Does Increased Lighting Reduce Crime?

Studying the Impact of the Summer Night Lights Program on Crime in Los Angeles

Siddheshwar "Sid" Salvi

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Advisor: Katharine Sims

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ABSTRACT

In the summer of 2008, the City of Los Angeles implemented a new program to prevent gang violence, "Summer Night Lights" (SNL). Since 2008, the program has expanded from eight parks to twenty-four parks across the city. SNL aims to reduce gang violence and crime by keeping park lights on until midnight each night from Wednesday through Saturday during the summer months. The SNL program provides a unique opportunity to properly determine whether increased lighting in communities reduces crime. Since it was only implemented in select neighborhoods, the program itself defines treatment and control groups. In this study, I determined if the SNL program reduced crime in the neighborhoods in which it was implemented, and if so, the mechanism through which the program has had an impact on crime. Specifically, I studied whether the SNL program reduced crime by a) affecting the decision calculus of criminals by increasing the probability of arrest due to increased surveillance, or b) increasing community pride and cohesion signaling to criminals that they should not commit offenses in the neighborhood. My identification strategy consisted of using a differences-in-differences approach and a fixed effects model. Since the Summer Night Lights program was not randomly implemented, it creates an endogeneity problem, selection bias, where the crime rate affects treatment and treatment affects the crime rate. To partially control for this selection bias, I and made the control group similar to the treatment group using neighbor-to-neighbor propensity score matching. I also excluded bordering neighborhoods to prevent any spillover effects or contamination of the control. The results of this study show that the Summer Night Lights program had little impact on crime in the neighborhoods in which it was implemented. Based on the evidence, it is unclear whether the surveillance theory or the community confidence theory best explains the relationship between lighting and crime.
Keywords: crime, lighting, Summer Night Lights, public economics

1. Introduction

In the summer of 2008, the City of Los Angeles implemented a new program to prevent gang violence, "Summer Night Lights" (SNL). Since 2008, the program has expanded from eight parks to twenty-four parks across the city.[1] SNL aims to reduce gang violence and crime by keeping park lights on until midnight each night from Wednesday through Saturday during the summer months. Developed in partnership with A Better LA, former USC coach Pete Carroll's non-profit organization, the program also provides free food and programming such as organized sports, skateboarding, movies, intervention and mentoring for at-risk youth. SNL hires "intervention workers" to maintain ceasefires between gangs and the community, and some youth have the opportunity to work as programming supervisors. Additionally, an audit counted that residents made 710,000 visits to the 24 sites between July 7th and September 4th 2010, and on average 10,929 people were served free meals each night (Gold 2010). The SNL program suggests a resurgence of structural solutions to crime among urban planning experts.

Though it was at first met with skepticism, SNL now enjoys widespread support and praise from the communities in which it has been implemented (Cathcart, 2009). After the first year of the program, Miguel Leon, a gang intervention worker from Boyle Heights said, "People were just waiting for it this summer. Last year it took a while to ramp up; now this place is packed." Sixty-year old Dorothy Poindexter-Bown of Harvard

[1] Costello Park, Jim Gilliam Park, Denker Park, Ramon Garcia Park, Cypress Park, Glassell Park, Mount Carmel Park, Harvard Park, Ross Snyder Park, Hubert Humphrey Park, Sepulveda Park, Ramona Gardens Recreation Center, Nickerson Gardens Housing Development, Jordan Downs Housing Development, Imperial Courts Housing Development, Edward R. Roybal Learning Center, Lemon Grove Park, Slauson Park, Normandale Park, Lake Street Park, South Park, Jackie Tatum Harvard Park, Highland Park, Van Ness Park.

Park remarked, "I'm taking it in, I'm thinking how nice it feels to be safe in the park at night." Reverend Jeff Carr, director of SNL and Mayor Villaraigosa's Gang Reduction and Youth Development division, reasons that "these neighborhoods with gang problems don't have a lot of assets. But there is a school, a park and a rec center. Those are public assets. Let's use those to create social connections that replace gangs." This new approach to crime contrasts with the old paradigm of increased police presence. For example, Paul Seave, director of Gov. Arnold Schwarzenegger's Office of Gang and Youth Violence Policy commented, "Until about five years ago, the approach to gang violence in California was largely a law enforcement one. But there has been a sea change in the way everyone, particularly law enforcement, thinks. We cannot arrest our way out of this problem."

The City of Los Angeles claims that SNL has been a huge success in reducing gang-related crime. The city boasts that since 2008 SNL has led to a 57% decrease in homicide-related deaths in its participating neighborhoods (Summer Night Lights, 2010). Using Los Angeles Police data, the Los Angeles Times reported that crime has fallen 40.4% since 2007 in neighborhoods surrounding SNL parks. Can the decline in homicides be attributed solely to the SNL program? Gang experts in Los Angeles like former LAPD lieutenant, Gary Nanson, and USC professor, Malcolm Klein have called into question the LAPD's gang statistics saying that they "don't come close to reality" (McDonald 2009).

The question of the Summer Night Light's program's efficacy has great economic significance. Since Gary Becker's seminal paper, *Crime and Punishment*, economists have tried to compare the deterrent effects of various criminal policy measures. With state budgets in shambles and city police departments constantly being asked to do more with less, policy experts struggle with how to best allocate resources to prevent and punish crime. To give a picture of crime in Los Angeles; in 2009, there were 23,779 violent crimes and 92, 271 property crimes (Crime and Arrest Weekly Statistics 2009). In 2009, the City Council's Ad Hoc Committee on Gang Violence estimated that Los Angeles had 400 gangs with 39,000 members, but only 10 percent of those gangs were responsible for 80 percent of the crime in the city. Even so, Los Angeles was not ranked in the top 15 of "America's Most Dangerous Cities" according to Forbes Magazine (O'Malley 2009).

The Summer Night Lights program cost 5.4 million dollars this past year, all funded by philanthropic donations. Therefore, the program cost $1,250 per park per hour (Gold 2010). With this amount of expenditure, the LAPD could have hired forty more police officers per hour per neighborhood. The total budget of the Los Angeles Police Department in 2009 was 1.17 billion dollars. Of that, 1.12 billion dollars were paid in salaries to 9,802 sworn personnel at an average hourly wage of $31. Per neighborhood, the Los Angeles Police Department spends on average 4.29 million dollars per neighborhood and has 36 sworn personnel. Keeping in mind these figures on the cost of crime prevention and discovery, it is important to consider the monetary cost of crime. A recent study estimated the average cost per murder to be higher than 17.2 million dollars, including victim cost, the cost of arrest and adjudication, the cost of incarceration, the opportunity costs of offenders' time and productivity (De Lisi et. al 2009). With the enormous costs of crime and the sizable amount of resources devoted to prevent, solve and punish crime, the relative effectiveness of various deterrence mechanisms continues to be a salient economic issue.

The SNL program provides a unique opportunity to properly determine whether increased lighting in communities reduces crime. Since it was only implemented in select neighborhoods, the program itself defines treatment and control groups. In this study, I want to determine if the SNL program reduced crime in the neighborhoods in which it was implemented, and if so, the mechanism through which the program has had an impact on crime. Specifically, I am interested in whether the SNL program reduced crime by a) affecting the decision calculus of criminals by increasing the probability of arrest due to increased surveillance, or b) increasing community pride and cohesion signaling to criminals that they should not commit offenses in the neighborhood. Section 2 discusses theory and previous literature on the impact of lighting on crime. Section 3 explains the methodology I employ and Section 4 details the dataset I use in this study. In Section 5, I present the results of various econometric tests. Lastly, in Section 6, I analyze the implications of my econometric analysis, provide possible avenues for further research and place this study within the broader crime prevention debate.

2. Literature Review

2.1 Economic Theory of Crime

When economists made their foray into criminology, they applied their all-encompassing model of individual rational behavior to the field (Eide 2006). In this model, an individual performs a criminal act if the total payoff, including the benefits of the crime minus the expected cost of punishments and other costs, exceeds the gain from legal alternatives. Jeremy Bentham wrote, “the profit of the crime is the force which urges man to delinquency: the pain of punishment is the force employed to restrain him from it. If the first of these forces be greater, the crime will be committed; if the second, the crime will not be committed" (Bentham, 399). In his seminal paper, *Crime and Punishment,* Becker gave new life to Bentham's ideas, and argued that criminals do not behave any differently than the average person – they are utility-maximizers (Becker, 170). Assuming that people act to maximize their utility and that utility is a positive function of income, an individual's expected utility from committing a crime is:

$$E[U] = PU(Y - f) + (1 - P)U(Y), \tag{2.1}$$

Where *U ()* is the individual's utility function, *P* is the probability of arrest and conviction, *Y* is the monetary equivalent of the total gain from the crime, and *f* is the monetary equivalent of any sanctions (Becker, 177). In this model, an individual will commit an offense when the expected utility of that action is positive. The comparative statics of the above model indicate that increases in either the probability or severity of punishment can change the criminal's expected utility from positive to negative. Becker presumes a greater response of criminals to changes in probability of conviction than to punishment. An increase in the probability of arrest compensated by an equal percentage decrease in punishment would not affect the expected income of crime, but could change the expected utility.[2] Consequently, since criminals are risk-preferers, an increase in *p* would reduce the expected utility, and thus the number of crimes, more than an equal percentage increase in *f*.[3] Although not specified in the basic model, individual discount

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[2] $EY = p(Y - f) + (I - p)Y = Y – pf$

[3]- $(\partial EU/\partial p)(p/U) = [U(Y) – U(Y – f)](p/U)$ as compared to $(\partial EU/\partial f)(f/U) = pU'(Y – f)f/U$
as $[U(Y) – U(Y – f)]/f$ as compared to $U'(Y – f)$

The term on the left is the average change in utility between Y – f and Y. It would be greater than, equal to, or less than U'(Y – f) depending on risk preference (U>0, U=0 or U<0) rates will also affect the decision to commit crime because the benefits of crime occur immediately, whereas punishment might come in the future, stretched over a long time. Thus, a high discount rate implies a greater propensity to commit crime because it lowers the present value of *f*. Since the development of this model of crime, numerous empirical studies have supported the hypothesis that "the probability of punishment, and to a lesser degree also the severity of punishment, has a deterrent effect on crime" (Eide 2006). These studies acknowledge that criminal behavior stems from a wide array of causes. Besides variations in crime levels between regions, gender, races, drug use, etc, norms, opportunities and context also influence the decision to commit a crime. In summary, the economic model suggests that the probability of conviction and punishment, combining with the discount rate and various environmental factors all influence an individual's decision to commit crime.

2.2 Empirical Research on the Economic Model of Crime

Since Becker's landmark paper, numerous economists have tested his economic model of crime, making alterations and using many different estimation methods. There is consensus in the literature that both the certainty and severity of punishment have a strong deterrent effect on crime. The widespread acceptance of this claim is reflected by its inclusion in most law and economics textbooks. For example, in Hirsch's *Law and Economics: An Introductory Analysis*,

> "Estimates of the magnitude of the deterrent effect vary, but it appears that an increase in law enforcement activity that increases either the probability of punishment or the severity of punishment by 1 percent is on average associated with a reduction in the number of offenses somewhere between .3 and 1.1 percent."

Below is a table summarizing the results of past studies on deterrence using aggregate, cross-section data (Farrington and Welsh 2002):

Study (Date)	Estimation Procedure	Crime Type	Probability of Arrest (P_A)	Probability of Conviction (P_C)	Probability of Punishment (P_P)	Severity of Punishment (S)
Ehrlich (1973)	OLS	All, 1960			-5.26***	-.585***
	2SLS				-.991***	-.1.123***
Sjoquist (1973)	OLS	Robbery, Burglary, Larceny	-.342***			-.212
Carr-Hill & Stern (1973)	2SLS	All, 1961	-.66***			-.28***
		All, 1966	-.59***			-.17***
Orsagh (1973)	OLS	Felonies		-.26***		
	2SLS			-1.8***		
Phillips & Votey (1975)	OLS	Felonies	-.622***			-.347***
	2SLS/ 3 eq		-.610***			-.342***
	2SLS/4 eq		-.701***			-.376***
Mathieson & Passell (1976)	OLS	Robbery, Murder	-1.06***, -.743***			
	2SLS		-2.95***, -1.96***			
Craig (1987)	3SLS	Felonies	-.57***			
Trumbull (1989)	OLS	All	-.217***	-.451***	-.325***	-.149***

As shown in the table, the estimated elasticities are consistent with the predictions of the theoretical model; the estimated coefficients of P_A, P_C, P_P and S are negative and $P_A < P_C < P_P$.

In more recent years, economists have studied the economic model of crime using a variety of datasets and methods. Witte (1980) uses individual data and develops a variant of Becker's model where the amount of crime a criminal commits is a monotonic function of the time allocated to illegal activity. In this model, the dependent variable is the number of arrests per month free. Witte realized that since more than 80 percent of the men in the sample were rearrested during the period their activities followed, their probability of arrest is quite high, and thus the probability of arrest would not greatly affect their time allocation decision. Using a hybrid of a probit and least squares model, and a maximum likelihood estimator, Witte found that the probability of punishment has a greater effect on arrests and convictions than the severity of punishment.

In another recent study, Cornwell and Trumbull (1984) use a panel dataset of North Carolina counties and both single and simultaneous equations panel data estimators to address sources of endogeneity in past studies. The authors argue that a fundamental flaw in previous studies has been the inability to control for unobserved heterogeneity in the unit of observation. Using panel data, they account for unoberservable country characteristics by conditioning on county effects in estimation. Using the ratio of FBI crimes to county population as the crime rate and proxying the probability of arrest by the ratio of arrest to offenses and controlling for police force, they adopted a log-linear specification and found that the arrest and conviction elasticities are -.355 and -.282. Their analysis suggests that the deterrent effects of arrest and conviction probabilities are much smaller than would be indicated from cross-section estimation.

Steven Levitt, skeptical of the past economic literature suggesting a negative empirical relationship between arrest rates and crime, conducted a study to discriminate between deterrence, incapacitation and measurement error. In the model of crime, total crimes is related to the true arrest rate (arrests/total crimes), however, empirical studies can only use reported crimes because total crime data is unavailable. Thus, Levitt argues that measurement error appears in both the left-hand and right-hand side variables in his model of crime. Moreover, Levitt shows that this measurement error will lead to negative bias, not attenuation bias as in the standard measurement error case (Levitt 1998). With only 38% of crimes reported, the possibility for measurement error is serious (Bureau of Labor Statistics 1994). Yet, Levitt finds that the use of reported crime in empirical studies does not lead to bias in the estimation of arrest effects.

Another important topic explored in the economic literature on crime is spillover effects. Greater crime deterrence efforts may shift criminal activity to a different time and place, possibly even resulting in an aggregate increase in crime. Hakim (1979) and other studies since then have found a positive and significant spillover effect.

2.3 Relationship Between Lighting and Crime: Theory and Mechanisms

Two theories can explain how increased or improved lighting affects crime (Farrington and Welsh 2002). Both theories argue that improved lighting affects *p*, the probability of apprehension, in a criminal's expected utility function. However, the two theories give different reasons for how improved lighting affects *p*. The first theory posits that increased or improved lighting increases the probability of arrest by facilitating surveillance by both residents and police. The second theory suggests that increased or improved lighting signals greater community investment leading to increased community pride, cohesion and informal social control.

Believers in the first theory fit increased or improved lighting into a broader category of "situational" approaches to crime, which concentrate on reducing crime opportunities and increasing risk of punishment through changes in the physical environment (Clarke, 1995). At its root, this theory posits that natural, informal surveillance is the best crime prevention. In her bestselling book, *The Death and Life of Great American Cities*, Jane Jacobs highlights the importance of having "eyes on the street" to neighborhood peace. For those eyes to catch crime, the streets of the neighborhood must be properly lit (Jacobs, 1961). Additionally, better lighting may encourage greater street usage, which facilitates natural surveillance. Most importantly, this theory predicts that increased or improved lighting especially reduces nighttime crime.

Proponents of the second theory have a different perspective on the effect of improved or increased lighting on crime: they stress the importance of bolstering informal social control and community cohesion (Jacobs, 1961; Angel 1968) through more effective street use and investment in the neighborhood (Taub et al, 1984; Taylor and Gottfredson 1986). First, better lighting fosters community confidence; it gives a clear signal that the local authorities are investing in the neighborhood. This can lead to initiatives by residents that prevent crime and disorder. Greater community confidence also affects the potential criminal's utility function by increasing p; offenders feel that any crimes are more likely to be reported due to residents' greater concern for their community. Second, improved illumination may reduce fear of crime because people feel well-lit areas are safer than darker ones. When actual and perceived risks of crime decrease, more residents use the lit area. This positive cycle changes the social mix and activity patterns in the neighborhood, reducing the risk and fear of crime. Supporters of this theory reason that better lighting will lead to decreases in both daytime and nighttime crime.

In summary, two possible mechanisms mediate the effect of improved or increased lighting on crime: better lighting increases surveillance or improves community confidence to reduce crime. Although not able to pin down the mechanism, economists have attempted to validate the overall hypothesis that improved illumination reduces crime.

2.4 Past Empirical Research on Lighting and Crime

While little recent research has been done on the effect of increased lighting on crime, research has been conducted in the United States and Great Britain over the past forty years on the impact of improved lighting on crime (Farrington and Welsh 2002). Interest in the relationship between better lighting and crime began in North America after the great increase in crime in the 1960s. The implementation of improved illumination projects across the country led to a comprehensive review by Tien *et al.* (1979) as part of the National Evaluation Program of LEAA (Law Enforcement Assistance Agency) funding. However, of the 103 street lighting projects, only fifteen collected data on its impact and were structured properly to allow for analysis. Their review yielded mixed and inconclusive results because most of the research projects suffered from various flaws: weak design, misuse or complete absence of sound analytic techniques, inadequate measures of street lighting, poor measures of crime, and insufficient appreciation of the impact of lighting on different types of crime (Farrington and Welsh, 1). Instead of prompting further research on the subject, academics in the United States concluded that lighting had no effect on crime and conducted little further study. In Great Britain, researchers began to study the effect of lighting on crime in the early 1990s, when three small-scale street lighting projects in London were implemented and evaluated (Painter, 1994). This study found that disorder and fear of crime decreased and pedestrian street use rose significantly after lighting modifications. Since then the Home Office (Great Britain) has funded regular reviews of street-lighting interventions.

In the most recent review, researchers conduct a meta-analysis of thirteen past studies (Farrington & Welsh, 2002). The studies included in the meta-analysis met five criteria: 1) improved lighting was the main intervention, 2) crime was the measured outcome, 3) high quality methodology, 4) the study included at least one experimental and control area, and 5) at least twenty crimes were committed in each area (9). Farrington and Welsh included five British studies from the past two decades and eight American evaluations from the 1970's in their review.

Beginning with the American studies, only four found that street lighting was effective in reducing crime. The studies which found a negative influence of lighting on crime measured both daytime and nighttime crime, whereas the inconclusive studies only measured nighttime crime. The authors' meta-analysis used odds ratios to measure the effect size to provide a comparable measure of the effect of each project. The odds ratio indicates the proportional change in crime in the control area compared with the experimental area. An odds ratio less than 1.0 suggests an adverse effect of improved lighting on crime, while an odds ratio above 1.0 implies a desirable effect of improved lighting. The meta-analysis of the American studies yielded an average odds ratio (weighted according to the standard error of each study) of 1.08 (28). In other words, crime decreased by seven percent in experimental areas as opposed to the control areas.[4] The five British studies showed that improved lighting led to a significant thirty percent decrease in crime. In two of these studies, the financial savings from reduced crimes greatly exceeded the financial costs of improved street lighting. Taking all thirteen studies together, improved lighting reduced crime by twenty percent in experimental

[4] Odds ratio calculated by dividing change in crimes in control area by change in crimes in experimental area. Crime decreased by 7 percent in the experimental area as compared with the control area because the change in the experimental area compared with the control area is the inverse of the odds ratio (1/1.08).

areas as compared with control areas. While the American studies were conducted in the 1970s, most of the British evaluations have been conducted in the last twenty years. These British studies did not find any difference in the reduction between nighttime and day-time crime, supporting the "community pride" theory.

One of the most rigorous studies included in the meta-analysis was by Painter and Farrington (1999). Using victim surveys, they compared the prevalence and incidence of crime twelve months before and twelve months after the installation of improved lighting with adjacent and control areas where street lighting remained unchanged. They found that the prevalence of crime decreased by 26 percent in the experimental area, as compared to 21 percent in the adjacent area and 12 percent in the control area.[5] In addition, the incidence of crime reduced by 43 percent in the experimental area, 45 percent in the adjacent area and only 2 percent in the control area.[6] Painter and Farrington used surveys to determine household victimization and respondents' perceptions, attitudes and behavior. The authors tested the extent to which changes in the prevalence of crime were significantly different from another area by using an interaction term in a logistic regression:[7]

$$Log\ (P) = \beta_0 + \beta_1 PrePost + \beta_2 ConExp + \beta_3 PrePost{*}ConExp$$

Using this method, they controlled for preexisting differences in crime rates between experimental and control areas. Thus, they confidently concluded that the

[5] Prevalence of crime: number of households victimized by crime/number of houses in area
[6] Incidence of crime: average number of crimes per 100 households
[7] Log – natural logartithm
P = probability of crime
PrePost = Dummy Before/After Variable
ConExp = Dummy Control/Experimental Varaible
PrePost*ConExp = Interaction term

change in crime in the experimental areas was significantly different from the change in crime in control areas (LRCS = 4.69, p = .003).[8]

Similarly, to test the significance of the difference in the incidence of crime between treatment and control areas, they used an interaction term in a Poisson regression equation. As with prevalence of crime, they found that the change in crime in the experimental area was significantly different from the change in crime in the control area (LRCS = 7.17, p=.007). Overall, the Painter and Farrington study showed that improved lighting reduces crime where it is implemented.

Even though the meta-analysis provides stable results, Farrington and Welsh argue that significant knowledge gaps in this area exist (10). They suggest that future research should measure crime using police records, victim surveys, and self-reports of offending. In addition, future evaluations should include experimental, adjacent and non-adjacent control areas, in order to test hypotheses about displacement and diffusion of benefits. Ideally, a long time series of crimes before and after improved lighting in experimental and control areas should be studied.

Based on these conclusions, the "Summer Night Lights" program in Los Angeles provides an excellent opportunity to study the relationship between crime and lighting because police crime data is readily available, and there are clearly-established treatment, adjacent and non-adjacent control areas.

3. METHOD

In designing this study, there are three important decisions to be made to ensure the best possible analysis of the effect of the Summer Night Lights program on crime. First, I must pick an appropriate unit of analysis. I can either use neighborhoods as

[8] LRCS = Likelihood Ratio Chi-Squared = interaction term in logisitc regression

defined by the Los Angeles Times/LAPD or distance from the park. I chose neighborhoods as my unit of analysis instead of using a fixed area around a park because the program was designed to reduce gang-related crime in the whole neighborhood. I realize that my choice of unit of analysis may slightly bias my study towards the "community pride and cohesion" theory, while choosing distance from the park would imply a credence to the "surveillance" theory. Second, I must identify an appropriate dependent variable: number of crimes or density of crime. Since most official statistics are reported as density of crime (crimes per 1000 people), I chose to use density of crime as my dependent variable. Third, I aggregated the crime data at two levels of specificity: week and hour. At both levels, I calculated the number of crimes per thousand people for every neighborhood. Fourth, I analyzed the effect on all crime and violent crime only. I defined violent crime as aggravated assault, rape, murder and robbery. Since the Mayor's office touts that the program reduced "gang-related" homicide by 57%, I wish to examine its effect on violent crime only (Summer Night Lights, 2010). Lastly, I must choose an appropriate identification strategy to isolate the effect of the Summer Night Lights program.

3.1 Identification Strategy

The nature of the Summer Night Lights program itself creates two complications. First, the program did not just increase lighting in particular neighborhoods, but also provided extensive programming (on average almost 11,000 people were fed each day this past summer). To disentangle the effect of lighting and programming, I looked at the differential impact of the program on overall crime versus nighttime crime. If the Summer Night Lights program reduced nighttime crime more, it would suggest that increased lighting plays a larger role in the impact of the project and also determines the mechanism by which lighting affects crime.

Second, the Summer Night Lights project is not simply a program that keeps lights on longer in random parks of the city, but was designed to target neighborhoods with high gang violence. The Mayor's office recognized that violent gang activity is heavily concentrated in certain areas across the city and initially chose twelve neighborhoods or "Gang Reduction Youth Development" zones for participation where violent gang-related crime is at least 400 percent higher than other parts of Los Angeles (Summer Night Lights, 2010). Since the Summer Night Lights program was not randomly implemented, it creates an endogeneity problem, selection bias, where the crime rate affects treatment and treatment affects the crime rate. Unfortunately, I could not find a good instrumental variable that was correlated with treatment but uncorrelated with the error term of crime rate. Instead, I controlled for time-invariant unobservables and made the control group similar to the treatment group using neighbor-to-neighbor propensity score matching.

Demographic factors associated with higher crime and correlated with a greater probability of being chosen for the program include population density (people per square mile, *PopDensity*), percent of neighborhood with a college degree (*College*), median income (*Income*), percent of African Americans (*Black*), and percent of Latinos (*Latino*) (Appendix 1, Table 2). Yet, there may be other unobservable factors affecting crime in particular neighborhoods or at certain times of the year.

To control for time-invariant unobservables I used two models: differences-in-differences and fixed effects.

1) Differences in Differences (D-D):

a) $\text{CrimeRate}_{2009} = \beta_0 + \beta_1 \textit{treated}_{2008} + \beta_2 \textit{treated}_{2009} + \beta_3 \textit{during}_{2009} + \beta_4 \textit{treated}_{2008} * \textit{during}_{2009} + \beta_5 \textit{treated}_{2009} * \textit{during}_{2009} + \beta_6 \textit{PopDensity} + \beta_7 \textit{Latino} + \beta_7 \textit{Black} + \beta_8 \textit{Income} + \varepsilon$

b) $\text{CrimeRate}_{2010} = \beta_0 + \beta_1 \textit{treated}_{2008} + \beta_2 \textit{treated}_{2009} + \beta_3 \textit{treated}_{2010} + \beta_4 \textit{during}_{2010} + \beta_5 \textit{treated}_{2008} * \textit{during}_{2010} + \beta_6 \textit{treated}_{2009} * \textit{during}_{2010} + \beta_7 \textit{treated}_{2010} * \textit{during}_{2010} + \beta_8 \textit{PopDensity} + \beta_9 \textit{Latino} + \beta_{10} \textit{Black} + \beta_{11} \textit{Income} + \varepsilon$

$\textit{Treated}_{2008}$, $\textit{treated}_{2009}$, $\textit{treated}_{2010}$, $\textit{during}_{2009}$ and $\textit{during}_{2010}$ are all dummy variables. The *treated* variables equal 1 when a neighborhood participated in the Summer Night Lights program beginning in the year in the subscript. For example, treated_{2008} equals 1 for all observations if the neighborhood was included in the program starting in 2008. The *during* variables equal 1 for the weeks that the program was in session: July 1 – Sept. 7 in 2009 and July 7 - Sept. 4 in 2010. Hence, the interaction variables of *treated* and *during* only equal 1 when the Summer Night Lights program was running and the neighborhood was included in the program. The sign and magnitude of the coefficients of the interaction variables indicate the impact of the Summer Night Lights program on the crime rate. The value of the coefficient of the interaction term is called the average treatment effect. To control for observable factors that may affect crime beyond treatment and the time period, I include demographic variables for population density, race and income.

2) Fixed Effects (FE):

a) $\text{CrimeRate}_{\text{neighborhood},t} = \beta_0 + \beta_1 \textit{lightson}_{\text{neighborhood},t} + \beta_2 \textit{hadlights}_{\text{neighborhood},t} + \delta_t + \delta_{\text{neighborhood}} + \varepsilon_{\text{neighborhood},t}$

b) $\text{CrimeRate}_{neighborhood,t} = \beta_0 + \beta_1 \textit{firstyearlightson}_{neighborhood,t} + \beta_2 \textit{secondyearlightson}_{neighborhood,t} + \beta_3 \textit{thirdyearlightson}_{neighborhood,t} + \beta_4 \textit{hadlights}_{neighborhood,t} + \delta_t + \delta_{neighborhood} + \varepsilon_{neighborhood,t}$

In the fixed effects model, *lightson*, *hadlights*, *firstyearlightson*, *secondyearlightson*, and *thirdyearlightson* are all dummy variables. *Lightson* equals 1 for neighborhoods participating in the initiative and weeks during the Summer Night Lights program. The three variables, *firstyearlightson*, *secondyearlightson*, and *thirdyearlightson*, segment the neighborhoods in the program by what year they were included. Lastly, *hadlights* equals 1 for all non-SNL time periods for an involved neighborhood after the first summer of participation. The table below details the values of each independent variable in all time periods:

Table 3.1

	1/1/09-6/30/09	7/1/09-9/7/09 (SNL)	9/8/09-7/6/10	7/7/10-9/4/10 (SNL)	9/5/10-11/30/10
lightson	0	1	0	1	0
$\textit{hadlights}_{2008}$	1	0	1	0	1
$\textit{hadlights}_{2009}$	0	0	1	0	1
$\textit{hadlights}_{2010}$	0	0	0	0	1
$\textit{firstyearlightson}_{2008}$	0	0	0	0	0
$\textit{firstyearlightson}_{2009}$	0	1	0	0	0
$\textit{firstyearlightson}_{2010}$	0	0	0	1	0
$\textit{secondyearlightson}_{2008}$	0	1	0	0	0
$\textit{secondyearlightson}_{2009}$	0	0	0	1	0
$\textit{thirdyearlightson}_{2008}$	0	0	0	1	0

In the FE model, the treatment effect is measured by coefficients of *lightson*, *hadlights*, *firstyearlightson*, *secondyearlightson*, and *thirdyearlightson*. If the Summer Night Lights program reduced crime during the treatment period, we would expect the coefficient of *lightson* to be negative. If multiple years of participation in the program affect the impact of the program, the coefficients of *secondyearlightson* and *thirdyearlightson* should be statistically different from zero. In the FE model, dummy variables for each year, neighborhood and week serve as controls for time-invariant unobservable factors. While these two models do not completely tackle the endogeneity problem due to the existence of time-varying unobservables, we can make their results stronger by using propensity scoring, which creates a control group "similar" to the treatment group.

I used propensity score matching to refine my control group to include only those neighborhoods that could have been chosen for treatment. Besley and Case (2000) show that bias in a fixed effects model originates from: 1) "omitted variable bias caused by observable variables that determine policy and that have independent influence on the outcome of interest," and 2) "Presence of unobservable variables that may determine both the policy and outcome of interest." To address these concerns they suggest selecting a control group that is "similar" to the control group, which I do using propensity score matching. The propensity score was generated using the nearest-neighbor approach, which matched treatment neighborhoods to three other neighborhoods. In this model, each treatment observation was matched to three neighbors using population density, percent of African-Americans, percent of Latinos, and the median income of the neighborhood. I only included matched neighborhoods in the control group. Thus, there were sixty control neighborhoods and twenty treatment neighborhoods.

Lastly, to help control for any spillover effects of the treatment, I removed neighborhoods bordering the treated neighborhoods from the control group. There are two possible types of spillover effects: crime could have been displaced from the treatment neighborhoods to bordering neighborhoods, or crime in the bordering neighborhoods could have decreased because people in these neighborhoods participated in the Summer Night Lights activities. These spillover effects would contaminate the control group, and thus affect the estimated impact of the program in divergent ways. If crime was displaced to the bordering neighborhoods, it would exaggerate the crime-reducing effect of the program. On the other hand, if the crime-decreasing influence of the program spread to the bordering neighborhood it would mask the Summer Night Lights initiative's effect. Therefore, I excluded the bordering neighborhoods to arrive at the most accurate estimate of the Summer Night Lights program's impact on crime. After removing bordering neighborhoods and using propensity score matching, twenty treatment and sixty control neighborhoods remained the sample.

3.2 Determining the Mechanism

Since the Summer Night Lights program involves more than increased lighting, it provides an opportunity to clearly test between the "community pride" and "natural surveillance" theories. Since I have information about the time each crime was committed, I will also run both the differences-in-differences and fixed effects models using only the hours that the program was operational (7 pm – 12 am). Thus, if I find a different impact of the program on crime during those hours as compared to the daytime, I can verify which theory is at work. If the "natural surveillance" theory actually underlies the relationship between lighting and crime, the coefficient of treatment in the nighttime regression should be much more negative than in the daytime regression. However, if the coefficient of treatment in the daytime regression is roughly equal to its counterpart in the nighttime regression, this suggests that the "community pride" mechanism is at work.

In summary, I designed my study to examine three questions: did the Summer Night Lights program have an impact on crime overall, did it influence violent crime in particular and what was the mechanism by which it effected crime rates in Los Angeles?

4. DATA

I use mapped crime data from the Los Angeles Police Department between January, 1 2009 and November 30, 2010. The Los Angeles Police Department records the place of the crime, time of the crime and the type of crime. In my dataset, I only include Part I crimes, violent and property crimes, because Part II crimes include offenses like electronic fraud and tax evasion that would likely not be affected changes in lighting. Below is a table summarizing the crime data I received from the LAPD/LA Times.

Table 4.1 – Summary Statistics (Entire Dataset)

# of Neighborhoods	272
# of Treated Neighborhoods	20
Total Part I Crimes Recorded	355,572
Aggravated Assault	34,234
Burglary	61,924
Grand Theft Auto	56,554
Homicide	1,015
Rape	2,602
Theft	87,524
Theft from Vehicle	80,155

Examining the relationships among demographic variables, I find as expected that higher population density correlates with higher proportion of Latinos and African-Americans, and lower median income and proportion of college graduates (Appendix 1, Table 1). In addition, the higher the percentage of Latinos and African-Americans in a neighborhood, the lower the median income and proportion of college graduates. Below is a table of summary statistics of the neighborhoods which participated in the program:

Table 4.2 – Summary Statistics (Treatment versus Control Groups[9])

Neighborhood	Population	Pop. Density	%Latino	%Black	Household Income	%4YearDegree
Baldwin Hills-Crenshaw	30,123	10,466	17.3	71.3	37,948	24.1
Glassell Park	23,467	8,524	66.1	1.4	50,098	19.7
North Hollywood	77,848	13,264	57.7	5.6	42,791	18.5
Echo Park	40,455	16,868	64	2	37,708	1.8
Van Nuys	103,770	11,542	60.5	6	41,134	15.3
Highland Park	57,566	16,835	72.4	2.4	45,478	14.3
Panorama City	65,766	18,028	70.1	4.3	44,468	13.7
East Hollywood	73,967	31,095	60.4	2.4	29,927	13.4
Harbor Gateway	39,688	7,720	53.4	16.3	47,849	12.4
Hyde Park	61,370	12,700	27.3	6.6	39,460	12.3
Westlake	103,839	38,214	73.4	3.9	26,757	12
Cypress Park	9,764	13,478	82.1	.06	42,615	8.4
Exposition Park	31,062	16,819	56.1	38.1	33,999	7.3
Boyle Heights	92,756	14,229	94	.9	33,235	5
Harvard Park	10,297	16,072	48.2	48.4	37,013	4.8
Pacoima	75,014	10,510	85.6	07.2	49,066	4.2
Vermont-Slauson	26,797	18,577	60.5	36.8	31,236	3.7
South Park	30,496	21,638	78.6	19.2	29,518	3.4
Watts	36,815	17,346	61.6	37.1	25,161	2.9
Central-Alameda	40,947	18,760	84.6	13.3	31,559	2.8
Average (Treatment)	**51,590**	**16,634**	**63.7**	**19.2**	**37,851**	**10.8**
Average (Control)	**33,869**	**7,741**	**37.1**	**8.9**	**70,857**	**27.3**

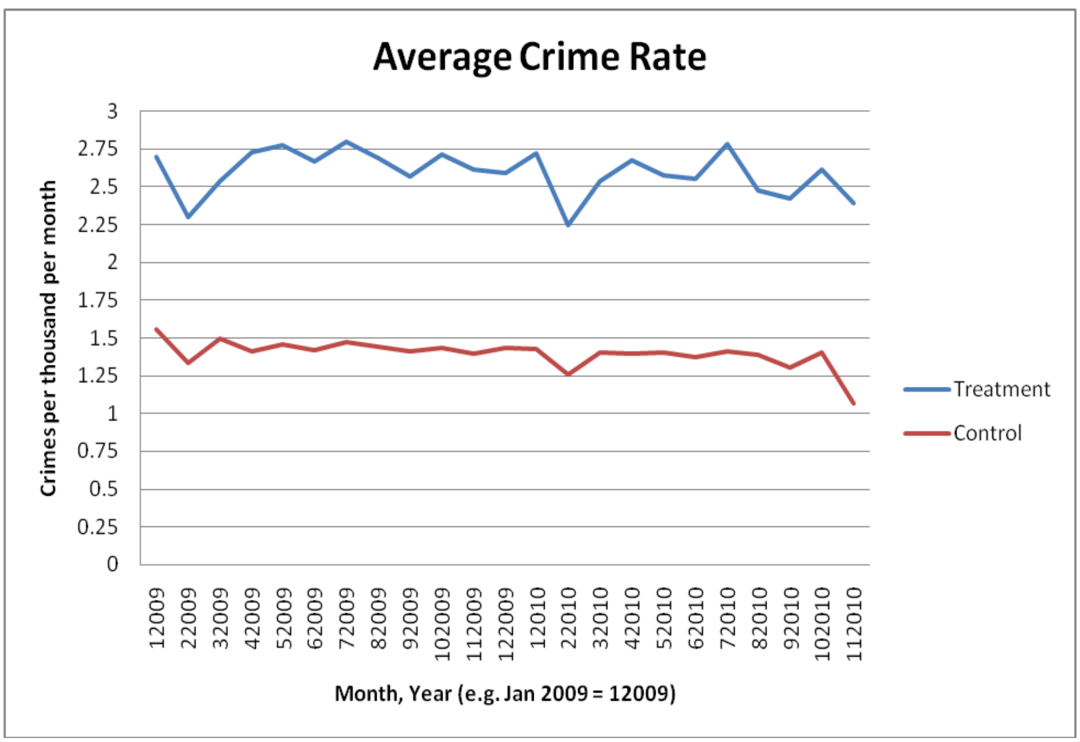
Comparing the averages of the treatment and control neighborhoods, we find that the neighborhoods which received the program have greater population density, higher minority populations and a lower level of educational attainment. To more rigorously examine how treatment is correlated with the demographic variables, I used a probit regression model to estimate the effect of *PopDensity*, *Latino*, *Black*, *Income* and *College* on the probability of being selected as a treatment neighborhood. I found that higher population density, larger percentage Latino or black in a neighborhood and

[9] Control Group here means all other neighborhoods in dataset, not excluding bordering neighborhoods or using propensity score matching.

greater median incomes increase the probability of treatment, while the proportion of college graduates does not affect the likelihood of treatment (Appendix 1, Table 2). The disparity in demographic characteristics between the control and treatment groups and the significant correlations between certain demographic variables and treatment confirm that the Summer Night Lights program was not implemented randomly.

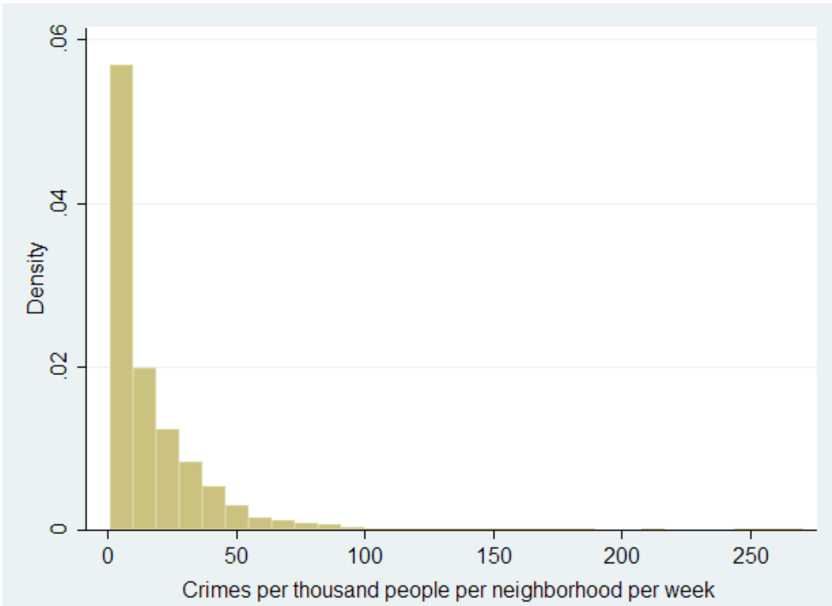
Looking for trends in the crime rate across the treated neighborhoods, I graphed the average monthly crime rate. In the graph below, we find that the average crime rate of the treated and control neighborhoods do not fluctuate much over the twenty-three month period. However, the average crime rate of the control group is much lower than the treatment group. In both groups, the only significant dips in crime occur in the month of February possibly due to the fewer number of days in that month.

Figure 4.1 – Crime Trends (Treatment versus Control)



Next, to visualize the distribution of crime in the whole dataset, I generated the following histogram of crimes per thousand people per week per neighborhood. The histogram shows that crime is not normally distributed across neighborhoods and weeks, and thus it makes sense to use a logistic regression.

Figure 4.2 – Distribution of Crime Rate



5. Results

I have divided the results from the differences-in-differences and fixed effects model by each level of specificity: overall weekly crime, violent crime, and daytime and nighttime crime.

5.1 Overall Weekly Crime

Tables 5.1 and 5.2 present the results of the differences-in-differences (D-D) model for each year in the dataset. The first two columns display the results after excluding bordering neighborhoods ("No Neighbors") from the sample. In columns 3 and 4, I not only excluded bordering neighborhoods, but also used propensity score matching to refine the control group further ("Using PS"). The D-D model controls for time-invariant factors correlated with higher crime, population density, race and income (coefficient estimates not displayed). Tables 5.1 and 5.2 suggest two conclusions. First, as expected, the significant positive coefficients of *treatment*$_{2009}$ show that being a treatment neighborhood is associated with higher crime rates. A neighborhood included in the program in 2009 has .108-1.223 or 5.61-43.1% more crimes per thousand people per week. In addition, neighborhoods included in 2010 had 3.01- 6.45% higher crimes per thousand people per week. Second, while some of the coefficients of the interaction variables are negative, suggesting that the Summer Night Lights program reduced the crime rate in the neighborhoods it in which it was implemented, these estimates are not statistically different from zero.

Table 5.1 - 2009[10]

Overall Crime	(1) (No Neighbors)	(2) (No Neighbors)	(3) (No Neighbors, Using PS)	(4) (No Neighbors, Using PS)
VARIABLES	Crimes per Week	Ln(Crimes per Week)	Crimes per Week	Ln(Crimes per Week)
during2009	0.00431	-0.00206	-0.0185	-0.00301
	(0.170)	(0.0120)	(0.0397)	(0.0201)
treatment2008	-0.110	0.0161	0.0433	0.0189
	(0.417)	(0.0296)	(0.0290)	(0.0147)
treatment2009	**1.136****	**0.176*****	**0.108*****	**0.0561*****
	(0.494)	**(0.0350)**	**(0.0297)**	**(0.0150)**
t08Xd09	-0.0178	-0.000522	0.00498	0.000709
	(0.854)	(0.0605)	(0.0568)	(0.0287)
t09Xd09	-0.0818	-0.0289	-0.0590	-0.0280
	(1.003)	(0.0711)	(0.0623)	(0.0315)
Observations	9,039	9,039	988	988
R-squared	0.026	0.061	0.245	0.294

[10] In all tables: standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 5.2 - 2010

Overall Crime VARIABLES	(1) (No Neighbors) Crimes per Week	(2) (No Neighbors) Ln(Crimes per Week)	(3) (No Neighbors, Using PS) Crimes per Week	(4) (No Neighbors, Using PS) Ln(Crimes per Week)
during2010	0.0607	0.0119	0.0305	0.0189
	(0.204)	(0.0128)	(0.0311)	(0.0186)
treatment2008	0.0478	0.0416	0.421*	0.338**
	(0.448)	(0.0282)	(0.224)	(0.133)
treatment2009	**1.223****	**0.178*****	**0.431***	**0.348*****
	(0.535)	**(0.0336)**	**(0.224)**	**(0.134)**
treatment2010	0.665	**0.0645****	0.342	**0.301****
	(0.450)	**(0.0282)**	(0.224)	**(0.134)**
t08Xd10	-0.0372	0.00596		
	(0.998)	(0.0627)		
t09Xd10	-0.0509	0.00113	-0.0173	-0.00551
	(1.174)	(0.0737)	(0.0482)	(0.0288)
t10Xd10	-0.0388	0.00455	-0.00868	-0.00240
	(0.997)	(0.0627)	(0.0440)	(0.0263)
Observations	8,675	8,675	929	929
R-squared	0.024	0.067	0.377	0.370

Using the fixed effects (FE) model, we control for neighborhood and time fixed effects using neighborhood, year and week dummy variables (not displayed in tabulated results). The model finds that although the coefficients of *lightson* and *hadlights* are negative, we cannot conclude that the Summer Night Lights program affected crime (Tables 5.3 and 5.4).

Table 5.3

Overall Crime VARIABLES	(1) (No Neighbors) Crimes per Week	(2) (No Neighbors) Ln(Crimes per Week)	(3) (No Neighbors, Using PS) Crimes per Week	(4) (No Neighbors, Using PS) Ln(Crimes per Week)
lightson	-0.107	-0.00869	-0.0427	-0.0217
	(0.199)	(0.0119)	(0.0294)	(0.0157)
hadlights	-0.0611	-0.00455	-0.0255	-0.0120
	(0.176)	(0.0105)	(0.0168)	(0.00894)
Observations	17,714	17,714	1,917	1,917
R-squared	0.884	0.911	0.714	0.730

Table 5.4

Overall Crime VARIABLES	(1) (No Neighbors) Crimes per Week	(2) (No Neighbors) Ln(Crimes per Week)	(3) (No Neighbors, Using PS) Crimes per Week	(4) (No Neighbors, Using PS) Ln(Crimes per Week)
oneyearlightson	-0.102	-0.0142	-0.0432	-0.0222
	(0.243)	(0.0145)	(0.0314)	(0.0167)
hadlights	-0.0649	-0.00266	-0.0208	-0.00942
	(0.185)	(0.0110)	(0.0187)	(0.00995)
twoyearson	-0.113	-0.00685	-0.0344	-0.0170
	(0.280)	(0.0167)	(0.0342)	(0.0182)
threeyearson	-0.116	0.00583	-0.0226	-0.0112
	(0.368)	(0.0220)	(0.0483)	(0.0258)
Observations	17,714	17,714	1,917	1,917
R-squared	0.884	0.911	0.714	0.731

5.2 Violent Crime

Descending a level of specificity to look at violent crime only, the results of the D-D model are similar to those for the overall crime rate (Tables 5.5 and 5.6). Neighborhoods that began participation in the Summer Night Lights program in 2009 are associated with .0355-.409 or 2.63-11.8% higher violent crimes per thousand people per week.

Table 5.5 - 2009

Violent Crime VARIABLES	(1) (No Neighbors) Crimes per Week	(2) (No Neighbors) Ln(Crimes per Week)	(3) (No Neighbors, Using PS) Crimes per Week	(4) (No Neighbors, Using PS) Ln(Crimes per Week)
during2009	0.0311	0.00650	-0.0105	-0.00849
	(0.0677)	(0.0104)	(0.0146)	(0.0110)
treatment2008	0.0346	0.0118	0.00556	0.00506
	(0.138)	(0.0211)	(0.0113)	(0.00845)
treatment2009	**0.367****	**0.102*****	**0.0355*****	**0.0263*****
	(0.157)	**(0.0240)**	**(0.0112)**	**(0.00840)**
t08Xd09	-0.0288	-0.000704	0.0206	0.0167
	(0.281)	(0.0430)	(0.0216)	(0.0162)
t09Xd09	-0.0461	-0.0153	-0.00163	0.000240
	(0.315)	(0.0482)	(0.0232)	(0.0173)
Observations	5,629	5,629	948	948
R-squared	0.031	0.059	0.327	0.358

Table 5.6 - 2010

Violent Crime VARIABLES	(1) (No Neighbors) Crimes per Week	(2) (No Neighbors) Ln(Crimes per Week)	(3) (No Neighbors, Using PS) Crimes per Week	(4) (No Neighbors, Using PS) Ln(Crimes per Week)
during2010	0.0178	0.00802	0.0201	0.0147
	(0.0880)	(0.0121)	(0.0167)	(0.0130)
treatment2008	0.0795	0.0182	0.121*	0.107*
	(0.157)	(0.0216)	(0.0718)	(0.0560)
treatment2009	**0.409****	**0.0918*****	**0.137***	**0.118****
	(0.182)	**(0.0250)**	**(0.0722)**	**(0.0563)**
treatment2010	0.210	0.0255	0.116	0.103*
	(0.152)	(0.0209)	(0.0721)	(0.0562)
t08Xd10	-0.0195	0.00191	0.000287	0.000890
	(0.348)	(0.0478)	(0.0223)	(0.0174)
t09Xd10	-0.00422	0.00522		
	(0.391)	(0.0537)		
t10Xd10	-0.0187	-0.00243	0.0201	0.0147
	(0.335)	(0.0460)	(0.0167)	(0.0130)
Observations	5,296	5,296	887	887
R-squared	0.031	0.059	0.341	0.363

Using the FE model, I find that the Summer Night Lights Program weakly reduces violent crime after the treatment period when controlling for time and neighborhood fixed effects. Without excluding bordering neighborhoods or using propensity score matching ("All"), the program decreases violent crime by 1.01% after the treatment period (Table 5.7).

Table 5.7

Violent Crime VARIABLES	(1) (All) Crimes per Week	(2) (All) Ln(Crimes per Week)	(3) (All, Using PS) Crimes per Week	(4) (All, Using PS) Ln(Crimes per Week)
lightson	-0.0459	-0.00645	0.00157	0.00177
	(0.0632)	(0.00656)	(0.0144)	(0.0111)
hadlights	-0.0391	**-0.0101***	-0.00844	-0.00586
	(0.0554)	**(0.00575)**	(0.00816)	(0.00625)
Observations	14,178	14,178	1,938	1,938
R-squared	0.850	0.928	0.579	0.594

Table 5.8

Violent Crime VARIABLES	(1) (No Neighbors) Crimes per Week	(2) (No Neighbors) Ln(Crimes per Week)	(3) (No Neighbors, Using PS) Crimes per Week	(4) (No Neighbors, Using PS) Ln(Crimes per Week)
lightson	-0.0641	-0.00863	-0.000838	-1.57e-05
	(0.0753)	(0.00701)	(0.0148)	(0.0113)
hadlights	-0.0591	**-0.0159*** **	-0.0132	-0.00951
	(0.0662)	**(0.00616)**	(0.00853)	(0.00651)
Observations	10,925	10,925	1,835	1,835
R-squared	0.851	0.940	0.582	0.597

Excluding bordering neighborhoods makes this result stronger (valid at higher significance level), the Summer Night Lights program reduces violent crime by 1.6 percent (Table 5.8). However, the lagging impact of the program becomes statistically insignificant when using a propensity score matching (Table 5.8, Columns 3 & 4). In addition, as shown by the coefficient estimates in Table 5.9, the Summer Night Lights project did not have a statistically significant differential impact on neighborhoods based on the number of years of participation.

Table 5.9

Violent Crime VARIABLES	(1) (No Neighbors) Crimes per Week	(2) (No Neighbors) Ln(Crimes per Week)	(3) (No Neighbors, Using PS) Crimes per Week	(4) (No Neighbors, Using PS) Ln(Crimes per Week)
oneyearlightson	-0.0530	-0.00779	-0.00146	-2.19e-05
	(0.0907)	(0.00844)	(0.0157)	(0.0120)
hadlights	-0.0646	**-0.0163** **	-0.0118	-0.00845
	(0.0698)	**(0.00649)**	(0.00948)	(0.00724)
twoyearson	-0.0727	-0.00953	0.00224	0.00184
	(0.106)	(0.00987)	(0.0174)	(0.0133)
threeyearson	-0.0925	-0.0101	0.00447	0.00476
	(0.143)	(0.0133)	(0.0247)	(0.0188)
Observations	10,925	10,925	1,835	1,835
R-squared	0.851	0.940	0.582	0.597

In summary, the results of the fixed effects model suggest that the Summer Night Program only had a lagged effect on violent crime, reducing it 1.6% (Table 5.8).

5.3 Nighttime Crime

Turning to nighttime crime only, I again find using the D-D model that a) treatment is positively associated with higher crime rates (estimated coefficient of $treatment_{2008}$, $treatment_{2009}$ and $treatment_{2010}$), and 2) the Summer Night Lights program had no statistically significant effect on nighttime crime as shown by the estimated coefficients of the interaction terms (Table 5.10 & 5.11). In addition, as shown in Table 5.10, I observe that the treatment period is associated with higher nighttime crime, as suspected by the creators of the Summer Night Lights program (Summer Night Lights, 2010).

Table 5.10 - 2009

Nighttime Crime	(1)	(2)	(3)	(4)
	(No Neighbors)	(No Neighbors)	(No Neighbors, Using PS)	(No Neighbors, Using PS)
VARIABLES	Crimes per Hour	Ln(Crimes per Hour)	Crimes per Hour	Ln(Crimes per Hour)
during2009	0.000110	-0.00116	-0.00369	-0.00329
	(0.0127)	(0.00394)	(0.00257)	(0.00232)
treatment2008	-0.0410	**-0.0154***	**0.00643*****	**0.00606*****
	(0.0256)	**(0.00793)**	**(0.00215)**	**(0.00194)**
treatment2009	**0.111*****	**0.0401*****	**0.0103*****	**0.00943*****
	(0.0289)	**(0.00893)**	**(0.00206)**	**(0.00186)**
t08Xd09	-0.00187	-0.00123	0.00100	0.000656
	(0.0498)	(0.0154)	(0.00383)	(0.00345)
t09Xd09	-0.00286	-6.28e-06	0.00349	0.00330
	(0.0566)	(0.0175)	(0.00414)	(0.00374)
Observations	18,997	18,997	3,471	3,471
R-squared	0.040	0.064	0.076	0.079

Table 5.11 - 2010

Nighttime Crime	(1) (No Neighbors)	(2) (No Neighbors)	(3) (No Neighbors, Using PS)	(4) (No Neighbors, Using PS)
VARIABLES	Crimes per Hour	Ln(Crimes per Hour)	Crimes per Hour	Ln(Crimes per Hour)
during2010	**0.0334****	**0.0126*****	**0.00735****	**0.00684****
	(0.0141)	(0.00451)	(0.00290)	(0.00268)
treatment2008	0.00711	-0.00548	0.0111	0.0101
	(0.0250)	(0.00797)	(0.0147)	(0.0136)
treatment2009	**0.138*****	**0.0429*****	0.0117	0.0105
	(0.0283)	**(0.00900)**	(0.0148)	(0.0136)
treatment2010	**0.0690*****	0.0106	0.00156	0.00123
	(0.0227)	(0.00724)	(0.0147)	(0.0136)
t08Xd10	-0.0302	-0.00904		
	(0.0546)	(0.0174)		
t09Xd10	-0.0270	-0.00609		
	(0.0608)	(0.0194)		
t10Xd10	-0.0303	-0.00726	-6.38e-05	1.41e-05
	(0.0484)	(0.0154)	(0.00368)	(0.00340)
Observations	17,721	17,721	3,307	3,307
R-squared	0.048	0.071	0.109	0.110

Using the FE model, we observe that the Summer Night Lights program weakly reduces nighttime crime both during and after the treatment period after excluding bordering neighborhoods (Table 5.12). During the treatment period, nighttime crime reduces by .55% and after the treatment period it decreases by .49%.

Table 5.12

Nighttime Crime	(No Neighbors)	(No Neighbors)	(No Neighbors, Using PS)	(No Neighbors, Using PS)
VARIABLES	Crimes per Hour	Ln(Crimes per Hour)	Crimes per Hour	Ln(Crimes per Hour)
lightson	-0.0217	**-0.00548***	-0.00129	-0.00113
	(0.0145)	**(0.00306)**	(0.00250)	(0.00228)
hadlights	-0.0165	**-0.00486***	-0.00138	-0.00110
	(0.0128)	**(0.00271)**	(0.00149)	(0.00135)
Observations	36,718	36,718	6,778	6,778
R-squared	0.791	0.907	0.415	0.415

However, the impact of the program again diminishes, becoming statistically insignificant when using propensity score matching. This is the second time that the perceived impact seems to hold when excluding bordering neighborhoods, but not when also using propensity score matching.

When trying to determine whether multiple years of inclusion in the program has a differential effect on nighttime crime, I cannot conclude with any certainty that any number of years of participation has an influence, even though the signs of the coefficients of *oneyearlightson, twoyearson,* and *threeyearson* suggest a reduction in nighttime crime (Table 5.13).

Table 5.13

Nighttime Crime	(No Neighbors)	(No Neighbors)	(No Neighbors, Using PS)	(No Neighbors, Using PS)
VARIABLES	Crimes per Hour	Ln(Crimes per Hour)	Crimes per Hour	Ln(Crimes per Hour)
oneyearlightson	-0.0176	-0.00387	-0.000365	-0.000243
	(0.0171)	(0.00363)	(0.00266)	(0.00243)
hadlights	-0.0189	**-0.00553***	-0.00176	-0.00148
	(0.0136)	**(0.00287)**	(0.00166)	(0.00151)
twoyearson	-0.0238	-0.00692	-0.00278	-0.00257
	(0.0207)	(0.00438)	(0.00295)	(0.00269)
threeyearson	-0.0379	-0.00900	-0.000814	-0.000708
	(0.0285)	(0.00603)	(0.00429)	(0.00391)
Observations	36,704	36,704	6,784	6,784
R-squared	0.791	0.907	0.415	0.415

To summarize, the Summer Night Lights program has a weak negative effect on nighttime crime, reducing crimes per thousand people per hour by about .55% (Table 5.12) during the treatment period and .49-.55% after (Tables 5.12-3). From these results, I can conclude that the impact of the program is weaker on nighttime crime than violent crime.

Given the disparate results from examining nighttime and violent crime individually, I looked at the Summer Night Lights program on nighttime violent crime.

Beginning with the D-D model, I cannot make any new conclusions except when looking at 2010 (Table 5.14).

Table 5.14 - 2010

Night Violent VARIABLES	(1) (All) Crimes per Hour	(2) (All) Ln(Crimes per Hour)	(3) (All, Using PS) Crimes per Hour	(4) (All, Using PS) Ln(Crimes per Hour)
during2010	0.0364***	0.0144***	0.103***	0.0962***
	(0.0116)	(0.00517)	(0.0274)	(0.0254)
treatment2008	0.0180	0.00588	-0.0109	-0.00971
	(0.0196)	(0.00874)	(0.0123)	(0.0115)
treatment2009	0.0353*	0.0159*	-0.00651	-0.00555
	(0.0203)	(0.00907)	(0.0124)	(0.0115)
treatment2010	0.0143	-0.000919	-0.0189	-0.0173
	(0.0165)	(0.00735)	(0.0123)	(0.0114)
t08Xd10	-0.0318	-0.0107	**-0.100*** **	**-0.0935*** **
	(0.0429)	(0.0192)	**(0.0275)**	**(0.0256)**
t09Xd10	-0.0261	-0.00442	**-0.0916*** **	**-0.0856*** **
	(0.0442)	(0.0197)	**(0.0275)**	**(0.0256)**
t10Xd10	-0.0156	0.000661	**-0.0943*** **	**-0.0879*** **
	(0.0384)	(0.0171)	**(0.0275)**	**(0.0256)**
Observations	7,562	7,562	1,572	1,572
R-squared	0.070	0.101	0.192	0.199

These results indicate that the Summer Night Lights program reduced nighttime violent crime by .1 crimes per hour in neighborhoods treated in 2008, .09 per hour in neighborhoods treated in 2009 and .09 per hour in neighborhoods treated in 2010. Or, treatment decreased nighttime violent crime by about 9 percent in all three types of treatment neighborhoods (9.35 percent, 8.56 percent and 8.79 percent). While these results are significant at less than 1 percent, they do not remain when excluding bordering neighborhoods (Appendix 2, Table 2.1).

Using the fixed effects model, we observe no impact of the program on nighttime violent crime as shown in Table 5.15. In addition, the signs of the *lightson* coefficients are now positive, opposite of intuition.

Table 5.15

Night Violent	(1)	(2)	(3)	(4)
	(No Neighbors)	(No Neighbors)	(No Neighbors, Using PS)	(No Neighbors, Using PS)
VARIABLES	Crimes per Hour	Ln(Crimes per Hour)	Crimes per Hour	Ln(Crimes per Hour)
lightson	0.00187	0.00178	3.81e-05	0.000109
	(0.00841)	(0.00745)	(0.00246)	(0.00224)
hadlights	-0.00422	-0.00400	-0.00142	-0.00127
	(0.00716)	(0.00634)	(0.00149)	(0.00137)
Observations	4,570	4,570	3,290	3,290
R-squared	0.652	0.657	0.611	0.611

As presented in Table 5.16, I observe no differential effect of multiple years of participation in the Summer Night Lights program. When excluding bordering neighborhoods, I find that the program has a lagged effect, decreasing nighttime violent crime by 6.6%.

Table 5.16

Night Violent	(1)	(2)	(3)	(4)
	(No Neighbors)	(No Neighbors)	(No Neighbors, Using PS)	(No Neighbors, Using PS)
VARIABLES	Crimes per Hour	Ln(Crimes per Hour)	Crimes per Hour	Ln(Crimes per Hour)
oneyearlightson	-0.0151	-0.00456	-0.000623	-0.000455
	(0.0162)	(0.00501)	(0.00260)	(0.00237)
hadlights	-0.0172	**-0.00662***	-0.00227	-0.00210
	(0.0125)	**(0.00387)**	(0.00166)	(0.00152)
twoyearson	-0.0216	-0.00674	-0.00108	-0.00103
	(0.0194)	(0.00600)	(0.00296)	(0.00270)
threeyearson	-0.0397	-0.0139*	-0.00526	-0.00480
	(0.0271)	(0.00840)	(0.00433)	(0.00396)
Observations	11,594	11,594	3,290	3,290
R-squared	0.827	0.894	0.612	0.612

5.4 DAYTIME CRIME

To determine whether the “surveillance” theory or “community confidence” theory better explains the effect of increased lighting on crime, I will compare the results of the D-D and FE models when limiting the dataset to either nighttime or daytime crime only. Looking at both the magnitude of the estimated coefficients of either the interaction terms or *lightson* and *hadlights*, and the statistical significance level of those estimates, I can determine which theory better explicates the mechanism.

Table 5.17 displays the results from the D-D model restricting the dataset to 2009, and then excluding bordering neighborhoods (Columns 1-2) and using propensity matching (Columns 3-4) to improve the control group. In neighborhoods that were included in the initiative beginning in 2009, the Summer Night Lights program reduced daytime crimes per thousand people per hour by .0051 crimes or .45%.

Table 5.17

VARIABLES	(1) (No Neighbors) Crimes per Hour	(2) (No Neighbors) Ln(Crimes per Hour)	(3) (No Neighbors, Using PS) Crimes per Hour	(4) (No Neighbors, Using PS) Ln(Crimes per Hour)
during2009	0.00241	0.00142	-0.00257**	-0.00242**
	(0.00670)	(0.00229)	(0.00125)	(0.00114)
treatment2008	-0.0306**	-0.0138***	0.00807***	0.00748***
	(0.0134)	(0.00457)	(0.00104)	(0.000954)
treatment2009	0.112***	0.0481***	0.0153***	0.0141***
	(0.0149)	(0.00507)	(0.000987)	(0.000901)
t08Xd09	-0.000234	-0.00126	0.000973	0.000954
	(0.0272)	(0.00930)	(0.00191)	(0.00175)
t09Xd09	-0.00469	-0.00616	**-0.00508****	**-0.00454****
	(0.0300)	(0.0102)	**(0.00204)**	**(0.00186)**
Observations	55,000	55,000	9,962	9,962
R-squared	0.048	0.079	0.147	0.153

However, when looking at 2010, the coefficients of the interaction variables are no longer significant (Table 5.18).

Table 5.18

VARIABLES	(1) (No Neighbors) Crimes per Hour	(2) (No Neighbors) Ln(Crimes per Hour)	(3) (No Neighbors, Using PS) Crimes per Hour	(4) (No Neighbors, Using PS) Ln(Crimes per Hour)
during2010	**0.0245***** **(0.00818)**	**0.0107***** **(0.00269)**	-0.00775 (0.0364)	-0.00757 (0.0332)
treatment2008	-0.0128 (0.0144)	**-0.00916*** **(0.00473)**	0.000430 (0.0163)	5.29e-05 (0.0149)
treatment2009	0.131*** (0.0163)	0.0498*** (0.00534)	0.00476 (0.0163)	0.00392 (0.0149)
treatment2010	0.0616*** (0.0132)	0.0131*** (0.00433)	-0.00932 (0.0163)	-0.00908 (0.0149)
t08Xd10	-0.0133 (0.0309)	-0.000881 (0.0101)	0.0180 (0.0364)	0.0169 (0.0332)
t09Xd10	-0.00982 (0.0348)	-0.000603 (0.0114)	0.0160 (0.0364)	0.0151 (0.0332)
t10Xd10	-0.0243 (0.0276)	-0.00880 (0.00906)	0.0111 (0.0364)	0.0107 (0.0332)
Observations	51,760	51,760	9,699	9,699
R-squared	0.046	0.077	0.162	0.167

Using the FE model without excluding bordering neighborhoods or using propensity score matching, I observe that the Summer Night Lights program decreases daytime crimes by .012 crimes per thousand people per hour or .38% (Table 5.19, Columns 1-2) and by .0029 crimes or .26% when using propensity score matching (Columns 3-4).

Table 5.19

VARIABLES	(1) (All) Crimes per Hour	(2) (All) Ln(Crimes per Hour)	(3) (All, Using PS) Crimes per Hour	(4) (All, Using PS) Ln(Crimes per Hour)
lightson	**-0.0117*** **(0.00707)**	**-0.00380**** **(0.00172)**	**-0.00290**** **(0.00130)**	**-0.00255**** **(0.00119)**
hadlights	-0.00580 (0.00626)	-0.00163 (0.00152)	**-0.00259***** **(0.000750)**	**-0.00231***** **(0.000685)**
Observations	139,236	139,236	20,459	20,459
R-squared	0.764	0.881	0.428	0.435

In contrast to the results from studying nighttime and violent crime, I find that the lagged effect of the Summer Night Lights program becomes only apparent after using propensity score matching (Columns 3-4). Specifically, the initiative decreased daytime crime by .0026 crimes per thousand people per hour or .23%.

Even when refining the control group by controlling for spillover effects (Table 5.20, Columns 1-2) and using propensity score matching (Columns 3-4), the statistically significant impact of the Summer Night Lights program remains:

Table 5.20

VARIABLES	(1) (No Neighbors) Crimes per Hour	(2) (No Neighbors) Ln(Crimes per Hour)	(3) (No Neighbors, Using PS) Crimes per Hour	(4) (No Neighbors, Using PS) Ln(Crimes per Hour)
lightson	**-0.0159***	**-0.00519*****	**-0.00375*****	**-0.00333*****
	(0.00840)	**(0.00200)**	**(0.00134)**	**(0.00122)**
hadlights	-0.00858	-0.00256	**-0.00304*****	**-0.00271*****
	(0.00743)	(0.00177)	**(0.000779)**	**(0.000710)**
Observations	106,760	106,760	19,661	19,661
R-squared	0.763	0.884	0.441	0.446

The FE model estimates that the program reduced daytime crime by .0038-.0159 crimes per thousand people per hour or .33-.52% (Table 5.20). In addition, the initiative had a negative lagged effect on daytime crime equal to .00304 crimes per thousand people per hour or .27%.

Turning to an examination of the differential impact of the program on daytime crime, I find that multiple years of participation Summer Night Lights program did not result in a greater reduction in crime. Table 5.21 shows that when using the strictest constraints on the dataset, daytime crime reduced by .004 crimes per thousand people per hour or .36% and by .63% when only controlling for spillover effects.

Table 5.21

VARIABLES	(1) (No Neighbors) Crimes per Hour	(2) (No Neighbors) Ln(Crimes per Hour)	(3) (No Neighbors, Using PS) Crimes per Hour	(4) (No Neighbors, Using PS) Ln(Crimes per Hour)
oneyearlightson	-0.0159	**-0.00628*** **	**-0.00403*** **	**-0.00360*** **
	(0.00989)	**(0.00236)**	**(0.00142)**	**(0.00129)**
hadlights	-0.00944	**-0.00190**	**-0.00161* **	**-0.00142* **
	(0.00784)	**(0.00187)**	**(0.000869)**	**(0.000793)**
twoyearson	-0.0156	-0.00396	-0.000991	-0.000822
	(0.0122)	(0.00290)	(0.00158)	(0.00144)
threeyearson	-0.0209	-0.00238	0.00205	0.00191
	(0.0162)	(0.00386)	(0.00224)	(0.00204)
Observations	106,739	106,739	19,669	19,669
R-squared	0.763	0.884	0.441	0.447

Lastly, I looked at the effect of the Summer Night Lights program on daytime violent crime. From the D-D model, we cannot make any new conclusions: the results only show that participation in the program or the treatment period is associated with higher daytime violent crime rates (Table 5.22-3).

Table 5.22

VARIABLES	(1) (No Neighbors) Crimes per Hour	(2) (No Neighbors) Ln(Crimes per Hour)	(3) (No Neighbors, Using PS) Crimes per Hour	(4) (No Neighbors, Using PS) Ln(Crimes per Hour)
during2009	-0.00492	-0.00155	-0.00112	-0.00105
	(0.00695)	(0.00356)	(0.00148)	(0.00137)
treatment2008	0.0134	0.00861	**0.00321*** **	**0.00310*** **
	(0.0111)	(0.00567)	**(0.00121)**	**(0.00111)**
treatment2009	**0.0516*** **	**0.0314*** **	**0.0116*** **	**0.0108*** **
	(0.0118)	**(0.00606)**	**(0.00112)**	**(0.00103)**
t08Xd09	0.00586	0.00251	0.00238	0.00230
	(0.0224)	(0.0115)	(0.00225)	(0.00207)
t09Xd09	0.00820	0.00283	-0.00151	-0.00131
	(0.0247)	(0.0127)	(0.00240)	(0.00221)
Observations	13,827	13,827	3,946	3,946
R-squared	0.094	0.131	0.171	0.181

Table 5.23

VARIABLES	(1) (No Neighbors) Crimes per Hour	(2) (No Neighbors) Ln(Crimes per Hour)	(3) (No Neighbors, Using PS) Crimes per Hour	(4) (No Neighbors, Using PS) Ln(Crimes per Hour)
during2010	0.0171	**0.00809***	**0.0587****	**0.0474****
	(0.0107)	**(0.00473)**	**(0.0187)**	**(0.0168)**
treatment2008	**0.0277***	**0.0178****	**-0.0719****	**-0.0628****
	(0.0151)	**(0.00671)**	**(0.00979)**	**(0.00882)**
treatment2009	**0.0810****	**0.0427****	**-0.0653****	**-0.0567****
	(0.0168)	**(0.00744)**	**(0.00983)**	**(0.00885)**
treatment2010	**0.0581****	**0.0250****	**-0.0780****	**-0.0685****
	(0.0139)	(0.00618)	(0.00980)	(0.00882)
t08Xd10	-0.0145	-0.00488	-0.0529***	-0.0418**
	(0.0318)	(0.0141)	(0.0188)	(0.0169)
t09Xd10	-0.0151	-0.00422	-0.0524***	-0.0414**
	(0.0359)	(0.0159)	(0.0188)	(0.0170)
t10Xd10	-0.0176	-0.00698	-0.0555***	-0.0442***
	(0.0279)	(0.0124)	(0.0188)	(0.0169)
Observations	12,733	12,733	3,650	3,650
R-squared	0.079	0.131	0.169	0.181

From the fixed effects model, we arrive at a result similar to when studying daytime crime overall: the program decreased crime both during and after the treatment period. Table 5.24 shows that daytime violent crime was reduced by .012 crimes per thousand people per neighborhood or .50% when excluding neighborhoods, but this estimate becomes insignificant when using propensity score matching. The model estimates the lagged decrease in daytime violent crime due to the program equal to .0018 - .011 crimes per thousand people per hour or .16-.42% (Table 5.24). However, there is no differential effect for multiple years of participation in the initiative (Table 5.25).

Table 5.24

VARIABLES	(1) (No Neighbors) Crimes per Hour	(2) (No Neighbors) Ln(Crimes per Hour)	(3) (No Neighbors, Using PS) Crimes per Hour	(4) (No Neighbors, Using PS) Ln(Crimes per Hour)
lightson	**-0.0122***	**-0.00489***	-0.00226	-0.00196
	(0.00737)	**(0.00266)**	(0.00149)	(0.00134)
hadlights	**-0.0107***	**-0.00420***	**-0.00178****	**-0.00156****
	(0.00638)	**(0.00230)**	**(0.000851)**	**(0.000769)**
Observations	26,560	26,560	7,596	7,596
R-squared	0.803	0.890	0.586	0.598

Table 5.25

VARIABLES	(1) (No Neighbors) Crimes per Hour	(2) (No Neighbors) Ln(Crimes per Hour)	(3) (No Neighbors, Using PS) Crimes per Hour	(4) (No Neighbors, Using PS) Ln(Crimes per Hour)
oneyearlightson	-0.0105	-0.00506	-0.00235	-0.00202
	(0.00865)	(0.00312)	(0.00158)	(0.00142)
hadlights	-0.0110	-0.00402	-0.000568	-0.000428
	(0.00683)	(0.00246)	(0.000952)	(0.000860)
twoyearson	-0.00998	-0.00310	0.000307	0.000433
	(0.0107)	(0.00385)	(0.00175)	(0.00158)
threeyearson	-0.0204	-0.00669	0.000776	0.000951
	(0.0144)	(0.00519)	(0.00249)	(0.00225)
Observations	26,566	26,566	7,598	7,598
R-squared	0.802	0.890	0.587	0.599

6. Conclusion

In this study, I had two main questions: did the Summer Night Lights program reduce crime and if so, by what mechanism? To answer the first question, I used a differences-in-differences model and fixed effects model to measure the impact of the program on crime overall (crimes per week per thousand people) and violent crime (aggravated assault, rape, homicide and robbery). There are two possible mechanisms by which increased lighting reduces crime (Farrington and Welsh 2002). Both theories argue that improved lighting affects *p*, the probability of apprehension, in a criminal's expected utility function. However, the two theories give different reasons for how improved lighting affects *p*. The first theory (surveillance theory) posits that increased or improved lighting increases the probability of arrest by facilitating surveillance by both residents and police. The second theory (community pride theory) suggests that increased or improved lighting signals greater community investment leading to increased community pride, cohesion and informal social control. Greater community pride then motivates residents to report crimes more often. By comparing the impact of the Summer Night Lights program on nighttime crime to daytime crime, we can identify which mechanism is at work. If the reduction of nighttime crime is greater than the decrease in crime overall, we can conclude that the first theory explains the relationship between lighting on crime.

Table 6.1 summarizes the results of this study, displaying the crime-reducing impact of the Summer Night Lights program on each type of crime.

Table 6.1

	Overall Crime	Violent	Night	Night-Violent	Day	Day-Violent
D-D	No effect	No effect	No effect	8.6-8.4%*** (2010)	.45%** (2009)	No effect
FE – during treatment period	No effect	No effect	.55%*	No effect	.33%***	.50%*
FE – after treatment period	No effect	1.6%***	.49-.55%***	.66%*	.27%***	.16%**

Looking only at the results of the differences-in-differences model, the Summer Night Lights program did not have much of an impact on crime in Los Angeles. In 2010, when restricting the dataset to nighttime violent crime we find that treatment reduced crimes by about .1 crimes per hour or 9 percent. On the other hand, in 2009, the program decreased daytime crime by .45%. These results provide a confusing result: both the surveillance theory and community confidence theory are at work because both night and daytime crime dropped. However, I will later argue that the differences-in-differences model did not accurately capture the impact of the Summer Night Lights program.

On the other hand, the results of the fixed effects specification draw a clearer picture of the relationship between crime and the Summer Night Lights program. The Summer Night Lights program had a lagged effect on violent (-1.6%), nighttime (-.5%), nighttime violent (-.66%), daytime (-.27%) and daytime violent (-.16%) crime. In addition, the program reduced nighttime (-.55%), daytime (-.33%) and daytime violent (-.5%) crime during the treatment period. These results suggest that both the surveillance and community confidence theories at work; the surveillance theory explains the greater drop in nighttime crime as compared to daytime crime during the treatment period, and the community confidence theory explicates the lagged effect of the program on violent, nighttime and daytime crime. Thus, I cannot conclude with certainty which theory best explicates the relationship between lighting and crime.

The lack of results from the differences-in-differences model can be attributed to three issues with the approach itself. First, D-D requires four distinct groups for it to isolate the impact of treatment: the control group before the change, the control group after the change, the treatment group before the change, and the treatment group after the change (Wooldridge 2006). The Summer Night Lights program and the data I received made it difficult to divide the dataset into those four groups cleanly. For the neighborhoods that started the Summer Night Lights program in 2008, the entire time period of the dataset (2009 and 2010) was technically "after treatment." Thus, for those neighborhoods, the entire dataset had been tainted; the crime rates observed in the summer of 2009 and 2010 were affected by the crime rate in the summer of 2008. Moreover, no "baseline" crime rate existed for the inaugural neighborhoods. Due to an inability to obtain earlier years of crime data, I have to simply recognize this shortcoming. Second, two identification assumptions must be maintained in D-D estimations (Besley & Case 2000): 1) apart from the control variables included, there are no other forces affecting the treatment and control groups differentially pre- and post-treatment, and 2) the composition of the treatment group and control group must remain stable over the time period. While I controlled for population density, racial makeup and income, there may have been time-varying unobservable factors that affected the treatment and control groups, such as gang activity or unemployment. In addition, the composition of the treatment and control groups was not static because six neighborhoods entered the program in 2009 and seven neighborhoods joined the program in 2010. I addressed this issue by creating three separate treatment groups: $treatment_{2008}$, $treatment_{2009}$ and $treatment_{2010}$. Even with all of these difficulties with the D-D model, I chose to utilize it because of its simplicity and ability to control for time-invariant unobservable variables.

Two major flaws hindered this study. First, it would have been helpful to have crime data from before the Summer Night Lights program was ever implemented (pre-

2008). This would have helped establish a better baseline crime rate of each neighborhood. Specifically, both models could have provided better results if there were more time periods (years) in the dataset. Second, the Summer Night Lights program aimed to reduce gang activity and gang-related violence. The crime statistics did not reflect gang activity completely because it did not include drug-related arrests (possession, trafficking, etc.) Thus, the program could have had a major role in reducing drug crimes, but it would not have appeared in this study.

I believe that much research still remains to be done on this issue and it is relevant to the larger question of what are the best ways to reduce crime. Crime prevention initiatives are often costly, on average the LAPD spends 4.29 million dollars per neighborhood, and thus finding cost-effective ways to reduce crime is important. The Summer Night Lights program cost 5.4 million dollars this past year. Using the RAND Corporation's Cost of Crime calculator, I calculated that daytime crime in the treatment neighborhoods cost 2.64 million dollars and nighttime crime cost 1.25 million dollars.[11] If the Summer Night Lights program reduced daytime and nighttime crime by .33% and .5% respectively, I estimate that the program saved a total of $14,422 of crime. On the other hand, the value of each additional police officer is $361,501 in less crime.[12] Thus, Summer Night Lights was not a cost-effective crime prevention initiative.

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[11] "Cost of Crime Calculator." *RAND Corporation*. <http://www.rand.org/ise/centers/quality_policing/cost-of-crime.html>.
[12] *Ibid.*

Appendix 1

Table 1
Correlation Coefficient Table

	Pop. Density	*Latino*	*Black*	*Income*	*College*
Pop. Density	1.000				
Latino	.5051	1.0000			
Black	.1770	-.0244	1.0000		
Income	-.4346	-.4595	-.2498	1.0000	
College	-.3635	-.7871	-.2452	.5846	1.0000

Table 2
Probit Regression:

EQUATION	VARIABLES	(1) treatment	(2) treatment
Treatment	PopDensity	.000024***	6.06e-05***
		(2.50e-06)	(2.03e-05)
	Latino	1.2041***	1.938
		(0.0843)	(1.387)
	Black	1.0926***	2.164**
		(0.0920)	(1.064)
	Income	-.000036***	
		(1.59e-06)	
	College		-0.000087
			(0.23785)
	Constant	-.7298***	-3.467***
		(0.12177)	(1.267)
	Observations	264	264

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 2

Table 2.1

VARIABLES	(5) crimesperthousand	(6) lncrimerate	(7) crimesperthousand	(8) lncrimerate
during2010	0.00784***	0.00722***	0.0143**	0.0135**
	(0.00189)	(0.00171)	(0.00614)	(0.00584)
treatment2008				
treatment2009	-0.00172	-0.00156		

	(0.00597)	(0.00540)		
treatment2010				
t08Xd10				
t09Xd10	0.00646	0.00632		
	(0.0137)	(0.0124)		
t10Xd10				
popdensity	-1.12e-06***	-1.05e-06***		
	(1.02e-07)	(9.26e-08)		
latino	-0.00501	-0.00538		
	(0.00442)	(0.00400)		
black	0.0359***	0.0328***		
	(0.00541)	(0.00489)		
income	-4.39e-07***	-4.22e-07***		
	(6.28e-08)	(5.68e-08)		
Constant	0.0686***	0.0664***	0.0290***	0.0285***
	(0.00542)	(0.00490)	(0.00265)	(0.00252)
Observations	2,121	2,121	43	43
R-squared	0.132	0.139	0.117	0.116

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