intervals for the effect of DST ( $\beta_2$ ) for estimates with an 8-weeks bandwidth. The second spikes, the effect of DST for estimates with a 6-weeks bandwidth, the third for a 4-weeks bandwidth, and the fourth with a 2-weeks bandwidth. Every model controls for area fixed effects, day-of-the-week effects, and month-year effects. The observations are weighted by area population. Standard errors clustered at the area level.

Figure AII.3: Impact on Theft Rates by Public Lighting  
Sensitivity of the Results to Different Bandwidths - Linear Polynomial



*Notes:* to construct the quartiles the index considered is the number of blocks with public lighting over the number of total blocks in the area. From left to right, at each graph, the first spikes represent the 99, 95 and 90-percent confidence intervals for the effect of DST ( $\beta_2$ ) for estimates with an 8-weeks bandwidth. The second spikes, the effect of DST for estimates with a 6-weeks bandwidth, the third for a 4-weeks bandwidth, and the fourth with a 2-weeks bandwidth. Every model controls for area fixed effects, day-of-the-week effects, and month-year effects. The observations are weighted by area population. Standard errors clustered at the area level.

Figure AII.4: Impact on Theft Rates by Public Lighting  
Sensitivity of the Results to Different Bandwidths - Quadratic Polynomial



*Notes:* to construct the quartiles the index considered is the number of blocks with public lighting over the number of total blocks in the area. From left to right, at each graph, the first spikes represent the 99, 95 and 90-percent confidence intervals for the effect of DST ( $\beta_2$ ) for estimates with an 8-weeks bandwidth. The second spikes, the effect of DST for estimates with a 6-weeks bandwidth, the third for a 4-weeks bandwidth, and the fourth with a 2-weeks bandwidth. Every model controls for area fixed effects, day-of-the-week effects, and month-year effects. The observations are weighted by area population. Standard errors clustered at the area level.