Ambient Lighting, Use of Outdoor Spaces and Perceptions of Public Safety: Evidence from a Survey Experiment*

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Abstract

Objectives: Observational evidence suggests that better ambient lighting leads people to feel safer when spending time outdoors in their community. We subject this finding to greater scrutiny and elaborate on the extent to which improvements in street lighting affect routine activities during nighttime hours.
Methods: We report evidence from a survey experiment that examines individuals' perceptions of safety under two different intensities of nighttime ambient lighting.
Results: Brighter street lighting leads individuals to feel safer and over half of survey respondents are willing to pay an additional $400 per year in taxes in order to finance a hypothetical program which would replace dim yellow street lights with brighter LED lights. However, poor lighting does not change people's willingness to spend time outdoors or to engage in behaviors which mitigate risk.
Conclusions: Results suggests that street lighting is a means through which policymakers can both control crime and improve community well-being.

Keywords: Place-based crime control, street lighting, perceived safety, survey experiment

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1 Introduction

Street lights are widely thought to be an effective tool in reducing crime and have therefore become a ubiquitous type of investment in environmental design (Painter and Farrington, 1999; Farrington and Welsh, 2002; Welsh and Farrington, 2008) and a key part of many crime prevention through environmental design (CPTED) efforts (Robinson, 2013).[1] The available evidence on street lighting suggests that its impact on public safety is promising, reducing crime by, on average, 20 percent (Welsh and Farrington, 2008) and perhaps by as much as 40 percent if lighting is deployed in order to maximize its salience to community residents (Chalfin et al., 2019). Findings are especially large for common street crimes like robbery (Doleac and Sanders, 2015; Domínguez and Asahi, 2019) and motor vehicle theft (Davies and Farrington, 2018) and possibly even homicide in a developing country setting (Arvate et al., 2018).[2]

Darkness is thought to generate a sense of insecurity because it decreases visibility and recognition at a distance, creating a limitless source of blindspots, shadows and potential places of entrapment (Painter, 1996; Haans and De Kort, 2012). In contrast with the concentration of police personnel at crime hot spots which tends not to reduce fear (Weisburd et al., 2011; Ratcliffe et al., 2015), research in criminology, public health and urban planning suggests that improvements in lighting are welcomed by residents (Atkins et al., 1991; Steinbach et al., 2015; Struyf, 2020) and modestly improve perceptions of community safety (Tien et al., 1977; Vrij and Winkel, 1991; Herbert and Davidson, 1994; Painter, 1996; Calvillo Cortés and Falcón Morales, 2016; Crosby and Hermens, 2019).[3,4] However, the majority of the evidence is more than twenty-five years old and was generated during a period of time when national crime rates in the United States and the United Kingdom, the setting for the lion's share of the research, were near their global maximum. Estimates

[1]As is noted by Chalfin et al. (2019), street lighting in the form of oil lamps has been used in cities since at least antiquity. As is noted by Ceccato and Nalla (2020), street lighting has been used in modern European cities including London and Paris since at least the 15th century.

[2]Recent evidence indicates that when municipal street lighting fails, the result may well be to push crime around the corner. Indeed, research by Chalfin et al. (2020) finds that street light outages in Chicago increase street crimes on surrounding blocks by approximately 3-7 percent.

[3]An exception is that of Atkins et al. (1991) who study perceptions of community safety in response to municipal investments in street lighting in London.

[4]As reported by Chalfin et al. (2019), in public housing communities in New York City, a recent survey conducted by the NYC Mayor's Office found that only 21 percent of public housing residents felt safe walking around their neighborhood at night, compared to 50 percent who felt safe during the daytime. More broadly, from 2010 to 2016, complaints about street lighting outages were the third most common complaint to the city's 311 system, indicating that residents notice and register concern when lights are not functional.

are also largely derived from evaluations which either do not employ a comparison group (Herbert and Davidson, 1994; Painter, 1996) or quasi-experimental evaluations which compare changes in perceived safety in a single community exposed to enhanced lighting to a community which did not receive enhanced lighting (Atkins et al., 1991; Painter and Farrington, 1999). Even when an untreated community is available, such comparisons can be problematic as community crime and perceived safety tend to fluctuate for many reasons (e.g., a salient but rare event such as a shooting or media coverage of crime). This type of unobserved heterogeneity may, in turn, lead to biased estimates of the impact of newly installed lighting. Likewise, to the extent that street lighting is installed in areas where crime is increasing, prior research will tend to underestimate the impact of lighting on perceptions of safety. While research that studies many communities which are treated at different times can net out this variation through the use of fixed effects, in a single community, the assumption that the timing of lighting upgrades is conditionally random can be difficult to defend.

Appreciating how ambient lighting affects perceptions of safety is of critical importance to understanding the scalability of public investments in street lighting as a crime control strategy for several reasons. First, perceived safety is an important outcome in its own right. While crime is typically the primary outcome of interest in research on place-based crime prevention programs, to the extent that an intervention simply makes people feel safer, it can substantially improve the welfare of a community (Johnson et al., 2009; Struyf, 2020). Second, perceptions of safety are a major driver of the use of public space and active and healthy living for residents in disadvantaged communities (Painter, 1996; Roman and Chalfin, 2008; Roman et al., 2009; Esteban-Cornejo et al., 2016; Patch et al., 2019). Even in national samples, research reports that many individuals never leave home after it is dark due to concerns regarding their safety (Kershaw et al., 2001; Cozens et al., 2003).

Third, the response of potential victims to a public safety intervention is a key mediator of an intervention's efficacy and, as such, evidence on victim behavior is needed to contextualize effects observed in the large and growing empirical literature that studies the effect of ambient lighting on crime (Welsh and Farrington, 2008; Doleac and Sanders, 2015; Arvate et al., 2018; Davies and Farrington, 2018; Chalfin et al., 2019, 2020). In particular, to the extent that lighting makes individuals feel safer and thus draws them outdoors during nighttime hours, the number of available crime victims might increase, an effect which would tend to counteract the principal goal of municipal investments in lighting (Cozens et al., 2005; Lorenc et al., 2012).[5] Accordingly scholars have worried that a lighting intervention that increases the use of outdoor spaces during nighttime hours might potentially cannibalize the beneficial effects of the intervention or, at a minimum, the ability of researchers to observe them. Given the age and nature of the available evidence, we continue to have a very limited understanding of the extent to which potential victims change their routine activities in response to better nighttime lighting (Welsh and Farrington, 2008; Struyf, 2020). Not limited to street lighting, this issue has broad applicability to a great many place-based crime control strategies including community greening (Branas et al., 2011; Garvin et al., 2013; Kondo et al., 2016), remediating blighted land (Branas et al., 2012; Garvin et al., 2013; Branas et al., 2018; Moyer et al., 2019) and hot spots policing strategies (Sherman and Weisburd, 1995; Weisburd and Green, 1995; Weisburd et al., 2009; Braga and Weisburd, 2010; Braga et al., 2014).

This research provides a critical update to prior quasi-experimental and experimental research on ambient lighting and perceptions of public safety. Drawing on an early survey experiment by Vrij and Winkel (1991) as inspiration, we randomly assign respondents to a treatment condition in which they are shown a photo of a block with enhanced lighting and a control condition in which they are shown a photo of a block in which "business-as-usual" lighting is used.[6] We ask respondents to reveal the extent to which they would feel safe walking alone at night on the block that is pictured in the photo that they were randomly assigned to view.[7] In order to ensure that our survey is closely connected to a policy-relevant counterfactual (Nagin and Sampson, 2019), the photos we use derive from an actual municipal program that upgraded the brightness of existing street lighting — using light-emitting diode (LED) lights — in Chicago.[8] Individuals who are randomly assigned to view the block in question under the brighter LED lighting are significantly more likely to report feeling safe than individuals who view the block in question under business-as-usual lighting. Treatment effects

[5] Short et al. (2010) refer to this phenomenon as a "reaction-diffusion" model of crime.

[6] This is the only survey experiment in the extant literature. In Vrij and Winkel (1991), researchers brought subjects to an area in Enkhuizen, a city in the Netherlands, on two different evenings. On one evening, business-as-usual street lighting was provided. On a second evening, the lighting was enhanced by a factor of five. Subjects reported feeling significantly safer under the brighter lighting condition.

[7] Vignette studies have been used in recent research on the effect of ambient lighting on feelings of safety. However, survey respondents have not been randomized to treatment and control conditions. See e.g., Calvillo Cortés and Falcón Morales (2016).

[8] Chicago is one of many cities including, among others, NYC and Los Angeles that is investing heavily in LED upgrades. For a review of the cost-effectiveness of LED lighting, see Cacciatore et al. (2017).

are broad-based and do not vary by gender, race, education level, income or recent victimization history.

We also ask a question that elicits how much time respondents plan to spend outdoors during nighttime hours given the photo which they are randomly assigned to view. Interestingly, while better lighting makes people feel safer, in our experimental sample, there is little evidence that improved lighting increases the willingness of respondents to spend time outdoors or that poorer ambient lighting increases individuals' willingness to engage in costly behaviors which mitigate risk. These results contrast somewhat with some of the early street lighting research – namely Painter (1996) and Painter and Farrington (1999) — who report evidence that lighting upgrades increase nighttime use of outdoor spaces.[9] The results are, however, consistent with research on street lighting by Atkins et al. (1991) and with a host of theoretical and empirical work which suggests that potential victims will tend to under-invest in private precautions because they do not fully internalize the costs of victimization (Ayres and Levitt, 1998; Clements, 2003). The results are also consistent with CPTED-oriented research which suggests that individuals are often reluctant to engage in low-cost precautionary behaviors such as locking car doors even if they understand that these behaviors may have an appreciable effect on victimization risk (Bopp, 1986; Budd, 1999; Weisel, 2002).

Next, using a contingent valuation survey, we ask respondents about their willingness to pay for improvements in municipal lighting. To our knowledge the only other research that estimates the willingness of taxpayers to fund investments in municipal street lighting is that of Willis et al. (2005) who use contingent valuation in a survey sample from the United Kingdom. Their research finds that few community residents are willing to allocate substantial resources to improved lighting. In their sample, just one third of survey respondents indicated a willingness to pay £25 (approximately $50US in 2019 constant dollars) to support a street lighting program and more than one third of respondents were not willing to pay even £1.[10] By contrast, in our sample, nearly 80 percent of respondents are willing to pay $50 for a lighting intervention which upgrades standard street lighting to a brighter LED-based light. More than half of respondents are willing to pay at least $400 for such an intervention. This figure is slightly larger than what the typical U.S. resident pays

[9] In contrast, Atkins et al. (1991) finds little evidence that individuals change their travel patterns in response to better street lighting.

[10] Willingness-to-pay $£25 was slightly higher (38 percent) in urban areas.

for municipal law enforcement and is substantially larger than what is currently spent on street lighting in U.S. cities.[11] Though a great deal of caution must be taken in comparing revealed versus stated preferences, our results suggest that individuals may be willing to invest considerably greater resources in street lighting than which is currently invested.

Our survey experiment, like all survey experiments, studies respondents' reactions to a hypothetical scenario rather than actual decision-making and, as such, carries with it several attendant limitations. Nevertheless, a substantial virtue of the approach is our ability to randomize individuals to treatment and control conditions — a feature which is virtually impossible to achieve in field research. The fact that respondents indicate significantly less fear when viewing a randomly assigned photo of a city street with improved lighting provides "gold standard" or at least "bronze standard" (Berk, 2005) evidence that individuals' perceived safety is sensitive to lighting conditions.

One final issue is worth noting. As this survey was administered during the COVID-19 pandemic and approximately five weeks after the death of George Floyd, there will naturally be concerns that our results are contaminated by the recent social and political upheaval which has disrupted ordinary life in the United States and around the world. In order to address this critically important issue, we test for contamination empirically, leveraging a small-sample pilot survey which we administered to a similar sample of survey respondents in February 2020, prior to the onset of the COVID-19 pandemic and subsequent quarantine measures. We compare the pre-pandemic sample to our survey sample and detect surprisingly little evidence in favor of either differential sample selection or mean differences in key outcome variables among respondents in the pre- and post-pandemic samples. While this finding is, of course, specific to our study domain, this result provides optimism that survey research conducted after March 2020 may provide information whose usefulness will endure even after the pandemic recedes.

[11] Precise expenditures are difficult to come by but, in 2012, San Diego, which is home to approximately 1.4 million residents spent \$4.7 million to light its streets, a cost of less than \$4 per resident (Berg, 2012).

2 Survey Experiment

2.1 Background

We study the effect of ambient lighting on perceptions of public safety using a survey experiment, a methodology which randomizes research participants to participate in either a treatment or a control version of a survey. The virtue of survey experiments is that they allow researchers to generate "gold standard" social science evidence at low cost, credibly allowing researchers to generate causal inferences which would have been difficult to defend based on observational research. This feature of survey experiments is especially welcome when an intervention of interest is difficult to randomize or provide in sufficient numbers to study using a rigorous research design, both of which have been noted as critical limitations to studying the effect of lighting on crime (Farrington and Welsh, 2002; Davies and Farrington, 2018; Chalfin et al., 2019). Likewise, survey experiments are particularly useful when key outcomes are attitudinal or are poorly measured using administrative data. Given their usefulness in many different contexts, survey experiments have a rich tradition in experimental economics (Chaudhuri, 2011; Cruces et al., 2013; Kuziemko et al., 2015) in public opinion research in political science (Harbridge and Malhotra, 2011; Samuels and Zucco Jr, 2014) and have a limited but growing presence in experimental criminology (Herzog, 2003; Berryessa et al., 2016; Buckley et al., 2016; Berryessa, 2017, 2018).

The key drawback of survey experiments — or any experiment in which key outcomes are measured using survey data — is that survey responses may suffer from a number of measurement problems which derive from the relative willingness or ability of respondents to report their experiences accurately to researchers. In this context, an important drawback of the survey experiment approach is that respondents are asked about a hypothetical scenario involving improved street lighting rather than an experience that they have actually had in the real world. As a result, there is some inherent difficulty in mapping survey responses on to actual preferences as respondents may not "do what they say" (Kroes and Sheldon, 1988). Concerns regarding the validity of survey data generally have been noted at length in every social science discipline. Nevertheless, owing to its ability to address hard-to-measure outcomes, survey data continues to be a ubiquitous and possibly even the dominant source of evidence in criminological research (Kleck et al., 2006). Indeed, survey research remains a critical and sometimes the primary source of what we know about the prevalence of crime (Baumer and Lauritsen, 2010; Gutierrez and Kirk, 2017), the deterrence value of sanctions (Pogarsky et al., 2005; Apel et al., 2009; Nagin et al., 2013) and life course criminology (Farrington, 2003; Apel et al., 2009) among many other core literatures.

A second set of concerns has to do with the representativeness of the respondent survey pool, especially degree to which research participants may be "professional research subjects" (Chandler et al., 2014) or the broad discretion that participants have to opt into a given research study. While survey experiments face legitimate challenges to their generalizability, recent research reports a reassuring degree of agreement between survey samples obtained from validated samples of the general population and convenience samples, including those obtained from Amazon Mechanical Turk, the source of the survey sample we analyze in this paper (Goodman et al., 2013; Mullinix et al., 2015; Coppock, 2019). As reported by Goodman et al. (2013), Mechanical Turk participants have attitudes about money that are different from a community sample's attitudes and are less extroverted and have lower self-esteem than other participants, presenting challenges for some research domains. However, they report that despite these differences, Mechanical Turk participants produce reliable results consistent with standard decision-making biases: they are present biased, risk-averse for gains, risk-seeking for losses, show delay/expedite asymmetries, and show the certainty effect—with almost no significant differences in effect sizes from other samples.[12]

While there is now considerable optimism that convenience samples derived from Amazon Mechanical Turk and national surveys typically tend to produce similar findings, we have taken several steps in order to assess the extent to which our results are sensitive to sample selection. First, we report estimates using raw data as well as data which have been re-weighted to resemble the population of U.S. adults with respect to age, gender, and race. Second, we report estimates separately by demographic subgroup and test whether there are important differences between respondents who have recently been the victim of a crime and those who have not. Finally, we note that our data were obtained during the COVID-19 pandemic which naturally raises questions about the degree to which respondents are primed to think about public safety as opposed to the disruption to ordinary living brought about by the pandemic. While we cannot address these concerns completely, we are

[12] Barabas and Jerit (2010) urge caution in interpreting estimates from survey experiments, noting that they were unable to substantively replicate estimates derived from a national sample using a convenience sample. However, it is difficult to distinguish between the unreliability of survey experiments and alternative sources of disagreement such as publication bias (Easterbrook et al., 1991; Rothstein et al., 2005) or "p-hacking" (Bruns and Ioannidis, 2016; Benjamin et al., 2018).

able to compare our survey responses with a pilot survey which we administered in February 2020 prior to the beginning of the pandemic. As we report in Section 4.3, results are extremely similar thus providing some assurance that estimates have not been contaminated by the pandemic.

2.2 Survey Instrument and Measures

We sought to obtain a sample of $N = 1{,}000$ survey respondents using Amazon's Mechanical Turk website, a crowd-sourced marketplace and online survey platform in which "workers" can be contracted to perform tasks — including completing a survey — by a requester.[13] Mechanical Turk has become a mainstay of research in psychology, political science and experimental economics. While MTurk, to date, has been not been as popular in criminological research (Ozkan, 2019), recent research has used Mechanical Turk to identify demographic heterogeneity in deterrence effects (Fine and Van Rooij, 2017) knowledge about "elite deviance" (Michel et al., 2015), and opinions on forensic evidence (Kaplan et al., 2020). We restrict respondents to those who live in the United States. All responses were collected on Friday July 3, 2020. In keeping with prior criminal justice research, participants were paid 25 cents for their participation in our 2-3 minute survey.

In order to assess the degree to which perceptions of safety are sensitive to better lighting, we show respondents one of two photographs of the same Chicago street, taken during nighttime hours. Photos used in the experiment are presented in **Figure 1**. The first photo depicts the street as has been lit using standard "business-as-usual" municipal street lighting — this is the control condition. The second photo depicts the street after the city of Chicago upgraded the lighting on this street, by installing brighter LED lights. Notably these photos reflect actual street conditions and the change in lighting brought about by a municipal lighting intervention, thus enhancing the policy relevance of the exercise. Upon randomizing respondents to see one of the two photos, we next asked a series of questions about perceptions of safety and a respondent's willingness to use public space at night. A complete copy of the survey instrument can be found **Appendix A**.

[13] This research was approved by our university's Institutional Review Board in February, 2020. The name of the university is, for the time being, redacted in order to comply with blinded peer review.

2.2.1 Fear of Crime and Use of Public Space

After reviewing a randomly assigned version of the photo, respondents were asked three questions intended to elicit their perceptions of public safety and their willingness to spend time outside at night.[14] In the spirit of prior survey research by Vrij and Winkel (1991), respondents are first asked to indicate the degree to which they "would feel safe walking alone at night on a street that looks like [the street in the photo]." Respondents were directed to answer on a five-point Likert-scale ranging from *Strongly Agree (1)* to *Strongly Disagree (5)*. A neutral response of *Neither agree nor disagree* was also provided.

Next, we ask two questions designed to assess a respondent's willingness to use public spaces at night under different intensities of street lighting. We begin with a short vignette in which the respondent is invited to a friend's house at night after the sun has gone down. The respondent is told that his/her friend lives a short distance (five blocks) away but that he/she is unable to drive to this friend's home because of car troubles. The complete vignette text is below:

> Imagine that you live on the street on which this photo was taken. A close friend who lives five blocks away from you invites you to hang out at 9:00pm after it is already dark outside. Your car is being repaired so driving is not an option. Thinking about any concerns you might have about your safety, which of the following best describes what you will do?

Respondents were asked to indicate what they would do in this situation, by selecting one of four multiple choice answers.[15]

(1) Walk to your friend's house

(2) Take a taxi or a car service (e.g. Uber, Lyft)

(3) Choose to stay home — I would be worried about my safety

(4) Choose to stay home — I prefer to stay at home for other reasons

[14] In all questions, respondents were prompted to "please think about the time period prior to the COVID-19 pandemic."

[15] The answers were presented in a random order to avoid priming a respondent based on the ordering of the answer choices.

By providing respondents with the choice to remain home for reasons having nothing to do with perceived safety, we ensure that we are not creating a false choice for respondents who are less social or who prefer to remain at home for another reason.

Finally, respondents are asked to how many nights per week they would likely spend outside their home given the amount of outdoor lighting in the photo they were shown. The purpose of this question to gain a more global perspective on how much time at risk changes in response to better lighting. In particular, we use this question as a proxy for victimization risk in terms of man-hours spent outdoors at night. While the question does not allow us to obtain granular information about exactly what types of activities a respondent plans to engage in while outdoors, it does give us a sense for the extent to which overall time spent outdoors during nighttime hours may be sensitive to street lighting.

2.2.2 Willingness-to-Pay for Improved Lighting

Next, we use contingent valuation to assess the degree to which respondents are willing to incur higher taxes in order to support enhanced municipal lighting. Contingent valuation is a survey-based valuation technique used to value goods that are not bought and sold in the free market and for which prices are therefore difficult to compute.[16] Often used by economists to determine the value of an environmental resource such as a national park or a pollution-free river, the methodology also has broad applicability to assessing the effect of crime on community well-being. Typically, contingent valuation survey questions ask individuals how much money they would be willing to pay for an increase in some non-market good (such as safety), or, alternatively, how much money they would need to be fully compensated for a decrease in the quantity of a non-market good (Roman et al., 2010; Chalfin, 2015).

One of the chief difficulties in using contingent valuation is that it elicits respondents stated rather than revealed preferences. As such, there are concerns about whether respondents will answer questions honestly and realistically, given that they face an implicit budget constraint. Given the importance of valuing non-market goods and the ubiquity of contingent valuation, a large

[16]For comprehensive reviews of the promise and limitations of contingent valuation see reviews by Carson and Hanemann (2005) and Boyle (2017). We also point readers to a broader literature which estimates the cost of victimization using a variety of different approaches. Particularly useful reviews can be found in Cohen et al. (2004) and Roman (2011).

methodological literature in economics as well as in other social sciences fields has arisen to counsel researchers on best practice in fielding contingent valuation surveys. Following a series of recommendations made to the National Oceanic and Atmospheric Administration by a panel that included several Nobel Prize winning economists, researchers typically eschew open-ended questions in favor of questions that ask respondents to pick a number from a list of choices (Arrow et al., 1993). While there are a variety of approaches have been used in the literature, it is particularly common for researchers to use a series of iterative binary choice questions asking respondents whether they would be willing to pay a particular amount of money for a given social program. Respondents are either then asked follow-up questions about different values in order to further narrow down their preferences or a single data point is used for each respondent.

In this research, we follow one such approach used in prior criminal justice research by Cohen et al. (2004) and Nagin et al. (2006), among others. Respondents are asked whether they would be willing to pay k dollars for a government program that improves municipal lighting in their community where k is randomly selected from the following list of values: \$25, \$50, \$75, \$100, \$200, \$400. We randomize the value of k that is shown to each survey respondent thus guaranteeing that k is uncorrelated with respondent characteristics.[17] We can then estimate the share of respondents who are willing to pay at least \$$k$ for improved street lighting for each of the values of k used in the survey. We use this design to estimate a quasi-demand curve plotting the share of respondents willing to support a lighting program against the universe of values of k. In order to anchor respondents to a standardized and, above all, realistic lighting program, we show them *both* the pre-LED and post-LED photo of the Chicago street segment they were asked to respond to earlier in the survey. Respondents were asked to indicate their willingness to pay for a program that will bring the amount of lighting from the pre-LED condition to the post-LED condition.

2.2.3 Respondent Demographics

Finally, we collect basic demographic information from our respondents. This information includes a respondent's age (in years), gender and self-reported race/ethnicity (American Indian or Alaska Native, Asian/Pacific Islander, Black, White, Hispanic/Latino, Other).[18]. Next, we asked each re-

[17]An F-test from a regression of the value of k on respondent characteristics confirms that randomization was successful — the p-value on this F-test is 0.48.

[18]Respondents were asked to indicate as many race/ethnicity groups as they desired.

spondent to indicate his or her highest level of completed education and 2019 household income.[19] We also ask each respondent a series of questions that capture his or her experience as the victim of a crime and overall perceptions of public safety. In particular, we ask each respondent whether he or she has been the victim of a crime in the prior twelve months and, using a Likert scale, the degree to which he or she feels safe walking around their own neighborhood after dark. Demographic information was collected at the end of the survey in order to guard against inappropriately priming respondents to answer questions on the basis of their demographic characteristics. Finally, the survey included an "attention check" question which allows us to purge the data of responses from individuals who answered survey questions without reading or comprehending them. In particular, we ask respondents about the nature of the photo they were shown at the beginning of the survey. The choices were: a city street, a farm, a classroom and the inside of a prison. We exclude 49 out of 1,000 respondents who failed to indicate that the photo was of a city street.[20] We excluded two additional respondents who reported their age to be under 18.

3 Empirical Methods

In this section we describe the empirical models which we use to estimate the effect of improved municipal street lighting on respondent perceptions. Upon being randomized to view either the treatment or the control version of the photo, respondents were asked three questions. First, respondents were asked to indicate their agreement (on a five-point Likert scale) as to whether they would feel safe being outdoors at night. Second, respondents were asked to describe what actions they would take if offered the opportunity to spend time at a friend's home after dark — the choices were: 1) Walk to friend's house, 2) Take a taxi, 3) Choose to stay home due to worries about safety and 4) Choose to stay home for other reasons. Finally, respondents were asked how many nights, in a typical week, that they would spend outside their home given the amount of lighting in the photo

[19]Education categories include: Less than high school, high school graduate, Some college, 2 year college degree, 4 year college degree, professional degree, master's degree and doctoral degree. Income categories include: < \$20,000, \$20,000-\$39,999, \$40,000-\$59,999, \$60,000-\$79,999, \$80,000-\$99,999 and > \$100,000. We directed respondents to think about their household income in 2019 to avoid the confounding effects on incomes that are due to the COVID-19 pandemic.

[20]An equal number of treatment and control group individuals failed the attention check question. As such, these respondents are "missing at random and can be excluded from the analysis sample without fear of bias. In practice, estimates do not substantively differ when the remaining responses are included.

shown.

From these survey questions we construct four primary dependent measures, three of which are binary and one of which is continuous:

- Respondent feels Unsafe: 1 if respondent disagreed or strongly disagreed that they feel safe; 0 if else
- Vignette study — Respondent would stay home due to worries about safety: 1 if yes, 0 if no
- Vignette study — Respondent would either stay home due to worries about safety or would take a taxi/rideshare: 1 if yes, 0 if no
- Number of nights respondent would spend outdoors each week

We focus on binary measures because they are clear and simple to interpret. However, we also preserve the ordinal information contained within the original variables and re-estimate models using ordinal and multinomial regressions. These estimates are substantively similar to estimates derived from the binary outcome models constructed above.

We begin by running a series of t-tests which test for mean differences in the proportion of "successes" between respondents in the treatment and control conditions. These tests make no functional form assumptions and, as such, constitute "pure" measures of the average treatment effect of the intervention. To generate our preferred estimates, we regress a given outcome, Y_i, on a binary treatment indicator, D_i, conditioning on a vector of respondent characteristics, X_i, which are included to improve precision and guard against finite sample bias due to imperfect randomization (Angrist and Pischke, 2008; Imbens, 2010). In practice, the estimates are insensitive to the inclusion of control variables. We formalize our approach in equation (1):

$$Y_i = \alpha + \beta D_i + X_i^{'}\psi + \varepsilon_i \tag{1}$$

In (1), β represents the average treatment effect of being in the treatment condition (the LED condition) on a given outcome. Covariates included in X are a respondent's age, race, gender, completed education level, income group, as well as an indicator for whether a respondent has been the victim of a crime in the past twelve months and the extent to which a victim feels safe in general walking around his or her own neighborhood. In all models, we cluster standard errors by age-race-gender-treatment condition groups to allow for within-group dependence in regression errors.[21]

To simplify the interpretation of estimated treatment effects, our primary models — including those for binary outcomes — are estimated via ordinary least squares regression. These models provide the best linear approximation to the true treatment effect. We provide estimates using logistic and probit regressions in an auxiliary analysis — estimates are substantively very similar across all three modeling approaches. We also present un-adjusted point estimates from (1) as well as point estimates from weighted least squares models in which we re-weight the data to resemble the U.S. population with respect to age, race and gender.[22] Finally, we test for treatment effect heterogeneity by age, gender, race and prior victimization by interacting, in separate models, each characteristic with the treatment indicator:

$$Y_i = \alpha + \beta D_i + \gamma X_i + \rho D_i X_i + \epsilon_i \tag{2}$$

In (2), for each outcome, ρ captures the additive effect of a given covariate. In order to guard against false rejections due to multiple hypothesis testing, we test for heterogeneity with respect to only a subset of theoretically important predictors. As we do not detect evidence of meaningful interaction effects, adjustment for multiple testing is, in practice, unnecessary.

4 Results

4.1 Summary Statistics

Table 1 presents descriptive statistics for our study sample of $N = 949$ respondents who passed the attention check question. In total, there are 476 respondents in the treatment (LED) group and 473 respondents in the control (business-as-usual) group. In Panel A we present descriptive statistics for respondent characteristics; in Panel B we present descriptive statistics for our four primary outcomes. Means and standard deviations (in parentheses) are presented separately for the

[21]There are 60 clusters in the data. Huber-Eicker-White robust standard errors which account for arbitrary heteroskdasticity are, in practice, extremely similar. If anything, the clustered standard errors are typically slightly larger thus making our inferences conservative.

[22]The weight for each age-race-gender group, $W_j = \frac{c_j}{s_j}$ where c_j and s_j are the group's share of individuals in U.S. Census data and our survey data, respectively.

treatment and control groups. On average, sample respondents were 36 years old and 56 percent of the sample is male. With respect to race, 70 percent of the sample is White, 11 percent is Black, 8 percent is Asian and another 11 percent of respondents indicated either that they were Hispanic or that they identify with multiple ancestry groups. 70 percent of our sample are college graduates and income varies considerably among the sample with nearly one third of respondents living in households earning more than $75,000 and more than one quarter living in households earning less than $35,000. 12 percent of respondents indicated that they have been the victim of a crime during the past 12 months which is similar to the prevalence rate of violent and property crimes in the National Crime Victimization Survey. More than three quarters of the sample generally feels safe walking around at night in their own neighborhoods. On average, it took respondents just under 3 minutes to complete the survey.

With respect to our four primary outcome measures, among the control group, 37 percent of respondents who were assigned to view the business-as-usual photo report that they would feel unsafe being outdoors during nighttime hours. Among the treatment group, the proportion is 29 percent, a difference that is significant at the α=0.01 level. In response to the vignette question, across the two groups, 23 percent of respondents indicated that they would remain at home due to concerns for their safety and nearly half of respondents indicated that they would either remain at home or that they would take a taxi/rideshare even though their destination is only a short walk away. Respondents in both groups indicated that they would, on average, spend 2.8 nights per week outside their home, having viewed their assigned photo.

4.2 Fidelity of Randomization

Respondents are randomized to the treatment or control condition using *Qualtrics* survey software. In this section, we provide evidence that the randomization was faithfully carried out by showing that respondent attributes are balanced evenly across the treatment and control conditions. For each covariate, Table 1 reports the p-value from a t-test of the equality of the sample means across the two randomly assigned treatment groups. Most of the p-values are large and, with only a single exception, are not significant at conventional levels of significance. The exception is education — individuals in the control group are less likely to be college educated. In order to construct an omnibus test of covariate balance, we regress the binary treatment indicator on the full vector of covariates and compute the F-statistic which tests for the joint significance of covariates in predicting treatment status. A statistically significant F-statistic would indicate that the covariates jointly predict treatment assignment and would call into question the validity of any results derived from the models presented in Section 3. The p-value on the F-statistic is 0.25, indicating that there is little evidence against the null hypothesis of successful randomization. As indicated in Section 3, we condition on covariates to account for any remaining imbalances between treatment and control respondents.

4.3 External Validity

Next we consider the robustness of the results to two dimensions of external validity. First, we consider the extent to which the survey sample obtained via Amazon MTurk is representative of the U.S. population as a whole. While we are unable to test this proposition along all possible dimensions, we can compare our study sample to the general population with respect to the covariates we have gathered. This information is presented in **Table 2**. Information on the demographic characteristics of the U.S. population come from the U.S. Census. Information on crime victimization during the last calendar year come from the National Crime Victimization Survey (NCVS). As is evident from the table, our sample is broadly balanced with respect to age and race though our sample is more male and is less likely to include both individuals without a high school degree or individuals living in households earning more than $100,000. We present all subsequent estimates both using raw survey data as well as using survey weights which ensure that our sample resembles the U.S. population. We also test for heterogeneous impacts by respondent characteristics and find little evidence that treatment effects vary — see Table 7.

Second, recognizing that the survey was administered during the COVID-19 pandemic, it is important to assess the degree to which survey responses are sensitive to the extraordinary disruption to normal life that the pandemic has caused. Three concerns, in particular stand out. First, the pandemic may have either decreased or heightened the extent to which Americans are worried about public safety as well as the extent to which they are willing to allocate money towards capital upgrades to street lighting. Second, the pandemic may have created differential selection into Amazon's MTurk respondent pool. Finally, as lighting could be viewed by some respondents as an alternative to law enforcement, attitudes towards street lighting might be sensitive to the murder of George Floyd and the national conversation around policing which has since transpired.

In order to assess the extent to which our data are contaminated by the onset of the COVID-19 pandemic and subsequent events, we use data from a small-scale pilot of our survey experiment which we administered to N=78 respondents on February 25th, 2020. Since the initial purpose of the pilot survey was to test the functionality of the Qualtrics software, we do not include the pilot data in our main estimates. Nevertheless, as the data were obtained prior to quarantine measures and the vast majority of the deaths that have since occurred due to the pandemic, these data allow us to construct a critically important test of the degree to which our results are sensitive to our survey's timing.

We begin by demonstrating 1) that the pilot survey was administered prior to the dramatic increase in public concern over COVID-19 and 2) that, on July 3rd, the date of the survey, public safety concerns among the general public were similar to pre-pandemic levels. In order to do so, we use Google Trends data which measure the volume of directed Google searches in the United States for "coronavirus," "COVID-19" and "crime" during the last five months. The data are expressed as an index which compares the number of daily searches to the highest daily search over a given time interval. A value of "100" is assigned to the date with the highest search volume for a given search term; a value of '50' indicates a search volume that is half as high as the that of the highest-volume date. Google search trends for U.S.-based searchers are presented in **Figure 2**. Panel A plots searches for "coronavirus" and "COVID-19"; Panel B plots searches for "crime." As is evident from the figure, our pilot survey was conducted prior to the large increase in public concern about the virus that occurred in early March. Interestingly, by July 3rd — the date of our survey — pandemic-related searches had declined considerably relative to peak volume. In Panel B, we consider searches for crime. While crime-related searches declined considerably starting in early March when concerns about COVID-19 pre-empted concerns about crime, they increased markedly after May 25th, the date of the killing of George Floyd by Minneapolis police officer, Derek Chauvin. By early July, crime searches had returned to baseline. Indeed, the search score on July 3rd is similar to scores in early February well before the COVID-19 pandemic had hit the United States.

In **Table 3** we present key demographic characteristics and outcomes for both the February 25th pilot sample and the July 3rd study sample. Perhaps surprisingly, there is little evidence for differential sample selection as the two samples are broadly balanced with respect to age, gender, race, income levels and prior crime victimization. There is, one exception — the study sample is less likely to have a college degree than the pilot sample. In this respect the study sample is, if anything, more similar to the U.S. population than the pilot sample rather than less similar. With respect to the four primary outcome variables that we study, there is very little evidence that the study sample differs from the pre-COVID-19 pilot sample. An F-test confirms that the outcomes are jointly balanced across the two samples.

4.4 Main Results

We present our main findings in **Table 4** and **Table 5**. In Table 4, we present regression estimates derived from equation (1) using the raw survey data. In Table 5, we re-weight the data so that each respondent's weight in the analysis accords with his or her representation with respect to age, race and gender in the U.S. population. In each table, least squares coefficients are reported alongside clustered standard errors in parentheses. Each column corresponds with a different outcome variable. We begin with the effect of the treatment (the LED version of the photo) on whether or not a respondent reports feeling unsafe walking at night. Relative to a base rate of 37 percent among the control group, respondents who were randomly assigned to the LED version of the photo were 7.8 percentage points (21 percent) less likely to report feeling unsafe. Several other points are worth noting. First, controlling for treatment assignment, concerns about safety rise with age and are greater among female than among male respondents. Both of these findings accord with the large descriptive literature on fear of crime (Roman and Chalfin, 2008; Roman et al., 2009). Second, Black respondents are less likely to report feeling unsafe than White respondents. Third, individuals who reported that they had been the victim of a crime during the prior 12 months do not appear to be especially likely to report feeling unsafe though standard errors are not small enough to rule out a modest association. Finally, individuals who report that they feel safe walking in their own neighborhood after dark are substantially less likely to report that they would feel unsafe given the photo they were assigned to view. This is sensible as a great deal of the variation in perceptions of safety will naturally be due to person-level heterogeneity. Overall, the model explains just over 17 percent of the variation in feelings of safety.

Next, we consider whether survey respondents' self-reported precautionary behaviors are affected by their assignment to view the treatment versus the control version of the photo. In columns (2) and (3), we consider the vignette exercise in which, upon viewing the randomly assigned photo, respondents were asked to indicate whether and, if so, how they might travel to a friend's home after dark. Relative to a base rate of 24 percent, respondents in the treatment group were 2.9 percentage points less likely to indicate that they would remain at home due to concerns for their safety. Likewise, relative to a base rate of 46 percent, respondents were 2.3 percentage points less likely to indicate either that they would remain at home due to safety concerns or that they would take a taxi/rideshare to travel just a few blocks. While the point estimates suggest that more lighting might lead to a small increase in the use of public space at night, the estimates are not significant at conventional levels of significance. Given that the standard error in model (3) is 0.026, we can be 95 percent confident that the true effect of the LED lighting on the use of public space is not greater than 11 percent.[23] Finally, referring to column (4), we see very little evidence that respondents in the treatment and control conditions would spend a different number of days outside their home. Referring to Table 5, we see that, while the standard errors are larger in the weighted regressions, estimates are extremely similar when we re-weight the sample to more closely resemble the U.S. population along key demographic factors.

In **Table 6**, we present estimates of the treatment effect for feelings of safety under a number of alternative functional forms. We begin by re-estimating (1) treating the safety variable, which is measured using a five-point Likert scale, as continuous. While the estimate is difficult to interpret given that the outcome variable contains no cardinal information, the sign of the coefficient indicates that the treatment version of the photo leads to a perceived increase in safety. Next, we re-estimate (1) using two common binary choice models — logit and probit regression — as opposed to ordinary least squares. Both the logit and probit coefficients are statistically significant and indicate that perceived safety is higher among respondents in the treatment group.[24] Next, leveraging the categorical nature of the Likert-valued variables, we re-estimate models using both ordered and multinomial logit/probit models. The ordered logit model estimates the odds of moving from one category to another as a result of the treatment. As is evident from the table, the odds of indicating a lower level of safety are lower for the treatment group. The multinomial logit model estimates the relative risk of each level of the response relative to a base group as a function of treatment

[23]This calculation is given by $\frac{1.96\sigma}{\bar{y}} = \frac{1.96 \times 0.026}{0.46} = 0.111$.

[24]For the logit model, the raw coefficient indicates that the treatment group had $e^{-0.435} = 35$ percent lower odds of feeling unsafe when viewing the assigned photo than the control group.

status. Here, the base group is the “Strongly agree” group — the group that felt the safest. While the estimates are noisier given that a larger number of comparisons are being made, the results indicate that treated individuals are less likely to feel unsafe in response to the photo.

4.5 Treatment Effect Heterogeneity

Next, we test for treatment effect heterogeneity with respect to a subset of theoretically important covariates: age, gender, race, income and previous victimization. We limit the number of covariates tested in order to reduce the number of tests and therefore the probability of false discoveries. As in all experiments, constraints on statistical power mean that our ability to detect meaningful interaction effects is more limited than it is for the main effects. In order to identify heterogeneity in treatment effects, we estimate the least squares regression in (1) adding an interaction term between the treatment indicator and a given covariate. For each of our four primary outcome variables, the coefficient on the interaction term along with its clustered standard error is presented in **Table 7**. Subject to constraints on statistical power, there is little evidence for treatment effect heterogeneity for any of our four outcomes. With respect to feelings of safety — the outcome variable for which there was an important and statistically significant main effect — the evidence suggests that these effects are broad-based and accrue equally by age, gender, race and income. With respect to prior victimization, there is some speculative evidence that individuals who were victimized within the prior year do not respond to enhanced lighting in the same way that other individuals do, though the result is not significant at conventional levels. The crime victim coefficient is significant and negative with respect to the number of nights per week that victims indicate they will spend outdoors. However, the result is no longer significant after applying a Bonferroni correction to account for multiple hypothesis testing.

4.6 Willingness-to-Pay

Finally, we turn to estimates of respondents’ willingness to pay for a municipal program to brighten street lights. Recall that respondents were asked whether or not they would be willing to pay an additional \$$k$ in taxes to support a program that brings street lighting in their community from the control (“business-as-usual”) condition to the treatment (LED) condition. Each respondent is randomly assigned to react to a different value of k. Critically, this allows us to plot the share of individuals who are willing to support the lighting program for each value of k without worrying that k varies with respondent characteristics. Results of our willingness-to-pay analysis are presented graphically in **Figure 3** which plots a quasi-demand curve for a lighting upgrade from the business-as-usual condition to the LED condition. Panel A presents results for the full sample. We see that the slope of the curve is negative indicating that support for the program falls as the price rises. Overall, nearly 80 percent of respondents indicate that they would pay at least \$75 for the lighting upgrade suggested by the survey question. Interestingly, this is roughly equal to the share of respondents who would pay \$25 for the lighting upgrade suggesting that a modest number of people are unwilling to support capital improvements to street lighting at any price. Demand for lighting falls with k over the remainder of the values. Still, 53 percent of respondents indicate that they would be willing to pay \$400 — or just over \$1 per day — to fund a capital upgrade to street lighting.

Following Nagin et al. (2006), we use our contingent valuation survey to generate an estimate of the average willingness to pay for the lighting upgrades among our survey participants. We derive a conservative estimate of the nonmarket value of the hypothetical lighting intervention by assuming that an individual's willingness to pay is given by:

$$WTP_i = \sum_{j=1}^{J} T_i^k \, k_i^j \tag{3}$$

In (3), k_i^j is the jth value of k and T_i^k is an indicator for whether individual i was willing to pay value k to fund the program. In computing WTP in this way, we are assuming that if an individual is willing to pay the \$k to which s/he was assigned, then this is the maximum the individual is willing to pay and if the individual is not willing to pay the \$k to which s/he was assigned then the individual's WTP is zero. In both cases, these are conservative assumptions.[25] Computed in this way, we estimate that the mean willingness to pay in our sample is at least \$84.

In Figure 3, Panel B, we assess whether estimates differ according to whether a respondent was initially assigned to the treatment or the control condition. This might be important if, by assigning

[25] A third conservative assumption is that public safety is the sole reason why better lighting is preferred. There may also be additional reasons such as the perception that better lighting improves traffic safety (Bullough et al., 2013).

individuals to the control condition, they are already primed to be more fearful of crime. We see little evidence for a priming effect thus providing support for the proposition that willingness-to-pay for street lighting is reasonably stable. Finally, we assess whether willingness-to-pay differs by demographic characteristics as well as by income. We do so by regressing minimum willingness to pay on our vector of covariates. Conditional on covariates, we find that men are willing to pay \$14 less than women ($p < 0.06$) and that while there is no Black-White difference in WTP, Asian respondents were willing to pay \$40 less than White respondents. College-educated respondents were, on the other hand, willing to pay more (\$24) for the program than those without a college degree. Whether or not we condition on covariates, there only limited evidence that willingness to pay for the program rises with income which is perhaps surprising given that lower-income respondents have less disposable income. Finally, we note that individuals who report a recent victimization are actually less willing to pay \$38 less for the hypothetical lighting intervention than respondents who had not been recently victimized. While we can only speculate as to the reasons behind this association, one possibility is that these individuals do not believe that better lighting would have prevented their victimization which causes them to be especially skeptical.

5 Conclusion

This research presents the results of a survey experiment which tests the sensitivity of individuals' feelings of safety and their willingness to use public space to improvements in nighttime ambient lighting. The virtue of this approach is that, by assigning a large number of individuals, at random, to two different lighting conditions, we are able to generate some of the first experimental evidence in this domain and the first experimental evidence in nearly thirty years.[26] This research thus compliments the existing quasi-experimental literature which surveys community residents before and after an area in a city has received enhanced lighting. We also leverage our experimental setting to derive the first estimate of individuals' willingness-to-pay for enhanced street lighting in the United States.

We find that individuals who were randomly assigned to view a photo of a city street which

[26] To our knowledge, the only other experimental study in this area is an early survey experiment by Vrij and Winkel (1991).

had received enhanced LED lighting expressed less fear of spending time outdoors than individuals who were randomly assigned to view a photo of the same street under business-as-usual lighting conditions. The effects are broad-based and hold equally strongly for men and women, for Black and White respondents and for respondents of all education and income levels. On the other hand, consistent with findings in Atkins et al. (1991) but in contrast with those in Painter (1996) and Painter and Farrington (1999), we observe little evidence for differences in the way that individuals in the treatment and control groups planned to use public space or the extent to which they are willing to engage in costly activities — e.g., remaining at home or taking a taxi — in order to mitigate victimization risk. Interestingly our contingent valuation estimates suggest that just over half of respondents would be willing to pay at least $400 per year for enhanced street lighting which raises several interesting questions about under what conditions potential victims are willing to bear the costs of crime control.

The remainder of this article considers how these findings inform our understanding of potential victims and the promise of place-based crime control strategies. Several points are worth noting. First, consistent with the majority of the prior research, ambient lighting makes people feel safer (Vrij and Winkel, 1991; Painter, 1996) and leads to improvements in general well-being (Hanslmaier, 2013).[27] On the other hand, there is little evidence that policing targeted to crime hot spots has the same ancillary benefits (Kochel and Weisburd, 2017; Ratcliffe et al., 2015). Indeed, there continue to be evidence-based concerns that, even though police presence leads to meaningful reductions in crime (MacDonald et al., 2012, 2016; Weisburd, 2016; Heaton et al., 2016; Ridgeway et al., 2019), the concentration of police personnel at crime hot spots may have deleterious impacts on the well-being of affected communities (Rosenbaum, 2006; Weisburd et al., 2011). Given the evidence that crime is responsive to ambient lighting (Doleac and Sanders, 2015; Davies and Farrington, 2018; Chalfin et al., 2019; Domínguez and Asahi, 2019; Chalfin et al., 2020) investments in street

[27] As is noted by Painter (1996), darkness generates a limitless source of blindspots and potential places of entrapment. At the same time, darkness also provides the opportunity for concealment, potentially making it more difficult for offenders to locate attractive victims (Welsh and Farrington, 2008). Precisely how lighting affects fear and perceived safety remains poorly understood. However, evidence from an experiment by Haans and De Kort (2012) indicates that, whether they are stationary or walking, individuals prefer having light in their own immediate surroundings rather than on the road that lies ahead. One implication of this finding is that lighting enhances safety primarily by giving a potential victim the ability to respond effectively to dangerous events rather than by allowing victims to more effectively avert risks that lie ahead. A second implication of this finding is that potential victims value visibility over concealment.

lighting potentially offers policymakers a viable means of controlling crime while, at the same time, improving community perceptions of safety.

Second, the results suggest that individuals prefer to internalize feelings of unease rather than change their behavior in order to mitigate risk. This result is consistent with a variety of theoretical and empirical evidence which suggests that because individuals do not fully internalize the cost of victimization (Clotfelter, 1978; Ayres and Levitt, 1998; Clements, 2003), because public spending on crime control may be treated as a subsidy (Guha and Guha, 2012) or because individuals are myopic or misinformed — victims may under-invest in precaution, relative to what is socially optimal (Chalfin et al., 2019). This finding is likewise consistent with a host of additional CPTED-related research which suggests that individuals do not engage in even the least costly precautions even though they can reasonably expect that such investments will reduce their risk of victimization. A particularly common example of this type of behavior can be found in the large share of burglaries and car break-ins in which the target location was unlocked (Bopp, 1986; Budd, 1999; Weisel, 2002).

Why might individuals be unwilling to take greater precautions when lighting is poor? One possibility is that individuals have trouble differentiating between their own level of risk and the risk that society faces more generally (Rothman et al., 1996). Another possibility is that individuals are present-oriented and place little value on future risks (Thaler and Sunstein, 2009), especially when those risks are uncertain (Mengel et al., 2016). A third possibility is that individuals may have an aversion to subsuming costs which they feel are being unfairly transferred to them by offenders. The latter point is one means of rationalizing our finding that many individuals who are unwilling to take greater precaution personally are nevertheless willing to generously support a publicly-financed lighting program. The implication is that many individuals believe that the costs of crime control should be socialized rather than internalized by potential victims.

Finally, with respect to municipal investments in place-based crime control strategies, in contrast with some prior research which finds that use of public space rises after lighting upgrades, the results of our survey experiment indicate that plans to use public space are relatively insensitive to lighting conditions. On the one hand, this finding highlights the promise of municipal street lighting as a means of maintaining public safety without generating efficiency losses due to compensatory behaviors among potential crime victims. On the other hand, this finding is considerably less optimistic with respect to concerns that fear of crime interferes with active and healthy living (Roman et al., 2009; Shinew et al., 2013; Esteban-Cornejo et al., 2016). Our contingent valuation survey suggests that there may be untapped demand for investments in enhanced street lighting, especially in an era in which policymakers and increasingly many members of the public are interested in identifying ways to maintain public safety in high-crime places without continuing to invest in enforcement-based strategies.

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Table 1: Summary Statistics

	Treatment (Upgraded LED Lighting)	**Control ('Business-as-Usual' Lighting)**	***p*-value**
Age	36.710 (12.353)	36.455 (11.885)	0.746
Male	0.563 (0.497)	0.560 (0.497)	0.932
White	0.687 (0.464)	0.708 (0.455)	0.476
Black	0.118 (0.323)	0.099 (0.299)	0.366
Asian	0.078 (0.268)	0.091 (0.288)	0.466
Multiple or Other Race	0.118 (0.323)	0.101 (0.302)	0.426
High School Diploma or Lower	0.080 (0.271)	0.070 (0.255)	0.556
Some College	0.179 (0.383)	0.266 (0.443)	<0.01**
College Diploma or Higher	0.742 (0.438)	0.664 (0.473)	<0.01**
2019 Household Income: Less than $25,000	0.143 (0.350)	0.127 (0.333)	0.471
2019 Household Income: $25,000-$34,999	0.113 (0.317)	0.140 (0.347)	0.227
2019 Household Income: $35,000-$49,999	0.170 (0.376)	0.195 (0.396)	0.332
2019 Household Income: $50,000-$74,999	0.263 0.441	0.266 (0.443)	0.895
2019 Household Income: $75,000-$99,999	0.174 (0.380)	0.142 (0.349)	0.168
2019 Household Income: More than $100,000	0.137 (0.344)	0.131 (0.338)	0.805
Crime Victim (in past 12 months)	0.122 (0.327)	0.125 (0.331)	0.893
Feel Safe Walking at Night (own neighborhood)	0.792 (0.406)	0.770 (0.422)	0.404
Time to Finish Survey (in seconds)	177.151 (166.159)	167.617 (152.304)	0.357

(a) Panel A: Demographic Variables

	Treatment (Upgraded LED Lighting)	**Control ('Business-as-Usual' Lighting)**	***p*-value**
Feel Unsafe Walking at Night (street in photo)	0.290 (0.454)	0.372 (0.484)	<0.01**
Stay at Home Because Worried about Safety	0.218 (0.414)	0.243 (0.429)	0.368
Stay at Home Because Worried About Safety or Take Taxi	0.439 (0.497)	0.461 (0.499)	0.500
# of Nights Outdoors (per week)	2.748 (1.189)	2.77 (1.864)	0.856

(b) Panel B: Outcome Variables

Note: Table presents covariate means and standard errors for the treatment group (the photo featuring LED lighting) and the control group (the photo featuring 'business-as-usual' lighting). For each variable, we provide the p-value from a t-test that tests the equality of the group means. Significance: * = p<0.05, ** = p<0.01

Table 2: Survey Sample Versus The U.S. Population

	Survey Sample	**U.S. Population**
Age (median)	34.0	37.9
Male	56%	49%
White	70%	73%
Black	11%	13%
Asian	8%	5%
High School Diploma or Higher	99%	88%
Income $< \$25,000$	13%	20%
Income $> \$100,000$	13%	28%
Crime Victim in past 12 months	12%	13%

Note: Table presents covariate means and standard errors for the survey sample along with estimated means for the U.S. population. Data on age, gender, race and education come from the 2014-2018 American Communities Survey 5-Year Data Profile (https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/); data on victimization come from the 2018 National Crime Victimization Survey which reported a rate per 1,000 people of 23.2 violent victimizations and 108.2 property victimizations (https://www.bjs.gov/content/pub/pdf/cv18.pdf).

Table 3: Summary Statistics, Pilot Study versus Full Sample

	Pilot Sample [Feb 25th]	**Study Sample [July 3rd]**	p**-value**
Age	35.846 (11.014)	36.582 (12.116)	0.571
Male	0.589 (0.495)	0.562 (0.496)	0.628
White	0.731 (0.44)	0.698 (0.460)	0.527
College degree or Higher	0.885 (0.322)	0.703 (0.457)	<0.01**
2019 Household Income: Less than $25,000	0.192 (0.397)	0.126 (0.333)	0.152
2019 Household Income: More than $100,000	0.154 (0.363)	0.134 (0.341)	0.637
Crime Victim (in past 12 months)	0.141 (0.350)	0.124 (0.329)	0.664
Feel Unsafe Walking at Night (street in photo)	0.321 (0.470)	0.331 (0.471)	0.851
Stay at Home Because Worried about Safety	0.167 (0.375)	0.231 (0.422)	0.149
Stay at Home Because Worried about Safety or Take Taxi	0.385 (0.490)	0.450 (0.498)	0.256
# of Nights Outdoors (per week)	2.949 (2.070)	2.759 (1.841)	0.430
N	78	949	–

Note: Table presents covariate means and standard errors for two survey samples: the "pilot" sample obtained on February 25th, 2020 and the study sample obtained on July 3rd, 2020. For each variable, we provide the p-value from a t-test that tests the equality of the group means.
Significance: * = p<0.05, ** = p<0.01

Table 4: Main Results (Unweighted)

	Feel Unsafe Walking at Night	**Stay at Home Because Worried About Safety**	**Stay at Home Because Worried About Safety or Take Taxi**	**# of Nights Outdoors (per week)**
Treatment (more light)	-0.078*	-0.029	-0.023	-0.075
	(0.031)	(0.023)	(0.026)	(0.079)
Age	-0.009	-0.007	-0.022**	-0.000
	(0.006)	(0.006)	(0.007)	(0.024)
Age squared	0.000*	0.000	0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.157**	-0.063*	-0.113**	0.274**
	(0.029)	(0.025)	(0.024)	(0.085)
Black	-0.101*	0.089*	0.167*	0.015
	(0.045)	(0.039)	(0.067)	(0.166)
Asian	-0.019	-0.003	0.085*	-0.813**
	(0.058)	(0.035)	(0.041)	(0.177)
Multiple or Other Race	0.025	-0.020	-0.021	0.038
	(0.051)	(0.039)	(0.039)	(0.128)
Some College	-0.051	-0.043	-0.073	-0.006
	(0.073)	(0.045)	(0.046)	(0.218)
College Diploma or Higher	-0.052	0.067	-0.058	0.430
	(0.069)	(0.051)	(0.048)	(0.232)
Income: Less than $25,000	-0.006	0.138**	0.065	0.159
	(0.062)	(0.039)	(0.048)	(0.200)
Income: $25,000-$34,999	-0.074	0.186**	0.100*	0.310
	(0.051)	(0.054)	(0.040)	(0.169)
Income: $35,000-$49,999	-0.079	0.105*	0.032	0.431**
	(0.053)	(0.044)	(0.052)	(0.126)
Income: $50,000-$74,999	-0.021	0.130**	0.062	0.550**
	(0.048)	(0.031)	(0.039)	(0.165)
Income: $75,000-$99,999	-0.031	0.094*	0.113**	0.145
	(0.051)	(0.036)	(0.038)	(0.219)
Crime Victim	0.032	0.044	-0.024	1.466**
	(0.041)	(0.047)	(0.052)	(0.145)
Feel Safe Walking at Night	-0.362**	-0.207**	-0.261**	1.032**
	(0.043)	(0.030)	(0.040)	(0.138)

Note: Table presents coefficients along with clustered standard errors in parentheses from the following least squares regression model: $Y_i^j = \alpha + \beta^j D_i + \gamma X_i + \varepsilon_i$. In the model, D_i is the treatment indicator for the LED version of the photo and β^j is the average treatment effect for outcome j. Significance: * = p<0.05, ** = p<0.01

Table 5: Main Results (Weighted)

	Feel Unsafe Walking at Night	**Stay at Home Because Worried About Safety**	**Stay at Home Because Worried About Safety or Take Taxi**	**# of Nights Outdoors (per week)**
Treatment (more light)	-0.065	-0.038	0.011	-0.093
	(0.037)	(0.034)	(0.033)	(0.105)
Age	-0.006	-0.008	-0.020**	0.018
	(0.006)	(0.007)	(0.007)	(0.028)
Age squared	0.000	0.000	0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.211**	-0.092**	-0.147**	0.560**
	(0.039)	(0.033)	(0.037)	(0.106)
Black	-0.127*	0.048	0.104	0.386
	(.054)	(0.060)	(0.077)	(0.217)
Asian	0.043	0.123	0.197**	-1.006**
	(0.083)	(0.076)	(0.065)	(0.234)
Multiple or Other Race	0.037	-0.005	-0.008	0.219
	(0.061)	(0.060)	(0.060)	(0.174)
Some College	-0.086	-0.108	-0.101	-0.032
	(0.067)	(0.054)	(0.059)	(0.210)
College Diploma or Higher	-0.106	-0.028	-0.119	0.442
	(0.065)	(0.069)	(0.065)	(0.231)
Income: Less than $25,000	-0.068	0.088*	0.010	0.216
	(0.087)	(0.039)	(0.060)	(0.249)
Income: $25,000-$34,999	-0.105	0.216**	0.091	0.086
	(0.066)	(0.068)	(0.058)	(0.178)
Income: $35,000-$49,999	-0.120	0.115*	0.052	0.259
	(0.102)	(0.052)	(0.062)	(0.198)
Income: $50,000-$74,999	-0.051	0.210**	0.175	0.282
	(0.086)	(0.050)	(0.070)	(0.208)
Income: $75,000-$99,999	0.021	0.104	0.187**	0.061
	(0.091)	(0.055)	(0.067)	(0.356)
Crime Victim	-0.084	0.006	-0.046	1.471**
	(0.059)	(0.063)	(0.059)	(0.205)
Feel Safe Walking at Night	-0.356**	-0.160**	-0.258**	0.895**
	(0.047)	(0.044)	(0.054)	(0.128)

Note: Table presents coefficients along with clustered standard errors in parentheses from the following least squares regression model: $Y_i^j = \alpha + \beta^j D_i + \gamma X_i + \varepsilon_i$. In the model, D_i is the treatment indicator for the LED version of the photo and β^j is the average treatment effect for outcome j. Significance: * = p<0.05, ** = p<0.01

Table 6: Alternative Functional Forms: Perceived Safety

			Multinomial Outcome			
	Continuous	**Binary**	**Somewhat agree**	**Neither agree nor disagree**	**Somewhat disagree**	**Strongly disagree**
OLS	0.201*					
	(0.096)					
Logit		-0.435**				
		(0.164)				
Probit		-0.263**				
		(0.098)				
Ordered Logit		-0.323*				
		(0.159)				
Ordered Probit		-0.180*				
		(0.090)				
Multinomial logit			-0.175	-0.247	-0.628**	-0.469
			(0.170)	(0.311)	(0.234)	(0.330)
Multinomial probit			-0.090	-0.152	-0.428**	-0.283
			(0.114)	(0.195)	(0.154)	(0.210)
$\bar{Y}$	2.71	0.33	0.41	0.11	0.24	0.09

Note: Table presents the coefficient on the treatment indicator along with its clustered standard error in parentheses for several different estimating equations. In the first row, we report a least squares estimate in which the dependent variable, a five-valued Likert scale, is treated as a continuous measure. In the next two rows, we use the binary version of this variable (1 if Disagree, 0 if not) but instead of estimating the model via least squares regression as in Table 4, we use logit regression (row 2) and probit regression (row 3). In the final two rows, we use multinomial logit regression (row 5) and multinomial probit regression (row 5) in which each level of the outcome variable is compared to a base group. Here, the base group is the "Strongly agree" group — that is, the group which felt the safest. The final row reports the mean of the outcome measure. Significance: * = p<0.05, ** = p<0.01

Table 7: Treatment Effect Heterogeneity

	Feel Unsafe Walking at Night	**Stay at Home Because Worried About Safety**	**Stay at Home Because Worried About Safety or Take Taxi**	**# of Nights Outdoors (per week)**
Age	0.004	0.000	0.003	-0.012
	(0.004)	(0.003)	(0.003)	(0.013)
Male	-0.008	0.059	0.047	-0.084
	(0.067)	(0.050)	(0.066)	(0.303)
Black	-0.047	0.073	-0.047	-0.028
	(0.109)	(0.077)	(0.143)	(0.436)
Income > $75,000	-0.010	0.029	-0.002	0.114
	(0.062)	(0.043)	(0.064)	(0.264)
Crime Victim	0.139	0.033	0.072	-0.84**
	(0.076)	(0.089)	(0.108)	(0.299)

Note: Table presents coefficients along with clustered standard errors in parentheses from the following least squares regression model: $Y_i^j = \alpha + \beta^j D_i + \gamma X_i + \rho^j X_i D_i + \varepsilon_i$. In the model, D_i is the treatment indicator for the LED version of the photo and X_i is a covariate of interest. The table reports ρ^j along with its standard error for each of five selected covariates and four outcome variables. Significance: * = p<0.05, ** = p<0.01

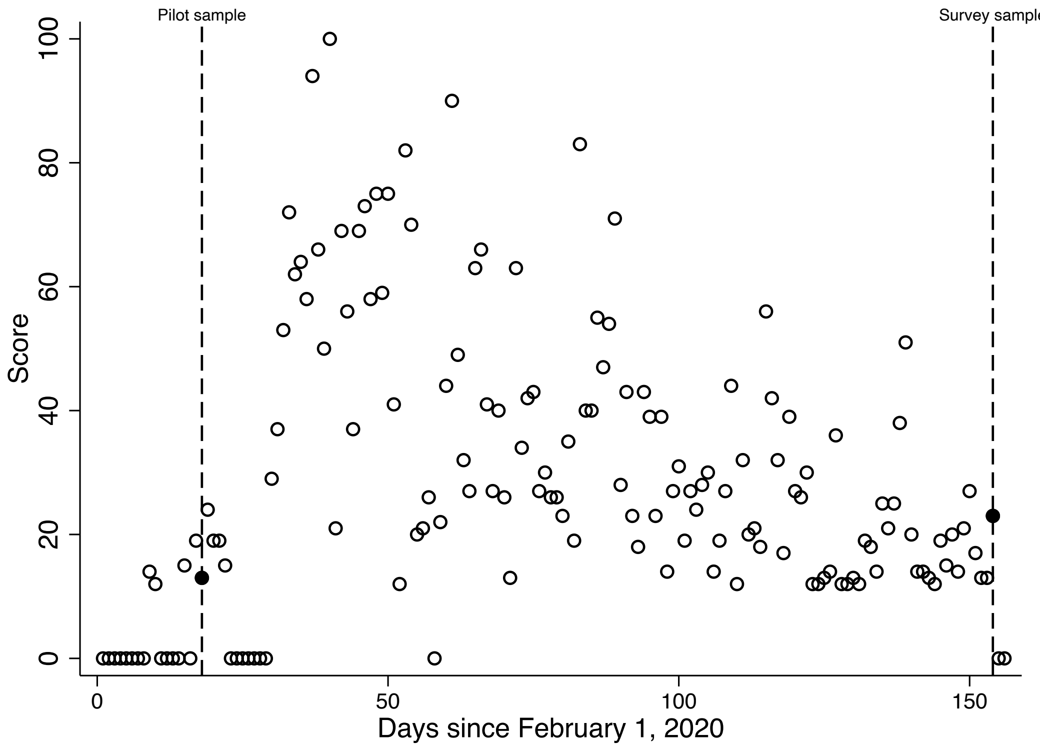
Figure 1: Control and Treatment Photos Utilized in the Survey Experiment

A: Control Condition ("Business-as-Usual" Lighting)

B: Treatment Condition (Upgraded LED Lighting)

Figure 2: Selected Google Trends Searches, February through July 2020

A: Coronavirus/COVID-19



B: Crime

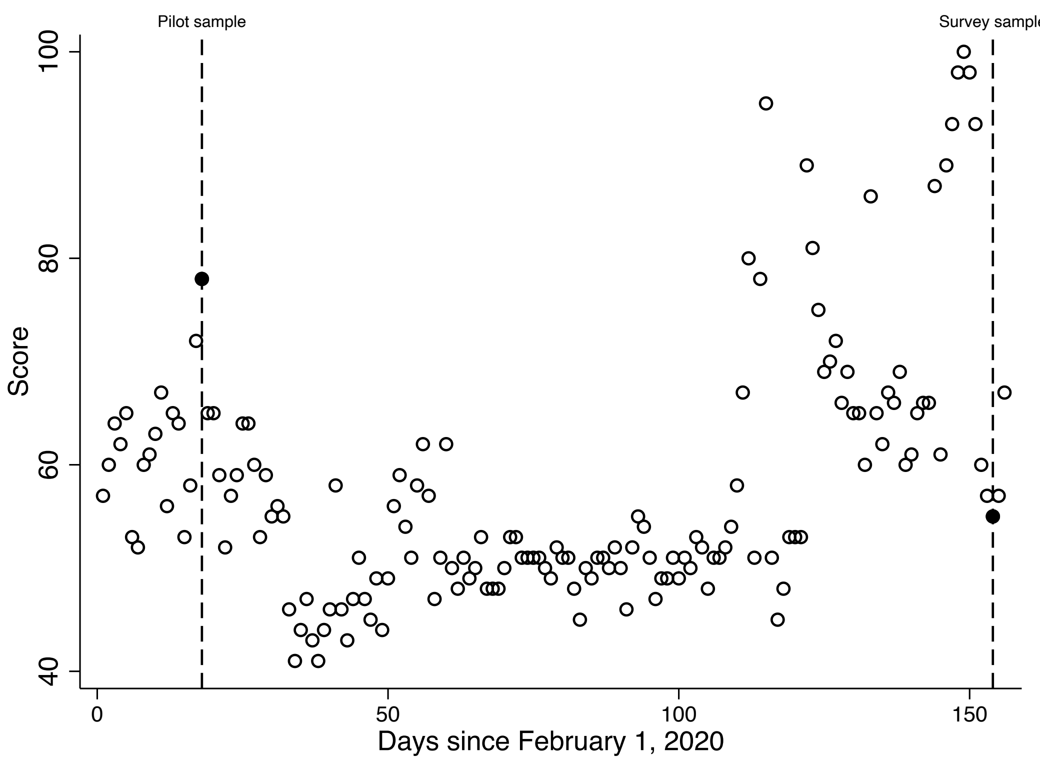
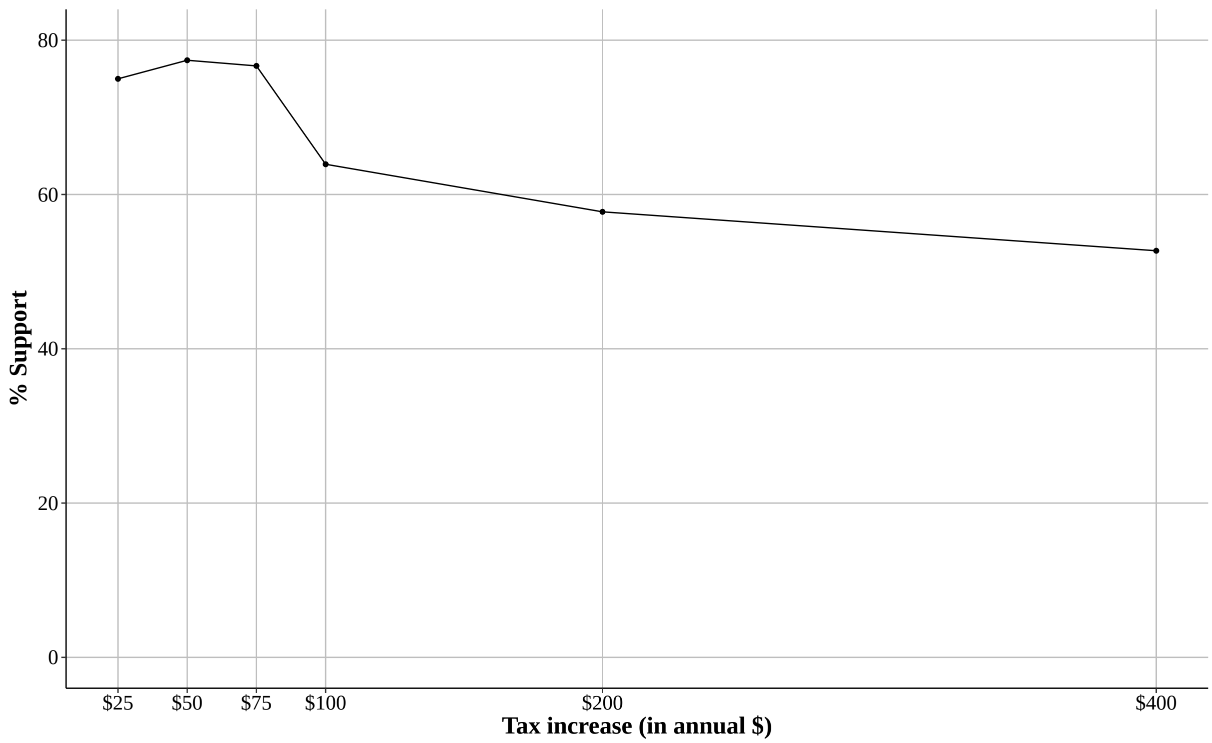
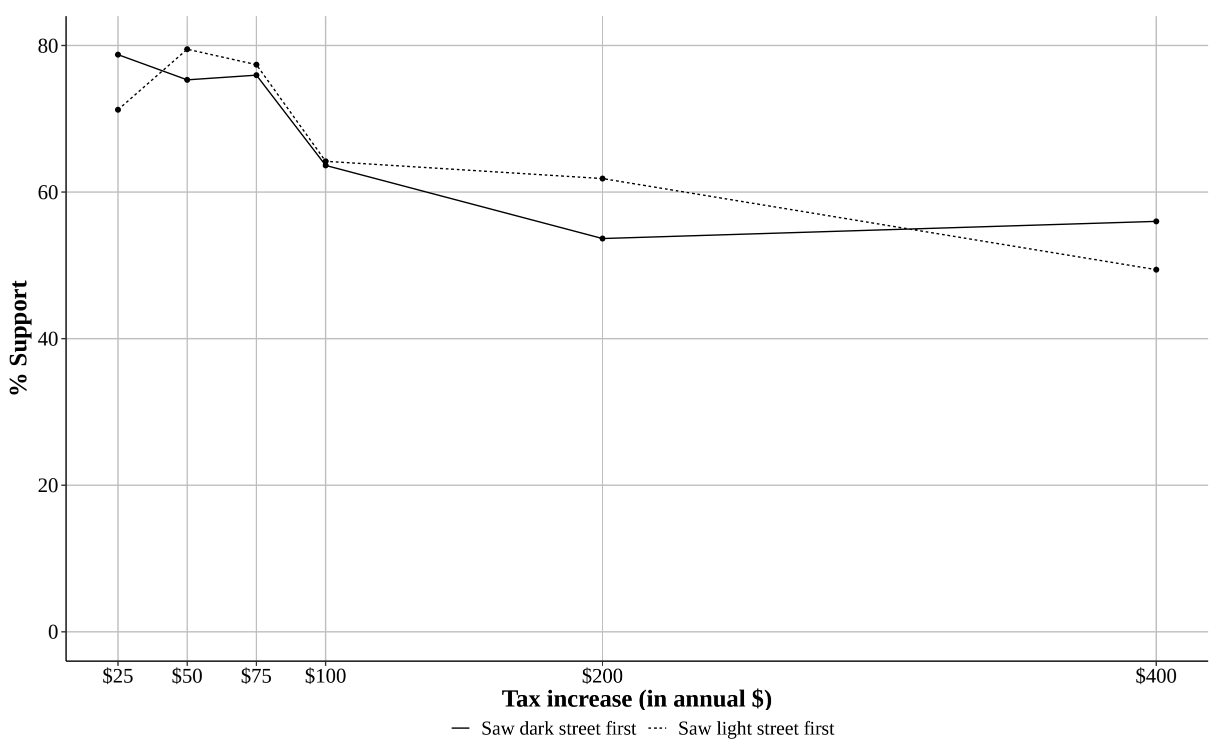


Figure 3: Willingness To Pay For Streetlight Improvements

A: Willingness To Pay For Entire Survey Sample



B: Willingness To Pay By Treatment Group



Appendix A: Survey Instrument

lighting_survey

Survey Flow

EmbeddedData
Random ID = ${rand://int/1:999999}

Standard: Instructions (1 Question)

BlockRandomizer: 1 - Evenly Present Elements

Block: Dark street (4 Questions)
Standard: Light street (4 Questions)

BlockRandomizer: 1 - Evenly Present Elements

Standard: Willingness to pay $25 (2 Questions)
Standard: Willingness to pay $50 (2 Questions)
Standard: Willingness to pay $75 (2 Questions)
Standard: Willingness to pay $100 (2 Questions)
Standard: Willingness to pay $200 (2 Questions)
Standard: Willingness to pay $400 (2 Questions)

Standard: Demographics (10 Questions)

EndSurvey: Advanced

Page Break

lighting_survey

Survey Flow

EmbeddedData
Random ID = ${rand://int/1:999999}

Standard: Instructions (1 Question)

BlockRandomizer: 1 - Evenly Present Elements

Block: Dark street (4 Questions)
Standard: Light street (4 Questions)

BlockRandomizer: 1 - Evenly Present Elements

Standard: Willingness to pay $25 (2 Questions)
Standard: Willingness to pay $50 (2 Questions)
Standard: Willingness to pay $75 (2 Questions)
Standard: Willingness to pay $100 (2 Questions)
Standard: Willingness to pay $200 (2 Questions)
Standard: Willingness to pay $400 (2 Questions)

Standard: Demographics (10 Questions)

EndSurvey: Advanced

Page Break

Start of Block: Instructions

Q1 Thank you for agreeing to respond to this survey. This survey is conducted by researchers at the University of Pennsylvania. We are interested in learning more about your perceptions of public safety. The survey consists of thirteen questions. We anticipate that it will take between 3 and 4 minutes to complete. Thank you very much in advance for your help. **When answering this survey, please think about the time period prior to the Covid-19 pandemic.**

End of Block: Instructions

Start of Block: Dark street

Q2 *Instructions: The above photo was taken in the late evening in a city in the United States. Please refer to this photo as you answer the following two questions.*

Q3 **When answering this question, please think about the time period prior to the Covid-19 pandemic.** Please indicate your agreement or disagreement with the following statement: I would feel safe walking alone at night on a street that looks like this.

- ◯ Strongly agree
- ◯ Somewhat agree
- ◯ Neither agree nor disagree
- ◯ Somewhat disagree
- ◯ Strongly disagree

Q4 **When answering this question, please think about the time period prior to the Covid-19 pandemic.** Imagine that you live on the street on which this photo was taken. A close friend who lives five blocks away from you invites you to hang out at 9:00pm after it is already dark outside. Your car is being repaired so driving is not an option. Thinking about any concerns you might have about your safety, which of the following best describes what you will do?

- ○ Walk to your friend's house
- ○ Take a taxi or a rideshare (e.g. Uber, Lyft)
- ○ Choose to stay home - I would be worried about my safety
- ○ Choose to stay home - I prefer to stay at home for other reasons

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Q5 **When answering this question, please think about the time period prior to the Covid-19 pandemic.** Given the amount of outdoor lighting shown in the photo, in a typical week, how many nights (when it is dark outside) do you think that you would spend outside your home?

	0 1 2 3 4 5 6 7
Nights per week	

End of Block: Dark street

Start of Block: Light street

Q6 *Instructions: The above photo was taken in the late evening in a city in the United States. Please refer to this photo as you answer the following two questions.*

Q7 **When answering this question, please think about the time period prior to the Covid-19 pandemic.** Please indicate your agreement or disagreement with the following statement: I would feel safe walking alone at night on a street that looks like this.

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Q8 **When answering this question, please think about the time period prior to the Covid-19 pandemic.** Imagine that you live on the street on which this photo was taken. A close friend who lives five blocks away from you invites you to hang out at 9:00pm after it is already dark outside. Your car is being repaired so driving is not an option. Thinking about any concerns you might have about your safety, which of the following best describes what you will do?

- Walk to your friend's house
- Take a taxi or a rideshare (e.g. Uber, Lyft)
- Choose to stay home - I would be worried about my safety
- Choose to stay home - I prefer to stay at home for other reasons

---

Q9 **When answering this question, please think about the time period prior to the Covid-19 pandemic.** Given the amount of outdoor lighting shown in the photo, in a typical week, how many nights (when it is dark outside) do you think that you would spend outside your home?

	0	1	2	3	4	5	6	7
Nights per week								

End of Block: Light street

Start of Block: Willingness to pay $25

Q10

Q11
A local politician has proposed a program to provide brighter street lighting to your community. In order to pay for the program, taxes would need to be increased.

Would you be willing to pay $25 in additional taxes every year to receive brighter street lighting in your community?

○ Yes

○ No

End of Block: Willingness to pay $25

Start of Block: Willingness to pay $50

Q12

Q13
A local politician has proposed a program to provide brighter street lighting to your community. In order to pay for the program, taxes would need to be increased.

Would you be willing to pay $50 in additional taxes every year to receive brighter street lighting in your community?

- ◯ Yes
- ◯ No

End of Block: Willingness to pay $50

Start of Block: Willingness to pay $75

Q14

Q15
A local politician has proposed a program to provide brighter street lighting to your community. In order to pay for the program, taxes would need to be increased.

Would you be willing to pay $75 in additional taxes every year to receive brighter street lighting in your community?

- ◯ Yes
- ◯ No

End of Block: Willingness to pay $75

Start of Block: Willingness to pay $100

Q16

Q17
A local politician has proposed a program to provide brighter street lighting to your community. In order to pay for the program, taxes would need to be increased.

Would you be willing to pay $100 in additional taxes every year to receive brighter street lighting in your community?

- ○ Yes
- ○ No

End of Block: Willingness to pay $100

Start of Block: Willingness to pay $200

Q18

Q19
A local politician has proposed a program to provide brighter street lighting to your community. In order to pay for the program, taxes would need to be increased.

Would you be willing to pay $200 in additional taxes every year to receive brighter street lighting in your community?

- ○ Yes
- ○ No

End of Block: Willingness to pay $200

Start of Block: Willingness to pay $400

Q20

Q21
A local politician has proposed a program to provide brighter street lighting to your community. In order to pay for the program, taxes would need to be increased.

Would you be willing to pay $400 in additional taxes every year to receive brighter street lighting in your community?

○ Yes

○ No

End of Block: Willingness to pay $400

Start of Block: Demographics

Q22 **The next few questions are about yourself.**

*

Q23 How old are you (in years)?

____

Q24 What is your gender?

○ Female

○ Male

○ Other

Q25 With which race or ethnic groups do you identify? You may choose as many groups as you like.

- ☐ American Indian or Alaska Native
- ☐ Asian/Pacific Islander
- ☐ Black
- ☐ White
- ☐ Hispanic/Latino(a)
- ☐ Other

Q26 What is the highest degree or level of school you have completed?

- ○ Less than high school
- ○ High school graduate
- ○ Some college
- ○ 2 year degree
- ○ 4 year degree
- ○ Professional degree
- ○ Master's Degree
- ○ Doctorate

Q27 What was your household income in 2019?

- Less than $25,000
- $25,000 - $34,999
- $35,000 - $49,999
- $50,000 - $74,999
- $75,000 - $99,999
- More than $100,000

Q28 What was in the photo that you were shown?

- A city street
- A farm
- A classroom
- The inside of a prison

Q29 Have you been the victim of a crime within the last 12 months?

- Yes
- No

Q30 Have you been the victim of a crime that happened outside in the last 12 months?

- ▢ Yes, my property was taken.
- ▢ Yes, I was attacked, threatened, or robbed.
- ▢ No.

Q31 **When answering this question, please think about the time period prior to the Covid-19 pandemic.** Please indicate your agreement or disagreement with the following statement: I feel safe walking around my community at night when it is dark.

- ○ Strongly disagree
- ○ Somewhat disagree
- ○ Neither agree nor disagree
- ○ Somewhat agree
- ○ Strongly agree

End of Block: Demographics
