Crime-differential responses to an environmental shock: Evidence from blackouts†

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Abstract

We examine how the supply of offenses respond to a large environmental shock in the urban space. We focus on blackouts which can abruptly change the provision of light, and potentially the distribution of criminal opportunities. Using high-frequency administrative data on more than 370,000 power outage incidents reported in Chile during 2014-2015, we analyze how they affect crime along several dimensions. We find no significant effect on the aggregate crime rate, but we also find two offsetting reactions driving this result: a positive increase in burglary, and a negative effect on robbery. By exploiting unique features of the data, we analyze several dimensions of treatment effect heterogeneity regarding the magnitude, size and duration of the blackout. In addition, we find that crime responses differ by municipality socio-economic status. We validate our findings by conducting a set of placebo exercises where we find no meaningful variation across different crime types and treatment definitions. Our results suggest that criminals react to changes in incentives by carrying out crimes that yield a higher expected return.

JEL Classification: K42, R41, D01
Keywords: Economics of Crime, Victims Behavior, Ambient Light

† We thank *Carabineros de Chile* and *Superintendencia de Electricidad y Combustibles* for the data used in this project, and especially Andres Jauregui and Francisco Balcazar from SEC-Chile. We also thank Nicolás Ajzenman, Samuel Berlinski, Aaron Chalfin, Rhiannon Jerch, Viviane Sanfelice, Giovanni Mastrobuoni, Diego Vera-Cossio, Paul Carrillo, and seminar participants at Universidad de San Andrés (UdeSA), Temple University, Pontificia Universidad Católica de Chile, Virtual Crime Economics (ViCE) series, the IADB Research Department and the Latin America Crime Policy Network workshop (AL CAPONE) for valuable comments and feedback. Patricio Domínguez acknowledges funding provided by Fondecyt de Iniciación No. 11220261 and The MIGRA Millenium Nucleus, ANID-MILENIO-NCS2022_051.

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1. Introduction

Several empirical applications in the economics of crime literature have shown that potential offenders react to changes in the distribution of criminal opportunities. These studies collectively show that, to some degree, offenders do respond to environmental factors such as the provision of ambient light (Doleac and Sanders, 2015; Domínguez and Asahi, 2023; Chalfin et al., 2022; Mitre-Becerril et al., 2022), police presence (Di Tella and Schargrodsky, 2004; Draca et al., 2011; Klick and Tabarrok, 2005) or weather shocks (Jacob et al., 2007), among others. One particularly salient issue is the extent to which the supply of offenses - specific for each type of crime - react to a common shock. This corresponds to the notion that offenders effectively respond to changes in expected payoffs by incorporating specific responses by crime type where substitution across different crime activities is possible. In this paper, we exploit an exogenous shock in the environment - the occurrence of a power outage during night hours i.e. blackout - to examine differential reactions in the supply of offenses.

Blackouts can be particularly disruptive and thus potentially affect criminal activity in multiple ways. An important first channel has to do with the provision of ambient light. Due to their unexpected nature, blackouts offer exogenous variation in the amount of ambient light. This is especially relevant at the beginning of the blackout where they provide variation in the amount of ambient light which may be presumably as good as random.[1] We use high-frequency crime data to take advantage of a total of 370,000 power outages which affected over 7.5 million customers during the 2014-2015 period. Our basic model specification exploits within-municipalities across time variation in criminal activity to analyze how blackouts affect crime.

Contrary to a set of recent studies that show an inverse relationship between ambient light and crime, we find no significant effect of blackouts on overall criminal activity. We exploit high-frequency data by constructing a municipality-hour level panel covering the entire country, and show that this finding is consistent across several blackout definitions. If the variation in ambient light induced by a blackout is similar to the one used in previous studies, our general results contrast with most findings in the literature which find a negative relationship between ambient light and criminal activity. We find that this null statistical effect in total crime is driven by two offsetting reactions across crime types: roughly, a 5 percent increase in burglary, and a 5 percent reduction in robbery. In some specifications, we also find smaller reductions in total thefts, around 1-2 percentage points. We discuss the extent to which ambient light is the main disruption associated with power outages that drives our results. Given that we observe all power outages, including those that happen during daytime hours i.e daytime outages, we conduct a series of placebo tests. We run our main specification on daytime outages, and we find no effect on any crime type. This finding is reinforced by a more general specification that shows that most of the variation across crime types is observed during nighttime hours.

We then show a set of additional results that help us interpret these findings. In terms of criminal activity we discuss whether our findings provide any evidence of substitution between robbery and

[1] Since we rely on data reported by customers, one might be worried about measurement error in the starting time of an incident (Chalfin et al., 2021). Although we have data on all incidents, our analysis is focused on those that affected a large number of customers, and thus, measurement error regarding starting time is likely to be negligible.

burglary. We show that this pattern is not homogeneous across municipalities and acknowledge that it may not necessarily take place at the offender-individual level. Rather, we document different reactions in the supply of offenses reflecting specific equilibrium crime levels as a function of the characteristics of the municipality and the interactions between potential offenders and victims. In other words, our results suggest that criminals react to changes in incentives (e.g. considering endogenous victim adaptations and the characteristics of the place) by carrying out crimes that yield a higher expected payoff.

Under a traditional rational offender model, a blackout may alter the relative expected gains of different crime types, affecting the likelihood of perpetrating one type of activity over another. While in the case of robbery and burglary the reduction in ambient light would predict a partial increase in crime activity - by reducing an offender's probability of being caught - responses may differ when considering, for example, endogenous reactions from potential targets. We argue that by modifying how potential victims (or targets) behave, blackouts can alter the distribution of crime opportunities. Burglary targets a particular address while robbery targets a person or a group of people. The different nature of these crimes potentially implies different abilities to endogenously adapt to the shock imposed by a blackout. It is plausible that potential victims adopt some precautionary measures to reduce the chances of being victimized in a robbery that usually takes place in public spaces, whereas effective measures to prevent a burglary are less likely to take place during the shock. We find suggestive evidence in favor of this hypothesis by showing that most of the increase of burglary is concentrated in commercial places as opposed to residential ones, whereas in the case of robbery the reduction is concentrated on incidents that take place in street and public spaces.

Of course, since we do not observe in the data individual-offender trajectories we are not able to document substitution at this level, but we further discuss the extent to which the opposing effects in two types of crime-activities could be interpreted as evidence of substitution across crime-categories induced by a shock. The main fact is that larger increases in burglary coincide with larger reductions in robbery. On average, municipalities where a blackout affected a larger group of people experienced, at the same time, a larger increase in burglary and a larger decrease in robbery. In addition, we show that the positive effect of burglary is concentrated at the same time-of-the-day at which the negative effect for robbery is more intense. However, we also show that this pattern of substitution across crime types is not perfectly contemporaneous nor homogeneous during the shock. First, we study the dynamics of crime substitution by analyzing in what specific window of time the observed effects are concentrated. By exploiting the duration of a blackout incident we are able to compare the effect during the first three hours and the rest of the incident, when presumably potential victims have more opportunity to react. We find that while most of the change in burglary takes place in the first three hours of a blackout, the reduction in robbery is concentrated during later hours. This piece of evidence would emphasize a particular feature of crime substitution that could be consistent with a dynamic model of criminal activity. If an offender chooses between burglary and robbery it is plausible that temporal increases in the former are followed by a decrease in the latter. In particular, this feature of the crime substitution hypothesis relates to the work of Jacob et al. (2007) who document a high degree of intertemporal substitution of criminal activity, though for a longer time horizon.

Finally, we document important differences across municipalities by their average per-capita income. We find that within high-income municipalities (top 10-20 of municipalities) there is a large reduction in robberies and no significant effect on burglaries. This result suggests that high-income municipalities experience none of the *costs* but most of the *gains* in crime associated with these type of shocks. However, within low-income municipalities we observe a large increase in both burglaries and robberies. We interpret this as suggestive evidence that both crime types are instead complements within this context.

This paper relates to several recent contributions in the economics of crime literature. First, since blackouts are mainly a disruption in the provision of ambient light, it connects to a set of recent empirical studies that measure the causal effect of ambient light on criminal activity. By exploiting variation in ambient light induced by daylight savings time policy, some empirical applications have shown that sunlight deters criminal activity. Doleac and Sanders (2015) use data from the NIBRS, which predominantly represents rural and low dense populated areas in the U.S, and find that ambient light substantially reduced the amount of criminal activity. Domínguez and Asahi (2023) extend this work to the highly densely populated area of Santiago, Chile, and their findings reinforce the idea that even in urban spaces the amount of light provided by the sun affects crime. In the case of artificial light, Chalfin et al. (2022) and Mitre-Becerril et al. (2022) find similar results in an experiment conducted in New York City.

Another branch of the literature that connects with this paper has to do with the interaction between potential offenders and victims. Although this issue was emphasized early on by Phil Cook, among others, it remains relatively understudied.[2] Recent examples in the empirical literature have emphasized different aspects of the role of victims such as their ability to harden a target (Vollaard and Van Ours, 2011; Ayres and Levitt, 1998; Gonzalez-Navarro, 2013), the level of resistance they oppose when victimized (Dominguez, 2022), or how interactions between offenders and victims shape the level and characteristics of crime (O'Flaherty and Sethi, 2010, O'Flaherty and Sethi, 2008, O'Flaherty, 2015). Although we cannot document specific victim reactions at the same granular level, our results are consistent with the idea that part of the change is induced by different strategies adopted by victims.

Finally, this paper discusses a particular dimension of crime displacement (e.g., offender's ability to substitute one type of crime for another). To the extent that opposing effects in robbery and burglary reflects substitution across crime activities, this paper connects with the literature on displacement. In general, displacement is an understudied issue, perhaps in part because it is hard to measure (McCrary et al., 2010). Displacement is the relocation of crime across several possible dimensions such as time, space, target, tactic or offense, among others (Guerette and Bowers, 2009). Most commonly, the literature has paid attention to spatial (Blattman et al., 2017, Gómez et al., 2021) or temporal displacement Jacob et al., 2007), but empirical applications examining displacement across crime activities remains scarce or non-existent. The policy implications of displacement are clear since it may undermine the effectiveness of targeted policies. This paper attempts to shed light on this issue as well.

[2] See for example: Van den Haag (1975), Cook (1977), Cook (1979), and Cook (1986). For a more recent assessment of this issue in the literature, see Cook et al. (2011).

2. Analytical Framework

In the economics of crime literature, most researchers follow Becker (1968) to characterize offender choice. A basic depiction of this framework suggests that an offender compares costs and benefits (Chalfin and McCrary, 2017). It states that a rational offender will commit a crime if $(1-p)U_{c1} + pU_{c2} > U_{NC}$, where p the probability of getting caught, U_{c1} represents the utility associated with choosing to commit a crime when not being caught, U_{c2} represents the utility associated with choosing to commit a crime but being caught and punished –it considers a generalized cost function C which encompasses all perceived costs that are related to the risk of receiving a sanction, and U_{NC} represents the utility associated with the alternative of choosing not to commit a crime. In other words, it predicts that an offender commits a crime when expected gains are larger than opportunity costs.

Under this simple model, we can hypothesize the conditions under which a blackout may induce differential responses by crime type. On one hand, lack of light can affect victims' ability to identify an offender, which may subsequently reduce an offender's probability of capture ($\downarrow p$). This may further induce other potential offenders to commit a crime. It is easy to see that, through this channel, a reduction in the amount of ambient light would increase both robbery and burglary (Robb $\uparrow$ and Burg $\uparrow$). However, this prediction can be modified if we consider endogenous adaptations by other agents such as potential victims who also perceive the environmental shock. Consider the case of a robbery. If potential victims are aware that a blackout increases the likelihood of being victimized they can also respond and adapt to the shock. In particular, potential victims can undertake additional precautionary measures such as avoiding places where they would be an easy target. This could subsequently reduce an offender's ability to identify a target which may reduce the likelihood of committing an offense. Thus, in the case of robbery, incorporating potential adaptations of victims leaves us with no clear theoretical prediction since we cannot be certain which potential channel will dominate. The specific response for this type of activity is one of the empirical questions we address in this paper.

As opposed to robbery, we argue that for burglary it is much more likely to find a clear theoretical prediction. If for robbery we can imagine that victims can endogenously adapt to reduce the chances of being victimized, it is much more unlikely to expect a similar endogenous reaction in cases where the target is a house or other particular address. More realistically, we can assume that the ambient light mechanism will dominate, predicting an unambiguous increase in burglary. In this case, the relevant empirical question is to examine the degree to which offenders respond to a shock that modifies the overall expected returns of a particular type of activity.

3. Empirical Analysis

3.1. Data

We combine two sources of administrative data. First, we gathered administrative information on all power outages during the 2014-2015 period in Chile. This information is managed by a government regulatory agency (SEC, *Superintendencia de Electricidad y Combustibles*) which centralizes information from all electric utility companies in the country. We obtained data at the incident level that includes information on the municipality, the number of customers (houses) affected, the potential cause, starting time and duration of all incidents. Incident characteristics are collected by the electric utility company at the moment that power is restored and must be reported periodically to the government regulatory agency (SEC).[3] During the period 2014-2015 we find 374,278 incidents across all 346 Chilean municipalities. Table 1 shows that blackouts differ considerably in terms of size (number of houses affected), magnitude (share of houses affected in municipality m), and duration (minutes). In our main specification, a median incident affected 66 houses, with an affecting magnitude of 4 out of 1,000 houses in a given municipality, and lasted around 280 minutes. Similarly, crime data was obtained from the Chilean national police (*Carabineros*) at the incident level. This data contains information on the time, type and location of all reported crimes in Chile during that same period.

In order to answer our empirical question we combine these two sources of data in a municipality-hour panel representing the 2014-2015 period. This panel includes information on all crimes and power outages reported in municipality m at hour h. Tables 1 and 8 describe all the incidents we use in our database. We exclude from the original sample all outages which affected less than 3 customers, as well as all scheduled incidents that may trigger different reactions and confound the unanticipated nature of the event we plan to exploit in our identification strategy. We exclude incidents that were particularly small - less than 3 customers affected - in size, which represented around 25% of the original sample. Scheduled incidents represent power outages that were reported by SEC as being done due to maintenance, repairs, cleaning, etc.[4] After excluding these incidents, we are left with 231,342 outages which affected a combined total of over 7.5 million customers. Out of this final sample of outages, 40% of them affected more than 37 and 0.25% of customers and lasted for longer than 30 minutes. These thresholds will be used for our treatment criteria. They will be further discussed in section 4.

In the appendix section, we describe the characteristics of blackouts across several dimensions. Table 8 describes the construction of our final database and how the incidents are distributed across regions, which are the largest subnational administrative level. The most important sample exclusion is the removal of small outages. We later discuss the robustness of our results to the inclusion of some of these incidents. Table 8 and Figure 7 shows the regional distribution of outages across space. We can observe a fairly homogeneous distribution across the territory, and particularly in densely populated areas such as region 5 and 13. For example, in the case of the metropolitan area of Santiago - which is region 13 in Figure 7 - where 45 percent of the population lives, the probability of having experienced a blackout is low and homogeneous across its 52 municipalities. Additionally, given the geographic location of the

[3] We originally requested data at a more granular level (e.g. geocoded information for each incident) but that kind of data is not available.

[4] In Appendix Table 16 we reproduce our main specification results considering only scheduled outages.

country and its large vertical extension we adjust our definition of nighttime and daytime (sunrise and sunset hours) by capturing regional monthly averages and adjusting for daylight savings time (DST) in 2014. During 2015 the government decided to temporarily abolish DST. In the appendix section, Figure 6 shows the concentration of power outages across time of day, month and day of the week after adjusting for these changes.

Given the detailed nature of our data there is the possibility of more than one power outage happening within a given municipality-hour. On one hand, concurrent incidents may have a single cause (*e.g* an earthquake can cause power outages in multiple places during the same period of time in a given municipality). On the other hand, simultaneous events in our database can simply be due to reporting since electric companies validate information on incidents when power is restored, and this can take place several times for a single event (for example, the restoration process of a single event can be done in multiple stages). In order to address the overlap of events in our panel data we assign outage characteristics using the following equation:

$$C_{h,m} = \sum_{j \in \{h,m\}} C_j \tag{1}$$

where $C_{h,m}$ represents the total number of houses affected by a power outage, and j indicates all contemporary incidents reported during hour h in municipality m. Based on the information of the largest (C_j) incident reported at $\{h, m\}$, we define the duration of the incidents in our panel as follows:

$$D_{h,m} = D_{i,h,m} \text{ where } \{i \in A | C_{i,h,m} = \max_{j \in \{h,m\}} C_j\} \tag{2}$$

which defines the duration of the power outage incident at $\{h, m\}$ using the starting time of the incident with the largest amount of affected houses, among all j contemporaneous incidents reported in the same municipality m at the same time h. This procedure assures us that we are capturing the real magnitude and duration of power outages.

Table 1: Distribution of Power Outages

Percentile (%)	Size (Nbr.Houses)	Magnitude (% Houses)	Duration (Minutes)
10	6	0.04	74
20	11	0.08	113
30	21	0.15	157
40	**37**	**0.25**	210
50	66	0.39	280
60	108	0.62	366
65	135	0.80	423
70	169	1.03	514
75	210	1.40	676
80	267	1.95	893
85	374	2.94	1,128
90	585	4.92	1,439
95	1,295	11.11	2,250
99	5,282	57.87	8,032

Notes: Table shows the distribution of incidents in our balanced panel by percentile on each relevant dimension. Size represents the number of houses affected by a power outage, distributed according to the percentile of the distribution indicated in the first column. Magnitude corresponds to the % of houses affected by a blackout and is estimated using the total number of households per municipality according to the 2017 census. Duration corresponds to the length (in minutes) of the incident. These percentile-thresholds are used when we study the heterogeneity by blackout size and length. Additionally, we use the 40th percentile for size and magnitude as thresholds for our treatment in all tables.

3.2. *Empirical Strategy*

Our aim is to capture the unanticipated effect of a power outage on criminal activity. Since the major environmental disruption associated with a power outage has to do with a change in ambient light provision, we restrict the set of incidents to outages that take place during nighttime hours, more commonly referred to as blackouts. Given the municipality-hour panel structure of our data we can capture this effect by controlling for differences in terms of crime across municipalities and time of day. In order to do so we estimate the following difference-in-differences equation:

$$y_{m,h} = \alpha + \beta B_{m,h} + f(\mu_m, \nu_{mo}, \tau_{dow}, \gamma_{hod}) + \epsilon_{m,h} \tag{3}$$

Where $B_{m,h}$ is an indicator function for whether a blackout was reported during hour h in municipality m. In other words, an interaction term between a dummy for night hours and a dummy for whether a power outage was reported during hour h. As discussed above, we define a blackout as all power outages that took place during nighttime and we adjust for DST and regional averages when defining night hours. Additionally, $y_{m,h}$ represents the crime rate, which is the number of crimes divided by the municipality population size. Our main specification uses the interacted: $\mu \times \nu \times \tau \times \gamma$ fixed effect, which represents municipality (m), month (mo), day of the week (dow) and hour of the day (hod). We do so to account for the seasonal and temporal pattern of criminal activity across several dimensions as well as other potential factors affecting crime rate across municipalities. Results from this estimation are presented in Table 2. We discuss the robustness of our results to different combinations of fixed effects in Table 10.

In order to validate the relevance of ambient light as the main mechanism driving our result, we estimate a series of *placebo* tests focusing on the effect of power outages during daytime hours. Due to the fact that a power outage has no virtually no effect on ambient light, daytime incidents could help us on identifying the role of ambient light. More specifically, we estimate the following variation of equation 3:

$$y_{m,h} = \alpha + \delta D_{m,h} + f(\mu_m, \nu_{mo}, \tau_{dow}, \gamma_{hod}) + \epsilon_{m,h} \tag{4}$$

Where $D_{m,h}$ is an indicator function for whether a daytime power outage was reported during hour h in municipality m. In other words, an interaction term between a dummy for daytime hours and a dummy for whether a power outage was reported during hour h. Results from this estimation are presented in section 5.1.[5]

We are aware of recent developments in the difference-in-differences literature which finds that settings with staggered treatment designs could produce biased estimates when there are heterogeneous treatment effects over time or across space (de Chaisemartin and D'Haultfœuille, 2022; Roth et al., 2023). The main reason for this issue has to do with earlier treated units which serve as controls for later treated units. Under heterogeneous effects the treatment can cause units, in our case municipalities, to be on different trends. This implies that earlier treated units may no longer work as valid comparisons for later

[5] As an additional check, we estimate a version of equations 3 and 4 in which we include both indicator variables in the same regression. Results for this estimations are presented in Table 12

treated units, potentially leading to biased estimates. Our empirical strategy differs from previous settings since our treatment, by construction, is not staggered but rather binary and it switches 'on' and 'off' multiple times across time and municipalities. This implies that municipalities may be treated several times during our study period. In fact, under our most strict treatment definition i.e biggest and longest blackouts, the average municipality gets treated 104 different times. Each time with varying duration and magnitude. Additionally, all municipalities are treated at least once. This setting complicates the usual approaches, however, we attempt to address some of them the following ways. First, by disentangling most potential sources of heterogeneity in our setting across municipalities (Section 4.1 and 5.5) and within blackouts (Section 5.4). Second, in the spirit of Cengiz et al. (2019) stacked regression design, by following an approach which (i) reduces potential sources of bias by restricting the pre-treatment time window and (ii) simplifies the estimation into a 2x2 design (Section 8.1 in the appendix). This approach estimates effects which are qualitatively similar to our main results and consistent with our event study in section 5.4.

4. Main Results

Since blackouts differ considerably in terms of magnitude, size and duration, and municipalities vary in terms of population and other characteristics, we analyze crime responses using different blackout definitions. Table 2 shows results for aggregate crime rates under different blackout treatment criteria depending on the size, magnitude and duration of the incident. For each panel we indicate - under the blackout definition - the criteria we use to define our blackout indicator. Total crime represents the sum of burglary, robbery, thefts, and vehicle thefts incidents reported during each municipality-hour.

In the first two panels of Table 2, we restrict blackout definitions to incidents where at least 37 houses or 0.25% percent of all municipality houses were affected, respectively. Both definitions exclude the smallest 40% of incidents, as seen in Table 1, where we are unlikely to detect an effect since we are using data at the municipality level. The distinction in terms of the size and magnitude is relevant given that there is large variation in regards to the size of municipalities. Therefore, the effect of a blackout that affected a large number of houses should be interpreted differently than the effect of a blackout that affected a large share of houses. Similarly, in the third panel we define a blackout as all incidents that lasted for at least 30 minutes. We argue that in order to be able to detect an effect we need to focus on blackouts that are sufficiently large in terms of size and magnitude, but also sufficiently long in terms of its duration. Since there is no clear threshold to define whether a municipality was sufficiently affected by the blackout, we conduct a series of checks and sensitivity analyses in section 4.1. Finally, in the bottom panel, a blackout is defined using a combination of all three previous criteria: size (>37 houses), magnitude (>0.25% of houses) and duration (>30 minutes) of the incident.

Results in Table 2 show that across all four specifications we fail to detect an effect on total crime [6]. However, we also observe that the null effect in crime masks a substantial degree of heterogeneity across crime types. First, we detect a significant 5 percent increase in burglary across all specifications. Column (1.1) shows that this result is robust to different specifications of the treatment status. Most importantly, in column (1.2) we observe that the increase in burglary seems to be offset by a similar decrease in robbery. We do not find a significant effect nor a meaningful response for vehicle theft. In Table 9 we show results for violent crimes and find a reduction in simple assaults of around the same magnitude as that for robbery. In Table 10 we show the robustness of our preferred specification - which is column 5 - to the omission or inclusion of fixed effects.

[6] Tables 13 , 14, and 15 show similar results using the number of crimes in a given municipality-hour as a dependent variable, a linear probability model where the dependent variable is whether a crime took place or not, and modifying the dependent variable using the inverse hyperbolic sine transformation, respectively. Additionally, to rule out potential low-dosage explanations for our null result on total crime we estimate a separate regression in which we look at the largest incidents >90th percentile. Results for this treatment definition are shown in Table 11.

Table 2: Estimated Effect of Blackouts on Crimes: Municipality-Hour Level

	Property Crimes:				
	(1) Total	(1.1) Burglary	(1.2) Robbery	(1.3) Theft	(1.4) Vehicle Theft
Blackout	0.0218	0.0348***	-0.0151*	0.00203	0.0115
[>37 Houses]	(0.0226)	(0.00977)	(0.00697)	(0.0148)	(0.0101)
N	5174141	5174141	5174141	5174141	5174141
Municipality Sample	327	327	327	327	327
R^2	0.247	0.145	0.158	0.271	0.205
Mean DV	2.974	0.708	0.417	1.849	0.611
Blackout	-0.0107	0.0406***	-0.0225*	-0.0288	-0.000538
[>0.25% Houses]	(0.0252)	(0.0111)	(0.00978)	(0.0152)	(0.0125)
N	5174059	5174059	5174059	5174059	5174059
Municipality Sample	327	327	327	327	327
R^2	0.246	0.145	0.159	0.270	0.205
Mean DV	2.957	0.706	0.412	1.839	0.603
Blackout	0.0189	0.0290***	-0.00899	-0.00108	0.0123
[>30 Minutes]	(0.0168)	(0.00825)	(0.00587)	(0.0118)	(0.00727)
N	5278461	5278461	5278461	5278461	5278461
Municipality Sample	327	327	327	327	327
R^2	0.245	0.143	0.156	0.269	0.202
Mean DV	2.964	0.708	0.418	1.838	0.610
Blackout	-0.0155	0.0395***	-0.0237*	-0.0313	-0.00191
[>All]	(0.0261)	(0.0114)	(0.0103)	(0.0160)	(0.0135)
N	5145886	5145886	5145886	5145886	5145886
Municipality Sample	327	327	327	327	327
R^2	0.246	0.145	0.160	0.270	0.205
Mean DV	2.959	0.706	0.413	1.841	0.604

Notes: This table represents 20 separate regressions for each type of crime and treatment. Treatments are defined as blackouts which 1) affected more than 37 houses (40th percentile) in the first panel, 2) affected more than 0.25% of all houses (40th percentile) in the second panel and 3) lasted more than 30 minutes in the third panel. The fourth panel uses all three criteria. We remove from our baseline 1) all daytime outages and 2) blackouts which do not meet the treatment criteria defined in each panel. The dependent variable is the crime rate per municipality per 1m people. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level. Data collapsed at the municipality-hour level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.1. *Heterogeneity by treatment definition*

Given the large variation in blackout size, magnitude and duration we examine coefficient robustness to varying thresholds. More specifically, we analyze response heterogeneity by modifying thresholds on the three dimensions we use to define the presence of a blackout in a particular municipality at a certain hour. To do this, we estimate equation 5 which effectively generalizes the treatment definition using a combination of thresholds criteria.[7] For this exercise we take advantage of the rich information we have about blackout characteristics. SEC data describes, at the incident level, the number of customers affected and the exact time when a power outage starts and ends. We combine that information to describe the treatment status in three dimensions: size (number of houses affected), magnitude (share of houses, which is equal to the number of houses divided by the number of houses of each municipality according to the 2017 CASEN Survey) and duration. Thus, we estimate a set of equations of the following form:

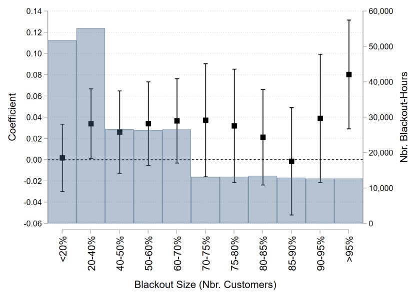
$$y_{m,h} = \alpha + \sum_i \beta_i B_{m,h,i} + f(\mu_m, \nu_{mo}, \tau_{dow}, \gamma_{hod}) + \epsilon_{m,h} \tag{5}$$

Where $B_{m,h,i}$ is an indicator function for whether a blackout, with a size, magnitude or duration falling within bin i, was reported during hour h in municipality m. Given that the difference in size and magnitude on the left of the distribution is small, we define 10 bins (i) using the following percentiles: [0-20), [20-40), [40-50), [50-60), [60-70), [70-75), [75-80], [80-85), [85-90), [90-95) and [95-100]. They are defined in a way that allow us to capture meaningful differences between coefficients. In terms of duration, we define the bins into standard deciles. Estimates from equation 5 are plotted in Figure 1 separated by row for each crime: burglary, robbery and theft. Bars represent the number of municipality-hours treated within each bin i - indicated along the secondary vertical axis. These bars show that a substantial portion of blackouts affected less than 66 customers, which on average represent less than 0.4% of households of a municipality. In addition, the bars in Figure 1c show that an average treatment effect of blackout will consider a much more homogeneous composition of municipality-hour events.

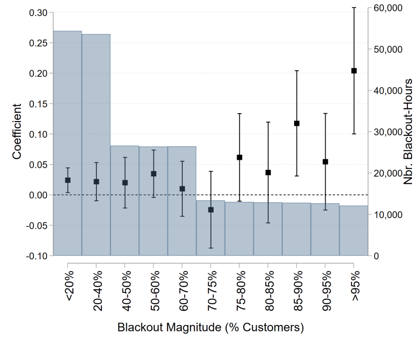
These results introduce a set of interesting patterns. First, we observe that the effect on burglary is robust to the treatment definition. Figures 1a, 1b, and 1c show that most of the coefficients are positive and significant. In spite of the specific definition of the treatment status, we do not observe large variation in their point estimates, except for cases when the blackout affected a large share and number of houses. In this case, we observe that the effect on burglary increases with the magnitude and size of the event. By contrast, we do not find a discernible pattern along blackouts with increasing duration. For robberies we find a similar pattern but in the opposite direction. Figures 1d, 1e, and 1f show that most of the coefficients are negative. We also find that the effect on robberies decreases with the magnitude and size of the event. Therefore, we find that the contrasting effects between burglaries and robberies shown in table 2 are driven by the largest – in terms of size and magnitude – blackouts. For theft (Figures 1g, 1h, and 1i) we find a similar pattern to that of robberies.

[7] For simplicity, in this section, we focus our analysis to the case of burglary, robbery and theft since - according to Table 2 - these are the crime types with the most significant responses to blackouts.

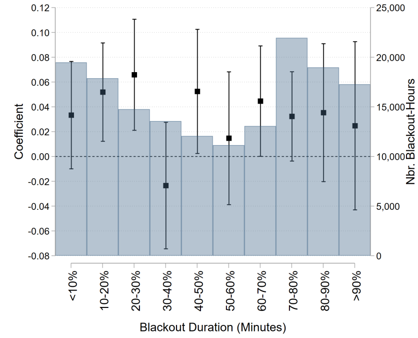
Figure 1: Burglary, Robbery, & Theft Coefficient Sensitivity to Blackout Characteristics



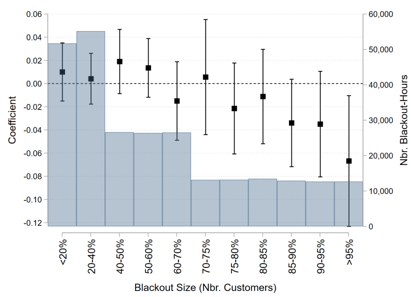
(a) Size (Nbr. Customers)



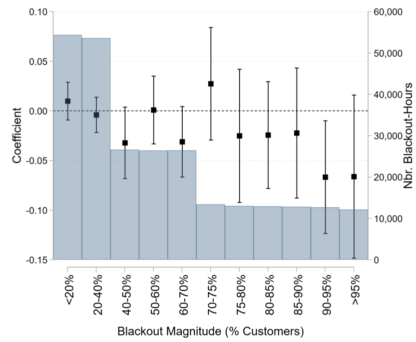
(b) Magnitude (% Customers)



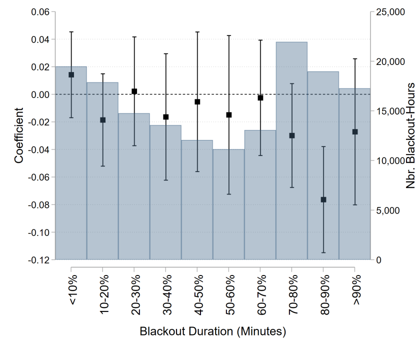
(c) Duration (Minutes)



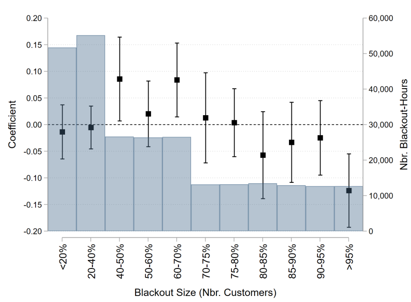
(d) Size (Nbr. Customers)



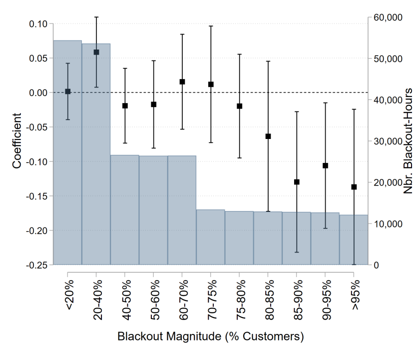
(e) Magnitude (% Customers)



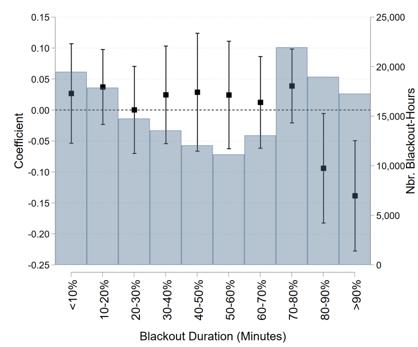
(f) Duration (Minutes)



(g) Size (Nbr. Customers)



(h) Magnitude (% Customers)



(i) Duration (Minutes)

Notes: We estimate 3 separate regressions for each crime type with interaction terms between each treatment and the respective bin of blackouts that fall between the thresholds specified in Table 1. Figures on the 1st row shows results for burglary. Figures on the 2nd row shows results for robbery. Figures on the 3rd row shows results for theft. Each dot represents a coefficient on the primary vertical axis and the vertical lines denote 95% confidence intervals. The bars represent the number of treated hours, i.e. blackout hours, on the secondary vertical axis for each bin. For figures 1a, 1b, 1d, 1e, 1g, and 1h we restrict to blackouts that lasted for longer than 30 minutes. For figures 1c, 1f, and 1i we restrict to blackouts that affected more than 37 houses. The dependent variable is the municipality-hour crime rate per 1m people. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level.

5. Mechanisms

An important question has to do with what specific aspect of a blackout is driving our results. We can think of a blackout triggering several reactions across agents. In this section we examine potential mechanisms that help explain our results. First, we perform a series of placebo tests to validate the relevance of the lack of ambient light induced by a blackout as the main driver. These tests focus on daytime power outages as a placebo exercise. Second, we narrow down on the location where the crime took place. This helps us better understand how offenders and potential victims adjust their behavior based on their perceived risk of capture or being victimized [8]. Third, we investigate the degree of substitution across crime types by disentangling the effect across the time of day. This allows us to focus on the contemporaneous relationship between our offsetting effects. First, by using a event study design we analyze the dynamics around the blackout itself to rule out potential confounders. Finally, we analyze responses by the socioeconomic status where reaction and adjustment capacity is likely different.

5.1. Daytime placebo

The most noticeable feature of a blackout has to do with the provision of ambient light, and particularly the degree to which a power outage affects public and private provision of artificial light. We analyze this issue by conducting a placebo experiment restricting the analysis to all power outages that took place during daytime hours. This exercise will help us to better interpret the results in Table 2, which might be caused by other potential responses associated with power outages that are not related to variation in ambient light [9]. We investigate this issue by estimating our main specification and reproducing results from Table 2, switching our treatment definition to only municipality-hours affected by an outage during daytime hours. More specifically, Table 3 shows estimates from equation 4. It is clear that during daytime hours (e.g. approximately from 8A.M. to 5P.M. based on DST and regional differences) a power outage incident does not modify the amount of ambient light regardless of the setting. Under this blackout placebo definition, we analyze variation in criminal activity associated with power outages during daytime. Results from Table 3 show that we fail to detect any significant variation in total crime under all four definitions. More importantly, we do not detect any significant response across crime types under all four treatment definitions. Although this simple test does not rule out all other possible responses that could have been driving our results, they strongly suggest that the amount of ambient light modified by a power outage during night hours is the main mechanism driving our results.[10]

In the case of burglary, we present a generalization of Table 3 by plotting all possible combinations of treatment status for both blackout definitions, during daytime and nighttime hours. Figure 2 depicts

[8] Ideally, we would want to control for human activity, such as data on human mobility, and interpret the results as the effect on the supply of offenses. Unfortunately, no data is available for our study period with the level of granularity specified in our main regressions. During the COVID-19 pandemic, some phone companies released mobility data at the province-day level, but this data is only available since February 2020. Therefore, we interpret our findings as the interaction between different types of agents and make progress in interpreting the findings based on the type of crime-activity we are describing and the possibility that it may be driven by one particular type of agent relative to others.

[9] In Table 16 we reproduce our main specification results considering only scheduled outages and we detect no discernible pattern for any crime type.

[10] Additionally, Table 12 shows robustness of our main result to including daytime outages and blackouts in the same regression.

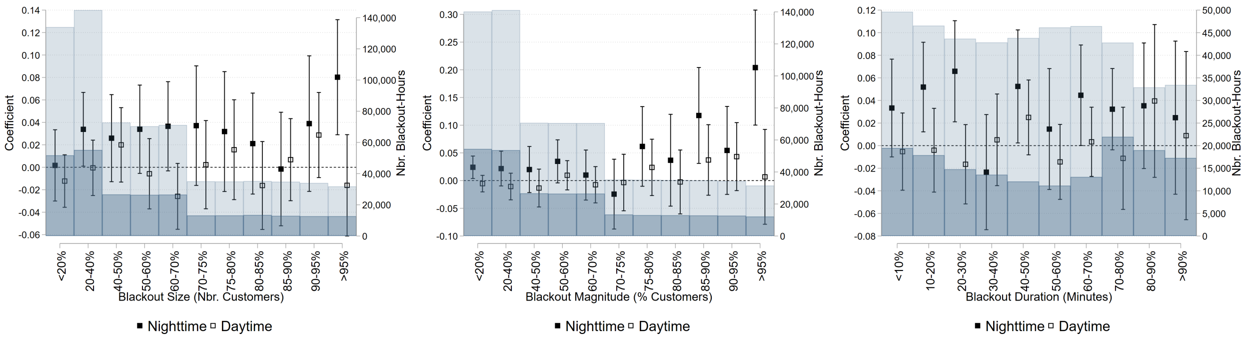
all the coefficients including the number of treated hours within each bin - indicated along the secondary vertical axis. We observe that only coefficients associated with nighttime treatment status are positive while there is no effect associated with any of the daytime blackouts.

Table 3: Estimated Effect of Daytime Outages on Crime: Municipality-Hour Level

	Property Crimes:				
	(1) Total	(1.1) Burglary	(1.2) Robbery	(1.3) Theft	(1.4) Vehicle Theft
Daytime Outage [>37 Houses]	-0.00810 (0.0194)	-0.000372 (0.00768)	-0.00313 (0.00405)	-0.00460 (0.0158)	0.0109 (0.00717)
N	5282375	5282375	5282375	5282375	5282375
Municipality Sample	327	327	327	327	327
R^2	0.245	0.142	0.158	0.268	0.201
Mean DV	3.069	0.709	0.405	1.955	0.609
Daytime Outage [>0.25% Houses]	-0.0211 (0.0214)	0.00739 (0.00842)	-0.00776 (0.00547)	-0.0208 (0.0166)	0.0119 (0.00707)
N	5282994	5282994	5282994	5282994	5282994
Municipality Sample	327	327	327	327	327
R^2	0.242	0.142	0.160	0.264	0.202
Mean DV	3.002	0.706	0.403	1.892	0.600
Daytime Outage [>30 Minutes]	-0.00603 (0.0141)	-0.00153 (0.00597)	-0.000234 (0.00381)	-0.00426 (0.0129)	0.00942 (0.00575)
N	5448681	5448681	5448681	5448681	5448681
Municipality Sample	327	327	327	327	327
R^2	0.241	0.139	0.156	0.263	0.198
Mean DV	3.086	0.710	0.401	1.974	0.605
Daytime Outage [>All]	-0.0217 (0.0222)	0.00779 (0.00881)	-0.00649 (0.00574)	-0.0230 (0.0174)	0.0107 (0.00748)
N	5234051	5234051	5234051	5234051	5234051
Municipality Sample	327	327	327	327	327
R^2	0.243	0.143	0.160	0.265	0.203
Mean DV	3.004	0.706	0.404	1.893	0.601

Notes: This table represents 20 separate regressions for each type of crime and treatment. Treatments are defined as daytime outages which 1) affected more than 37 houses (40th percentile) in the 1st panel, 2) affected more than 0.25% of all houses (40th percentile) in the 2nd panel and 3) lasted more than 30 minutes in the 3rd panel. In the 4th panel we use all three criteria. We remove from our baseline 1) all blackouts and 2) daytime outages which do not meet the treatment criteria defined for each panel. The dependent variable is the crime rate per municipality per 1m people. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level. Data collapsed at the municipality-hour level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 2: Burglary Coefficient Sensitivity to Blackout Size, Magnitude, & Duration: Blackouts vs. Daytime Outages



(a) Size (Nbr. Customers)

(b) Magnitude (% Customers)

(c) Duration (Minutes)

Notes: We estimate 6 separate regressions with interaction terms between each treatment, separated by blackouts and daytime outages, and the respective bin of blackouts that fall between the thresholds specified in Table 1. Black dots represent blackouts and transparent dots represent daytime outages. Each dot represents a coefficient on the primary vertical axis and the vertical lines denote 95% confidence intervals. The bars represent the number of treated hours, i.e. blackout hours, on the secondary vertical axis under each bin. For Figures 2a and 2b we restrict to blackouts that lasted for longer than 30 minutes. For Figure 2c we restrict to blackouts that affected more than 37 houses. The dependent variable is the municipality-hour crime rate per 1m people. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level.

5.2. Responses by crime location

In order to further explore offenders and potential victims adaptation capacity to the environmental shock induced by a blackout we pay attention to the location where crimes take place. We disaggregate burglaries, robberies, and thefts by the location where the incident occurred. Specifically, we separate burglaries by whether the incident happened within a residential or commercial location. Robberies and thefts by whether they happened within a commercial location or public space. The separation for burglaries is meaningful given that residential and commercial locations have different reaction capacity to an unexpected event such as a blackout. In other words, we hypothesize that blackouts reduce the risk of capture for potential offenders in commercial locations, where in residential locations people are probably more likely to stay home, hence increasing apprehension risk for potential offenders. Similarly, robberies and thefts are separated in a way such that we capture differences in the circulation of people after a blackout, hence reducing potential targets for offenders. In other words, blackouts reduce the stock of potential victims in the streets or public spaces, such as parks, bus stops, etc. This argument is consistent with current evidence showing that changes in ambient light during nighttime hours modifies risk perceptions (Chalfin and Kaplan, 2022). Table 4 shows results for each crime-location combination.

These findings show interesting patterns. First, we find that the positive effect on burglaries is driven entirely by crimes within commercial locations - and in some cases, *other* locations. Since blackouts likely induce individuals to stay at their residences, a plausible explanation is that the increase in burglary is driven by potential offenders focusing on locations where the risk of capture is likely lower. For thefts, there is a reduction in commercial places, which can simply reflect the fact that blackouts induce those places to close. Finally, we find that the negative effect on robbery is driven entirely by crimes committed in public spaces. There are different interpretations for this pattern. On one hand, if the supply of potential offenders remains stable and they can easily switch between different types of crime, the observed decrease in robbery could be due to a change in behavior among offenders, who now prioritize more profitable crime opportunities. On the other hand, regardless of changes in the supply of offenses, this pattern can also reflect potential victims adapting their behavior to the updated likelihood of being victimized –i.e. by staying at home and avoiding locations where the risk of victimization is higher due to the lack of ambient light. We will discuss the merits of each of these views in the next section.

Table 4: Estimated Effect of Blackouts on Burglary, Robbery & Theft by Location

	Burglary:			Robbery:			Theft:		
	(1) Residential	(2) Commercial	(3) Other	(4) Commercial	(5) Pub. Space/ Street	(6) Other	(7) Commercial	(8) Pub. Space/ Street	(9) Other
Blackout	0.0105	0.0121**	0.0122***	0.000954	-0.0200***	0.00400	-0.0148**	-0.00838	0.0252*
[>37 Houses]	(0.00739)	(0.00435)	(0.00363)	(0.00268)	(0.00520)	(0.00235)	(0.00568)	(0.00620)	(0.0120)
N	5174141	5174141	5174141	5174141	5174141	5174141	5174141	5174141	5174141
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.142	0.135	0.133	0.132	0.155	0.129	0.237	0.168	0.196
Mean DV	0.398	0.164	0.146	0.0544	0.318	0.0446	0.589	0.342	0.918
Blackout	0.00925	0.0166***	0.0147***	-0.000895	-0.0231**	0.00151	-0.0293***	-0.00657	0.00704
[>0.25% Houses]	(0.00827)	(0.00445)	(0.00426)	(0.00303)	(0.00795)	(0.00273)	(0.00741)	(0.00588)	(0.0135)
N	5174059	5174059	5174059	5174059	5174059	5174059	5174059	5174059	5174059
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.142	0.135	0.133	0.133	0.157	0.130	0.236	0.168	0.195
Mean DV	0.395	0.164	0.146	0.0538	0.315	0.0440	0.588	0.340	0.911
Blackout	0.00902	0.0105**	0.00949**	0.00283	-0.0156***	0.00383	-0.0136**	-0.00737	0.0198*
[>30 Minuntes]	(0.00633)	(0.00384)	(0.00347)	(0.00226)	(0.00440)	(0.00197)	(0.00515)	(0.00543)	(0.00903)
N	5278461	5278461	5278461	5278461	5278461	5278461	5278461	5278461	5278461
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.140	0.132	0.131	0.129	0.153	0.126	0.235	0.166	0.193
Mean DV	0.399	0.164	0.146	0.0547	0.319	0.0446	0.583	0.339	0.915
Blackout	0.00730	0.0165***	0.0157***	-0.000475	-0.0245**	0.00130	-0.0303***	-0.00552	0.00453
[>All]	(0.00856)	(0.00458)	(0.00450)	(0.00323)	(0.00820)	(0.00287)	(0.00789)	(0.00636)	(0.0141)
N	5145886	5145886	5145886	5145886	5145886	5145886	5145886	5145886	5145886
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.143	0.135	0.134	0.134	0.157	0.131	0.237	0.169	0.196
Mean DV	0.395	0.164	0.146	0.0538	0.315	0.0440	0.589	0.341	0.911

Notes: Table represents 40 separate regressions for each type of crime and location combination. Treatments are defined as blackouts which 1) affected more than 37 houses (40th percentile) in the 1st panel, 2) affected more than 0.25% of all houses (40th percentile) in the 2nd panel and 3) lasted more than 30 minutes in the 3rd panel. In the 4th panel we use all three criteria. We remove from our baseline 1) all daytime blackouts and 2) blackouts which do not meet the treatment criteria. For the location of each crime we include different categories based on the information available within each police record. Other burglaries, robberies and thefts refer mostly to incidents within schools/universities, religious or sporting centers, public entities or unidentified locations. The dependent variable is the crime rate per municipality per 1m people. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level. Data collapsed at the municipality-hour level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5.3. Responses across crime types

We now investigate the degree of substitution between crime types. We do so by showing further results regarding the effect of blackouts on criminal activity across time of the day. In a way, the ability to identify different responses along these dimensions has to do with the issue of displacement which has not been extensively discussed - at least, empirically - in the economics of crime literature, perhaps in part because it is hard to measure (McCrary et al., 2010). Differential crime responses can be associated with substitution between crime types, which is a certain form of displacement from one type of activity to another. Displacement can take place in many additional ways - relocation of crime from one place, time, target, offense, or tactic to another as a result of some crime prevention initiative (Guerette and Bowers, 2009) - and it is a key issue in evaluation of crime control programs. In the context of social interventions, if it is difficult to define a treated group, understanding how treatment spills over other nontreated areas can be even harder.

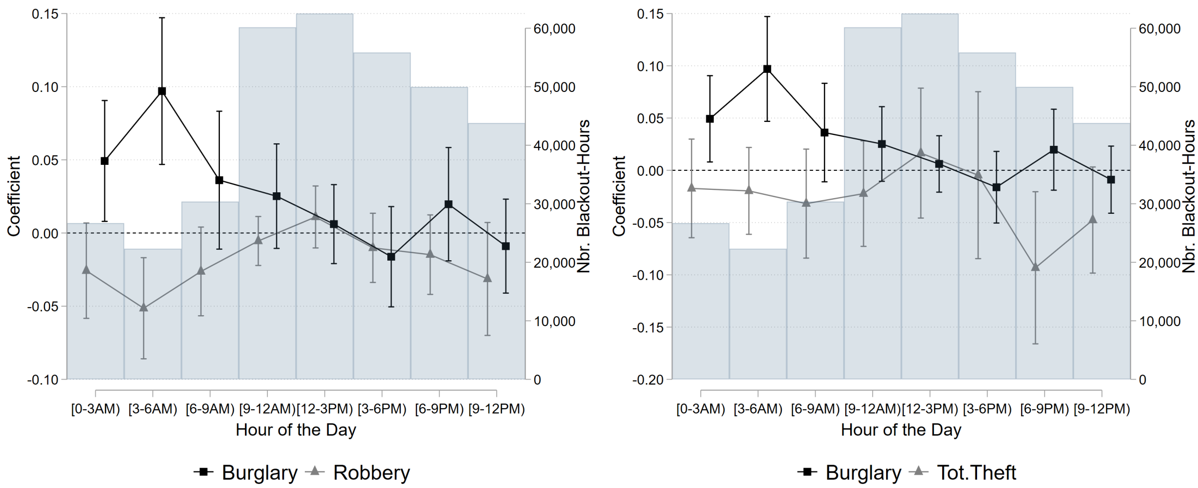
Therefore we examine the extent to which the effects on burglary, robbery, and theft relate to each other. We compare variation in criminal activity induced by blackouts along two dimensions. The first piece of evidence comes from Table 2 that shows, along several margins, that the increase in burglary is associated with a reduction in robbery and, to a lesser extent, theft. We extend that by analyzing the treatment effect across hours of the day, and we do that by interacting our treatment status with hours of the day using the following equation:

$$y_{m,h} = \alpha + \sum_{t} \beta_t B_{m,h,t} + f(\mu_m, \nu_{mo}, \tau_{dow}, \gamma_{hod}) + \epsilon_{m,h} \qquad (6)$$

Where $B_{m,h,t}$ is an indicator function for whether a power outage was reported during hour h, belonging to time frame t, in municipality m. In other words, we interact our treatment indicator with the following 8 time frame bins (t): [0-3AM), [3-6AM), [6-9AM), [9-12AM), [12-3PM), [3-6PM), [6-9PM) and [9-12PM). We include the same set of fixed effects as in our main specification. Figure 3 displays the results first comparing robbery and burglary, and then burglary and theft.

It is interesting to notice that the largest increases in burglary and the largest decreases in robbery follow a similar pattern. This contemporaneous reaction suggests that a blackout triggers differential reactions by crime type. Importantly, Figure 3 also reinforces our previous findings that all observed effects of power outages take place during nighttime hours. These findings can be seen as a generalization of our placebo test conducted in section 5.1.

Figure 3: Burglary vs. Robbery & Theft: Coefficient Sensitivity to Time of Day



(a) Blackout > All

(b) Blackout > All

Notes: We estimate three separate regressions (Figures 3b and 3b) with interaction terms between our main treatment and the respective blackouts that fall within each 3 hour period of the day. In Figure 3b we compare burglary (black) vs robbery (gray); similarly, in Figure 3b we compare burglary (black) vs theft (gray). Each dot represents a coefficient on the primary vertical axis and the vertical lines denote 95% confidence intervals. For both figures we restrict to blackouts that affected more than 37 houses, 0.25% of all houses and lasted longer than 30 minutes. The dependent variable is the municipality-hour crime rate per 1m people. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level.

5.4. *Intertemporal dynamics*

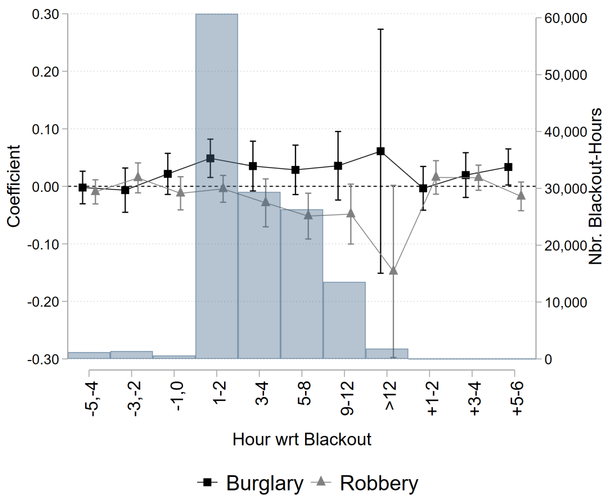
We also analyze what happens before, during and after a blackout. This analysis serves several purposes: (i) it helps us to evaluate potential confounding trends that could bias our results, especially regarding pre-trends, (ii) it allows us to examine whether changes across crime types take place contemporaneously, and (iii) it allows us to evaluate the presence of any intertemporal substitution within a specific type of crime. Intertemporal crime substitution has been documented in longer time frameworks such as weeks. By exploiting exogenous crime variation induced by weather shocks, Jacob et al. (2007) show that in a given jurisdiction, and over weeks, offenders substitute effort from one period to another. Given the specific crime responses induced by a blackout we evaluate whether an unexpected increase in burglary is related to a subsequent decrease in burglary. We evaluate the dynamics of a blackout by running the following event-study regression:

$$y_{m,h} = \alpha + \sum_{t=-6}^{6} 1[t = h] \times \beta_t B_{m,h} + f(\mu_m, \nu_{mo}, \tau_{dow}, \gamma_{hod}) + \epsilon_{m,h} \quad (7)$$

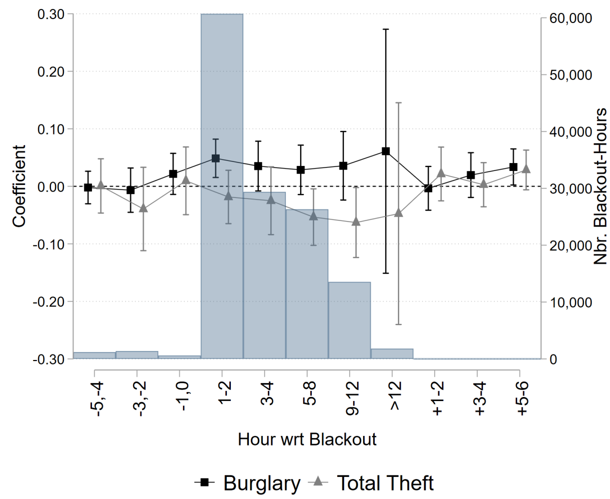
Where each β_t captures the observed variation observed in crime, relative to t hours before or after the beginning or end of a blackout. The interaction with the blackout indicator $B_{m,h}$ allows us to identify the set of β_t coefficients only relative to a blackout in municipality m at hour h. For simplicity, we group all 6 hours before and after the blackout into two hour bins. Similarly, we group hours during the blackout into two hour bins and for those that lasted longer than 12 hours we bin them together. Finally, we include the same set of fixed effects as in our main specification. Figure 4 shows the results of equation 7. We plot two figures comparing the temporal evolution of burglary and robbery, and burglary and theft. In addition, we show in bars the change in the number of hour-incidents considered in each interval. As expected, the number of blackouts decreases with the duration of the incident. We observe that for burglary the effect is evenly distributed whereas in the case of robbery and theft the negative effect is concentrated during the later hours of the blackout episode. We fail to detect any relevant pre-trends that might question the exogenous timing of the blackouts. Similarly, there is no evidence of intertemporal substitution when examining the six-hour period afterwards.

Additionally, we estimate a simplified version of these results in Table 5 where we contrast the effect of the blackout during the first three hours and the remainder of the incident. Consistent with our event study specification we find that the effect on burglary is positive but concentrated during the first three hours. For robbery and theft we find the opposite, a consistent negative effect but heavily concentrated during the later hours of the blackout. Taken together, these results imply that if substitution across crime activities is the main mechanism at play then we must consider a more complex interaction.

Figure 4: Pre-Trends and Intertemporal Substitution



(a) Burglary vs. Robbery



(b) Burglary vs. Theft

Notes: We estimate 3 separate regressions, one for each type of crime. Each dot represents a coefficient on the primary vertical axis and the vertical lines denote 95% confidence intervals. Coefficients are indicated on the x-axis which represents the hours before and after the blackout. The bars represent the number of treated hours, i.e. blackout hours, on the secondary vertical axis under each bin. On average, a blackout lasts for 3 hours and 54 minutes under the following treatment definition: affected more than 37 houses (40th percentile), affected more than 0.25% of all houses (40th percentile) and lasted more than 30 minutes. We remove from our baseline 1) all daytime outages and 2) blackouts which do not meet the treatment criteria defined in each panel. The dependent variable is the crime rate per municipality per 1m people. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level.

Table 5: Coefficient Sensitivity to Hour within Blackout: Municipality-Hour Level

	(1) Burglary	(2) Robbery	(3) Theft
First 3 Hours	0.0476**	-0.00473	-0.0193
	(0.0166)	(0.0117)	(0.0232)
Rest (>3 Hours)	0.0319*	-0.0430**	-0.0432*
	(0.0146)	(0.0149)	(0.0183)
N	5145727	5145727	5145727
Municipality Sample	327	327	327
R^2	0.145	0.160	0.270
Mean DV	0.706	0.413	1.841

Notes: This table represents 3 separate regressions with interaction terms between our treatment and its first three hours vs the remainder. Treatment is defined as blackouts which affected more than 37 houses (40th percentile), affected more than 0.25% of all houses and lasted more than 30 minutes. We remove from our baseline 1) all daytime outages and 2) blackouts which do not meet the treatment criteria defined in each panel. The dependent variable is the crime rate per municipality per 1m people. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level. Data collapsed at the municipality-hour level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

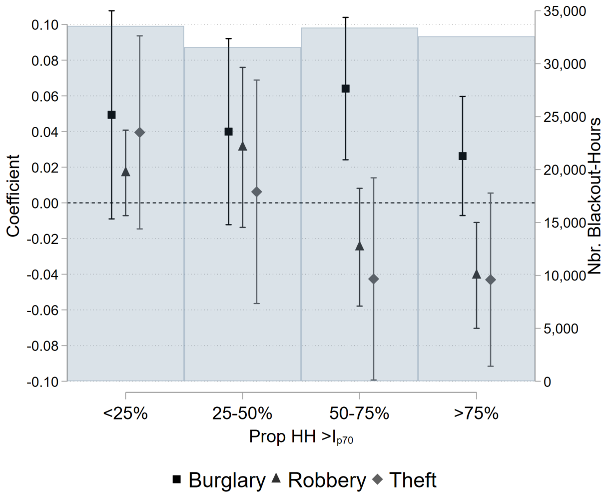
5.5. *Responses by municipality income level*

We finally discuss the degree to which the effects of blackouts on crime depend on the characteristics of the municipality where a blackout takes place. Crime responses to a shock can be different in high- and low-income municipalities. We believe that differences across municipalities could be due to their ability to control crime opportunities, which could force offenders in more secured areas to substitute their effort away from one type of activity to another, whereas in less restricted areas it may complement offender crime efforts for multiple crimes affected by a temporal shock. Additionally, differences reactions across types of municipalities could help us to rule out the possibility of substitution across crime activities as the main driver of our results relative to or other potential mechanisms at play.

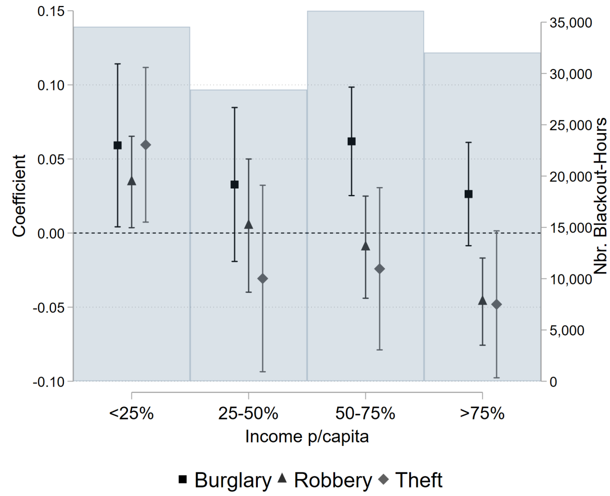
Therefore, we compare crime responses across municipalities of different income levels. We use a national household survey (CASEN) to create groups of municipalities by socioeconomic status, and then we estimate our basic specification for each group of municipalities. In practice, we divided all municipalities into ten groups by two criteria: 1) average per capita income and the 2) proportion of people among the top 30% of the national income distribution. We plot all estimates in Figure 5. We observe that although the result for burglary is fairly stable across income groups, the reduction in robbery is heavily concentrated among higher income municipalities. This finding is consistent whether we use per capita income or the share of people among the top 30% of the income distribution. This pattern suggests that groups of municipalities have different reactions that allows them to prevent criminal activity from taking place in some group and not in another. In particular, wealthier municipalities experience almost no change in burglary, and most of the reduction in robbery and theft is concentrated within the richest municipalities. This contrasts with the fact that low-income municipalities seem to experience increases in robbery.

We simplify these results in Table 6 where we pool all municipalities into two groups, above and below the median municipality per capita income. Again, coefficients in Table 6 show that the contrasting reaction between burglary and other crimes only takes place in higher-income municipalities. In a way, results from Table 6 are consistent with the idea that high-income municipalities respond more effectively to environmental shocks that affect opportunities across crime types. Although the burglary effect is robust to the level of income, only in above-median-income municipalities do we observe a burglary effect that is compensated for with a reduction in other types of crime.

Figure 5: Burglary, Robbery & Theft Coefficient Sensitivity to Municipality Socioeconomic Status



(a) Prop HH > Ip70



(b) Income P/Capita

Notes: We estimate 6 separate regressions with interaction terms between our treatment and an ordinal variable for the distribution of municipalities by 1) the proportion of households within the top 30% of the national income distribution (Figure 5a and 2) average income per capita (Figure 5b). We remove from our baseline 1) all daytime outages and 2) blackouts which do not meet the treatment criteria. Each dot represents a coefficient on the primary vertical axis and the vertical lines denote 95% confidence intervals. The treatment is defined as a blackout that affected more than 37 houses, more than 0.25% of all houses and lasted for longer than 30 minutes. The dependent variable is the municipality-hour crime rate per 1m people. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level.

Table 6: Estimated Effect of Blackouts by Socioeconomic Status: Municipality-Hour Level

	Burglary:		Robbery:		Theft:	
	(1)	(2)	(3)	(4)	(5)	(6)
Prop HH > I_{p70}	Low	High	Low	High	Low	High
Blackout	0.0435*	0.0389**	0.0257	-0.0354**	0.0188	-0.0429*
[>All]	(0.0200)	(0.0133)	(0.0152)	(0.0117)	(0.0229)	(0.0191)
N	2508104	2518023	2508104	2518023	2508104	2518023
Municipality Sample	160	160	160	160	160	160
R^2	0.138	0.152	0.135	0.162	0.144	0.309
Mean DV	0.620	0.727	0.151	0.475	0.817	2.083
	(1)	(2)	(3)	(4)	(5)	(6)
Income P/Capita	Low	High	Low	High	Low	High
Blackout	0.0431*	0.0390**	0.0165	-0.0332**	0.00467	-0.0396*
[>All]	(0.0198)	(0.0133)	(0.0151)	(0.0119)	(0.0229)	(0.0190)
N	2520884	2505243	2520884	2505243	2520884	2505243
Municipality Sample	160	160	160	160	160	160
R^2	0.136	0.152	0.136	0.163	0.144	0.310
Mean DV	0.587	0.737	0.180	0.473	0.829	2.102

Notes: Table represents 12 separate regressions in which we compare the effect of a blackout on the poorest (Columns 1, 3 and 5) vs richest (Columns 2, 4 and 6) municipalities. We use 1) the proportion of top 30% households, 1st panel, and 2) average income per capita, 2nd panel, to estimate socioeconomic status. Treatments are defined as blackouts which affected more than 37 houses (40th percentile), affected more than 0.25% of all houses (40th percentile) and lasted more than 30 minutes. We remove from our baseline 1) all daytime outages and 2) blackouts which do not meet the treatment criteria. The dependent variable is the crime rate per municipality per 1m people. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level. Data collapsed at the municipality-hour level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6. Conclusion

In this paper we examine the impact of a significant environmental shock on criminal activity and investigates how the supply of offenses adjusts in response. We use high-frequency data and the unforeseen occurrence of blackouts to explore the effects of this event on crime. Despite the large disruptive environmental shock we show that the average effect of blackouts on aggregate crime is not significantly different from zero. However, we observe that this null statistical result at the aggregate crime category can be decomposed in two offsetting reactions which provide important insights for understanding criminal activity. We find that a blackout causes both an increase in burglary and a decrease in robbery. This result is consistent across several specifications, alternative treatment definitions, and it is heavily concentrated for blackouts that affect a large amount of houses. We find that changes in ambient light seem to be the main channel through which power outages alter criminal activity. We examine this issue by comparing daytime and nighttime incidents –where the disruption in terms of ambient light is noticeable in the latter– and we find significant responses on crime activity only in the latter.

Our set of results can also speak to the interaction between potential offenders and victims –or the differential ability to adapt to a shock of each crime-activity potential target, and we provide several suggestive facts on that regard. In the case of burglary, we find that most of the effect of blackouts on burglary occurs in commercial as opposed to residential places. One potential interpretation of this result is that offenders adapt to changes in the demand for crime opportunities. Blackouts may induce potential victims to stay at home, which could be anticipated by potential offenders, whereas the demand for crime opportunities is less likely to adapt in commercial locations. Similarly, in the case of robbery we observe that most of the reduction induced by blackouts took place in public places as opposed to other places such as inside commercial or residential locations. This finding is at least consistent with the idea that potential victims could adjust their behavior based on the perceived risk of victimization (e.g. adopting precautionary measures) which may subsequently affect potential offenders ability to find a profitable target.

Overall, we find suggestive evidence indicating that most of the offsetting reactions in robbery and burglary are more likely to be driven potential offenders searching for the most profitable crime opportunity on each context rather than simply substituting across crime opportunities. In favor of direct substitution across crime activities we find that (i) when we disaggregate the effect by time of day the largest drop in robberies happens contemporaneously with the largest increase in burglaries; and (ii) this opposing result is heavily concentrated among the largest blackouts. However, full substitution across crime-activities is not supported by what we observe when we examine the dynamics of blackouts and its effects on different types of municipalities. Using an event study framework we find that for burglary the effect is evenly distributed within its occurrence whereas for robbery and theft the negative effect is concentrated during the later hours. Additionally, we also show that municipality characteristics play a key role in mediating these results. Wealthier municipalities experienced both a reduction in robbery and no discernible change in burglary, whereas in low-income municipalities both robbery and burglary increased during blackouts. This latter finding also indicates that high-income municipalities are more resilient to shocks such as the ones induced by a blackout. Collectively, these results suggest that criminal behavior is strongly shaped by environmental factors.

7. References

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8. Appendix

8.1. *Alternative 2x2 Specification*

In order to address potential sources of bias, as shown by recent development in the difference-in-differences literature, we implement the following procedure in the spirit of Cengiz et al. (2019) stacked regression approach. We use a two step process which (i) restricts the pre-treatment time window so as to mechanically reduce potential sources of bias and (ii) simplifies the estimation into a 2x2 design. This approach also restricts our sample of observation to those in which units switch 'on' instead of 'on' and then 'off'. This simplifies the interpretation of our analysis. Specifically, we estimate the following.

First, we regress y on the fixed effects:

$$y_{m,h} = \alpha + f(\mu_m, \nu_{mo}, \tau_{dow}, \gamma_{hod}) + \epsilon_{m,h} \tag{8}$$

Where $y_{m,h}$ represents the crime rate and $\epsilon_{m,h}$ the error term. We include the interacted fixed effect as in our baseline specification: $\mu \times \nu \times \tau \times \gamma$. We then save the residuals and collapse the panel at the event level by restricting to an specific pre-treatment window: 24 hours or 12 hours, and averaging the residuals. In other words, we collapse the panel down to a 2x2 design which only includes 2 observations for each event i.e blackout. Therefore, we are left with units which switch 'on' and not 'off' representing a single blackout. Then, we estimate the following regression:

$$\hat{\epsilon}_{e,t} = \alpha + \beta B_{e,t} + f(\tau_{dow}, \gamma_{hod}) + \eta_{e,t} \tag{9}$$

Where $\hat{\epsilon}_{e,t}$ is the mean residual for event e at time t. As before, $B_{e,t}$ is an indicator function for the single post-treatment observation. We further include τ_{dow} and γ_{hod} fixed effects to control for hourly and weekly crime patterns. Finally, $\eta_{e,t}$ is the error term. Results for this estimation are shown in Table 7. Using this approach we estimate effects which are qualitatively similar to our main result shown in table 2. We do not detect an effect on total crime regardless of which pre-treatment window we select. When we restrict to 24 hours prior to a blackout we find a non-significant inverse relationship between burglary and robberies. When we restrict to 12 hours we can only identify the effect on burglaries. This finding is consistent with the event study result which shows that the drop in robberies is only felt on the later hours of a blackout.

Table 7: Estimated Effect of Blackouts on Crime: Collapsed Event Level Estimation

	(1) Total	(1.1) Burglary	(1.2) Robbery	(1.3) Theft	(1.4) Vehicle Theft
	24 Hours				
Blackout [>All]	0.00686	0.00916	-0.0104	0.00812	0.00492
	(0.0214)	(0.0107)	(0.00833)	(0.0165)	(0.0101)
N	47,466	47,466	47,466	47,466	47,466
Nbr. Events	23,733	23,733	23,733	23,733	23,733
	12 Hours:				
Blackout [>All]	0.0632	0.0424*	0.0221	-0.00117	-0.00466
	(0.0408)	(0.0211)	(0.0145)	(0.0316)	(0.0182)
N	55,932	55,932	55,932	55,932	55,932
Nbr. Events	27,966	27,966	27,966	27,966	27,966

Notes: Table represents 10 separate regressions, two for each type of crime, following the approach outlined by equations 8 and 9. In the 1st panel we restrict the pre-treatment window to 24 hours. In the second panel we restrict the pre-treatment window to 12 hours. Treatment is defined as blackouts which 1) affected more than 37 houses (40th percentile), 2) affected more than 0.25% of all houses (40th percentile) and 3) lasted more than 30 minutes. We remove from our baseline 1) all daytime outages and 2) blackouts which do not meet the treatment criteria. The dependent variable are the residuals from estimating equation 8. Standard errors are clustered at the event i.e blackout level. Equation 8 regressions are weighted by the population of each municipality. Data collapsed at the event level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

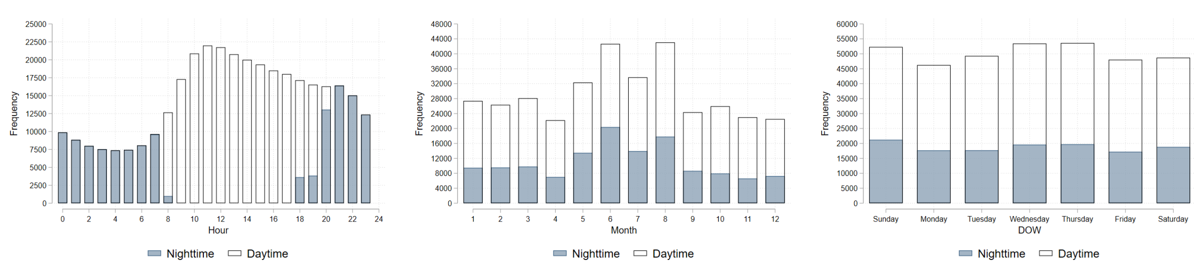
8.2. Additional Tables and Figures

Table 8: Distribution of Power Outages by Region: 2014-2015

Region Nbr.	Nbr. Municipalities	Nbr. of power outages: Original	Final	% of power outages that affected/lasted: >37 Houses	>0.25% Houses	>30 Minutes	>All
1	5	5,540	3,179	85	55	87	45
2	6	6,627	4,192	85	39	93	34
3	9	4,677	3,417	78	65	85	49
4	15	9,818	8,589	70	47	97	41
5	36	47,733	17,410	76	58	95	51
6	33	30,996	18,623	55	57	91	43
7	30	31,429	22,821	56	55	91	41
8	54	64,033	40,370	57	56	91	43
9	32	58,832	38,119	46	52	90	36
10	30	33,455	22,551	50	51	88	33
11	7	4,839	3,144	67	75	66	36
12	4	1,682	1,432	76	60	79	42
13	52	54,658	34,045	62	42	90	35
14	12	17,377	11,773	49	51	91	37
15	2	2,582	1,677	77	40	88	31
Total	327	374,278	231,342	58	52	90	39

Notes: From the original number of power outages during our study period – 374k – we remove: 1) planned and/or scheduled outages (60k), 2) sufficiently small outages i.e affected less than 3 customers (83k), 3) exact duplicates and/or outages with missing ending or starting time (0.3k). Exact duplicates may be caused by several households reporting the same event or double counting on behalf of the utility company. We are left with a final sample of 231k outages out of which 39% affected more than 37 houses, affected more than 0.25% of houses and lasted for longer than 30 minutes. To estimate the percentage of houses affected we use the total number of households per municipality according to the 2017 census.

Figure 6: Power Outages Concentration by Time of Day, Month & Day of the Week



(a) Time of Day (b) Month (c) Day of the Week

Notes: This figure illustrates the distribution of all power outages which affected more than 37 houses, more than 0.25% of all houses and lasted longer than 30 minutes. The navy bars represent nighttime blackout hours and the transparent bars represent daytime blackouts. We adjust sunrise and sunset hours for daylight savings time (DST) using regional monthly averages for 2014. During 2015 the government decided to temporarily abolish DST.

Table 9: Estimated Effect of Blackouts on Crimes: Municipality-Hour Level

	Violent Crimes:			
	(2) Aggravated Assault	(3) Simple Assault	(4) Murder	(5) Rape
Blackout	-0.00421	-0.0223**	-0.00137*	0.000169
[>37 Houses]	(0.00319)	(0.00693)	(0.000583)	(0.000988)
N	5,174,141	5,174,141	5,174,141	5,174,141
Municipality Sample	327	327	327	327
R^2	0.129	0.138	0.125	0.129
Mean DV	0.0685	0.461	0.00360	0.0128
Blackout	-0.000739	-0.0266***	-0.00155*	0.000210
[>0.25% Houses]	(0.00369)	(0.00743)	(0.000742)	(0.00127)
N	5,174,059	5,174,059	5,174,059	5,174,059
Municipality Sample	327	327	327	327
R^2	0.129	0.138	0.124	0.130
Mean DV	0.0684	0.461	0.00361	0.0128
Blackout	-0.00194	-0.0175**	-0.000687	0.000628
[>30 Minutes]	(0.00253)	(0.00654)	(0.000540)	(0.000992)
N	5,278,470	5,278,470	5,278,470	5,278,470
Municipality Sample	327	327	327	327
R^2	0.126	0.136	0.120	0.127
Mean DV	0.0689	0.460	0.00364	0.0129
Blackout	-0.00191	-0.0267***	-0.00163*	-0.000165
[>All]	(0.00392)	(0.00766)	(0.000760)	(0.00130)
N	5,145,892	5,145,892	5,145,892	5,145,892
Municipality Sample	327	327	327	327
R^2	0.130	0.139	0.125	0.130
Mean DV	0.0683	0.461	0.00361	0.0128

Notes: This table represents 16 separate regressions for each type of crime and treatment. Treatments are defined as blackouts which 1) affected more than 37 houses (40th percentile) in the first panel, 2) affected more than 0.25% of all houses (40th percentile) in the second panel and 3) lasted more than 30 minutes in the third panel. The fourth panel uses all three criteria. We remove from our baseline 1) all daytime outages and 2) blackouts which do not meet the treatment criteria defined in each panel. The dependent variable is the crime rate per municipality per 1m people. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level. Data collapsed at the municipality-hour level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 10: Coefficient Robustness to Fixed Effects: Municipality-Hour Level

	Total:				
Blackout [>All]	0.0341	0.0304	0.00891	0.000962	-0.0155
	(0.0411)	(0.0411)	(0.0386)	(0.0390)	(0.0261)
N	5146337	5146337	5146337	5146337	5145886
Municipality Sample	327	327	327	327	327
R^2	0.0917	0.0933	0.0984	0.0924	0.246
Mean DV	2.960	2.960	2.960	2.960	2.959
	Burglary:				
Blackout [>All]	0.0579***	0.0465***	0.0492***	0.0445***	0.0395***
	(0.0137)	(0.0133)	(0.0131)	(0.0131)	(0.0114)
N	5146337	5146337	5146337	5146337	5145886
Municipality Sample	327	327	327	327	327
R^2	0.0110	0.0112	0.0130	0.0112	0.145
Mean DV	0.706	0.706	0.706	0.706	0.706
	Robbery:				
Blackout [>All]	-0.0145	-0.0170	-0.0265*	-0.0245*	-0.0237*
	(0.0113)	(0.0115)	(0.0115)	(0.0116)	(0.0103)
N	5146337	5146337	5146337	5146337	5145886
Municipality Sample	327	327	327	327	327
R^2	0.0271	0.0272	0.0306	0.0277	0.160
Mean DV	0.413	0.413	0.413	0.413	0.413
	Theft:				
Blackout [>All]	-0.00920	0.000880	-0.0138	-0.0190	-0.0313
	(0.0300)	(0.0303)	(0.0288)	(0.0286)	(0.0160)
N	5146337	5146337	5146337	5146337	5145886
Municipality Sample	327	327	327	327	327
R^2	0.108	0.110	0.114	0.108	0.270
Mean DV	1.841	1.841	1.841	1.841	1.841
Fixed Effects:					
Municipality (M)	Yes	Yes	Yes	Yes	No
Month (MO)	No	Yes	No	No	No
Day of the week (DOW)	No	Yes	No	No	No
Hour of the day (HOD)	Yes	Yes	No	No	No
Interacted Fixed Effects:					
M x MO x DOW x HOD	No	No	No	No	Yes
MO x DOW x HOD	No	No	Yes	No	No
MO x HOD	No	No	No	Yes	No

Notes: Table represents 20 separate regressions for each type of crime and specification. Treatment is defined as blackouts which 1) affected more than 37 houses (40th percentile), 2) affected more than 0.25% of all houses (40th percentile) and 3) lasted more than 30 minutes. We remove from our baseline 1) all daytime outages and 2) blackouts which do not meet the treatment criteria. The dependent variable is the crime rate per municipality per 1m people. Standard errors are clustered at the municipality level. Regressions are weighted by the population of each municipality. Data collapsed at the municipality-hour level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 11: Estimated Effect of Blackouts on Crime: Municipality-Hour Level

	Property Crimes:				
	(1) Total	(1.1) Burglary	(1.2) Robbery	(1.3) Theft	(1.4) Vehicle Theft
Blackout	-0.0604	0.119***	-0.0621*	-0.117**	-0.0501
[>90th p-tile]	(0.0652)	(0.0349)	(0.0303)	(0.0392)	(0.0312)
N	4909227	4909227	4909227	4909227	4909227
Municipality Sample	320	320	320	320	320
R^2	0.251	0.149	0.164	0.275	0.210
Mean DV	2.966	0.705	0.411	1.850	0.603

Notes: Table represents 5 separate regressions for each type of crime and treatment. Treatment is defined as blackouts which 1) affected more than 585 houses (90th percentile), 2) affected more than 4.92% of all houses (90th percentile) and 3) lasted more than 30 minutes. We remove from our baseline 1) all daytime outages and 2) blackouts which do not meet the treatment criteria. The dependent variable is the crime rate per municipality per 1m people. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level. Data collapsed at the municipality-hour level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 12: Estimated Effect of Blackouts and Daytime Outages on Crime: Municipality-Hour Level

	Property Crimes:								
	Total:			Burglary:			Robbery:		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
B: Blackout [>All]	-0.0155		-0.0141	0.0395***		0.0393***	-0.0237*		-0.0236*
	(0.0261)		(0.0262)	(0.0114)		(0.0113)	(0.0103)		(0.0102)
D: Daytime Outage [>All]		-0.0217	-0.0237		0.00779	0.00739		-0.00649	-0.00693
		(0.0222)	(0.0222)		(0.00881)	(0.00885)		(0.00574)	(0.00574)
(B)=(D): p-value			0.755			0.0163			0.131
N	5145886	5234051	5366039	5145886	5234051	5366039	5145886	5234051	5366039
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.246	0.243	0.241	0.145	0.143	0.140	0.160	0.160	0.156
Mean DV	2.959	3.004	2.997	0.706	0.706	0.708	0.413	0.404	0.407

Notes: This table represents 9 separate regressions, 3 for each type of crime. The 1st row represents blackouts i.e nighttime power outages. The 2nd row represents daytime power outages. Treatment is defined as outages which affected more than 37 houses (40th percentile), affected more than 0.25% of all houses (40th percentile) and lasted more than 30 minutes. For columns 1, 4, and 7 we remove from our baseline 1) all daytime outages and 2) blackouts which do not meet the treatment criteria. For columns 2, 5, and 8 we remove from our baseline 1) all blackouts and 2) daytime outages which do not meet the treatment criteria. For columns 3, 6, and 9 we remove from our baseline 1) all daytime outages and blackouts which do not meet the treatment criteria. For columns 3, 6, and 9 we report the p-value for a test on the equality of the blackout and daytime outage coefficients. The dependent variable is the crime rate per municipality per 1m people. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level. Data collapsed at the municipality-hour level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 13: Estimated Effect of Blackouts on Crime: Monthly Totals

	Property Crimes:					Violent Crimes:			
	(1) Total	(1.1) Burglary	(1.2) Robbery	(1.3) Theft	(1.4) Vehicle Theft	(2) Aggravated Assault	(3) Simple Assault	(4) Murder	(5) Rape
Blackout [>37 Houses]	-0.00453	0.00474	-0.00552*	-0.00375	0.000268	-0.00104	-0.00316*	-0.000260	0.0000627
	(0.00834)	(0.00266)	(0.00232)	(0.00482)	(0.00281)	(0.000835)	(0.00151)	(0.000168)	(0.000265)
N	5174141	5174141	5174141	5174141	5174141	5174141	5174141	5174141	5174141
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.553	0.228	0.247	0.538	0.313	0.146	0.214	0.131	0.135
Mean DV	0.598	0.120	0.0933	0.385	0.132	0.0117	0.0782	0.000636	0.00231
Blackout [>0.25% Houses]	-0.0120	0.00491*	-0.00799*	-0.00892*	-0.00180	-0.000536	-0.00296*	-0.000220	0.000165
	(0.00721)	(0.00247)	(0.00318)	(0.00389)	(0.00305)	(0.000848)	(0.00132)	(0.000191)	(0.000280)
N	5174059	5174059	5174059	5174059	5174059	5174059	5174059	5174059	5174059
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.557	0.234	0.251	0.542	0.318	0.152	0.219	0.137	0.141
Mean DV	0.587	0.118	0.0907	0.378	0.129	0.0115	0.0768	0.000626	0.00227
Blackout [>30 Minutes]	-0.00142	0.00464	-0.00300*	-0.00306	0.00167	-0.000661	-0.00192	-0.000114	0.000175
	(0.00552)	(0.00253)	(0.00150)	(0.00363)	(0.00176)	(0.000541)	(0.00153)	(0.000141)	(0.000229)
N	5278461	5278461	5278461	5278461	5278461	5278461	5278461	5278461	5278461
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.551	0.225	0.245	0.536	0.311	0.142	0.211	0.128	0.132
Mean DV	0.597	0.120	0.0937	0.383	0.133	0.0118	0.0782	0.000644	0.00233
Blackout [>All]	-0.0130	0.00450	-0.00826*	-0.00924*	-0.00178	-0.000428	-0.00327*	-0.000219	0.0000872
	(0.00737)	(0.00263)	(0.00328)	(0.00397)	(0.00321)	(0.000929)	(0.00145)	(0.000201)	(0.000287)
N	5145886	5145886	5145886	5145886	5145886	5145886	5145886	5145886	5145886
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.557	0.234	0.252	0.542	0.318	0.152	0.219	0.138	0.141
Mean DV	0.587	0.118	0.0908	0.379	0.129	0.0115	0.0769	0.000626	0.00226

Notes: Table represents 36 separate regressions for each type of crime and treatment. Treatments are defined as blackouts which 1) affected more than 37 houses (40th percentile) in the 1st panel, 2) affected more than 0.25% of all houses (40th percentile) in the 2nd panel and 3) lasted more than 30 minutes in the 3rd panel. In the 4th panel we use all three criteria. We remove from our baseline 1) all daytime outages and 2) blackouts which do not meet the treatment criteria. The dependent variable is the total number of crimes. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level. Data collapsed at the municipality-hour level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 14: Estimated Effect of Blackouts on Crime: Linear Probability Model

	Property Crimes:					Violent Crimes:			
	(1) Total	(1.1) Burglary	(1.2) Robbery	(1.3) Theft	(1.4) Vehicle Theft	(2) Aggravated Assault	(3) Simple Assault	(4) Murder	(5) Rape
Blackout	-0.00315	0.00360	-0.00499*	-0.00283	0.000799	-0.000923	-0.00336*	-0.000257	-0.0000673
[>37 Houses]	(0.00241)	(0.00216)	(0.00193)	(0.00266)	(0.00174)	(0.000766)	(0.00139)	(0.000167)	(0.000252)
N	5174141	5174141	5174141	5174141	5174141	5174141	5174141	5174141	5174141
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.422	0.219	0.240	0.416	0.285	0.145	0.210	0.131	0.136
Mean DV	0.340	0.106	0.0816	0.240	0.109	0.0114	0.0704	0.000630	0.00224
Blackout	-0.00559*	0.00416*	-0.00691**	-0.00466**	-0.000748	-0.000595	-0.00357**	-0.000216	0.000125
[>0.25% Houses]	(0.00248)	(0.00186)	(0.00250)	(0.00178)	(0.00205)	(0.000828)	(0.00130)	(0.000191)	(0.000250)
N	5174059	5174059	5174059	5174059	5174059	5174059	5174059	5174059	5174059
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.424	0.224	0.244	0.419	0.288	0.151	0.214	0.138	0.141
Mean DV	0.335	0.104	0.0796	0.236	0.106	0.0111	0.0692	0.000619	0.00221
Blackout	-0.00230	0.00364	-0.00271*	-0.00312	0.00127	-0.000457	-0.00199	-0.000115	0.0000850
[>30 Minutes]	(0.00207)	(0.00199)	(0.00134)	(0.00235)	(0.00119)	(0.000495)	(0.00135)	(0.000141)	(0.000209)
N	5278461	5278461	5278461	5278461	5278461	5278461	5278461	5278461	5278461
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.419	0.216	0.238	0.413	0.282	0.142	0.207	0.128	0.132
Mean DV	0.340	0.106	0.0820	0.239	0.109	0.0115	0.0704	0.000638	0.00227
Blackout	-0.00673*	0.00382	-0.00703**	-0.00567**	-0.000897	-0.000483	-0.00386**	-0.000214	0.0000367
[>All]	(0.00262)	(0.00197)	(0.00256)	(0.00193)	(0.00218)	(0.000906)	(0.00144)	(0.000201)	(0.000257)
N	5145886	5145886	5145886	5145886	5145886	5145886	5145886	5145886	5145886
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.424	0.224	0.244	0.419	0.289	0.151	0.214	0.138	0.141
Mean DV	0.335	0.104	0.0797	0.236	0.106	0.0112	0.0693	0.000620	0.00221

Notes: Table represents 36 separate regressions for each type of crime and treatment. Treatments are defined as blackouts which 1) affected more than 37 houses (40th percentile) in the 1st panel, 2) affected more than 0.25% of all houses (40th percentile) in the 2nd panel and 3) lasted more than 30 minutes in the 3rd panel. In the 4th panel we use all three criteria. We remove from our baseline 1) all daytime outages and 2) blackouts which do not meet the treatment criteria. The dependent variable is a binary variable for whether a crime was perpetrated within that hour in that municipality. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level. Data collapsed at the municipality-hour level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 15: Estimated Effect of Blackouts on Crime: Inverse Hyperbolic Sine Transformation

	Property Crimes:					Violent Crimes:			
	(1) Total	(1.1) Burglary	(1.2) Robbery	(1.3) Theft	(1.4) Vehicle Theft	(2) Aggravated Assault	(3) Simple Assault	(4) Murder	(5) Rape
Blackout [>37 Houses]	-0.00334	0.01000*	-0.00866**	-0.00297	0.00308	-0.00195	-0.00760**	-0.000562	0.0000567
	(0.00664)	(0.00416)	(0.00327)	(0.00557)	(0.00385)	(0.00146)	(0.00286)	(0.000290)	(0.000460)
N	5174141	5174141	5174141	5174141	5174141	5174141	5174141	5174141	5174141
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.375	0.189	0.205	0.387	0.261	0.140	0.180	0.129	0.134
Mean DV	0.887	0.243	0.174	0.597	0.242	0.0251	0.159	0.00135	0.00478
Blackout [>0.25% Houses]	-0.0115	0.0109**	-0.0127**	-0.0106*	-0.00110	-0.00109	-0.00815**	-0.000568	0.000279
	(0.00684)	(0.00400)	(0.00445)	(0.00452)	(0.00474)	(0.00159)	(0.00271)	(0.000328)	(0.000522)
N	5174059	5174059	5174059	5174059	5174059	5174059	5174059	5174059	5174059
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.376	0.192	0.208	0.389	0.264	0.144	0.182	0.133	0.137
Mean DV	0.876	0.239	0.171	0.590	0.237	0.0247	0.157	0.00134	0.00473
Blackout [>30 Minutes]	-0.00125	0.00937*	-0.00484	-0.00357	0.00385	-0.00117	-0.00506	-0.000280	0.000287
	(0.00508)	(0.00365)	(0.00262)	(0.00454)	(0.00264)	(0.00105)	(0.00275)	(0.000249)	(0.000436)
N	5278461	5278461	5278461	5278461	5278461	5278461	5278461	5278461	5278461
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.373	0.186	0.202	0.385	0.259	0.136	0.177	0.126	0.130
Mean DV	0.885	0.243	0.175	0.595	0.242	0.0252	0.159	0.00137	0.00482
Blackout [>All]	-0.0140	0.0102*	-0.0130**	-0.0123*	-0.00136	-0.000995	-0.00857**	-0.000584	0.000114
	(0.00713)	(0.00418)	(0.00465)	(0.00481)	(0.00507)	(0.00174)	(0.00295)	(0.000343)	(0.000536)
N	5145886	5145886	5145886	5145886	5145886	5145886	5145886	5145886	5145886
Municipality Sample	327	327	327	327	327	327	327	327	327
R^2	0.376	0.192	0.208	0.389	0.264	0.144	0.183	0.134	0.138
Mean DV	0.877	0.240	0.171	0.591	0.237	0.0247	0.157	0.00134	0.00472

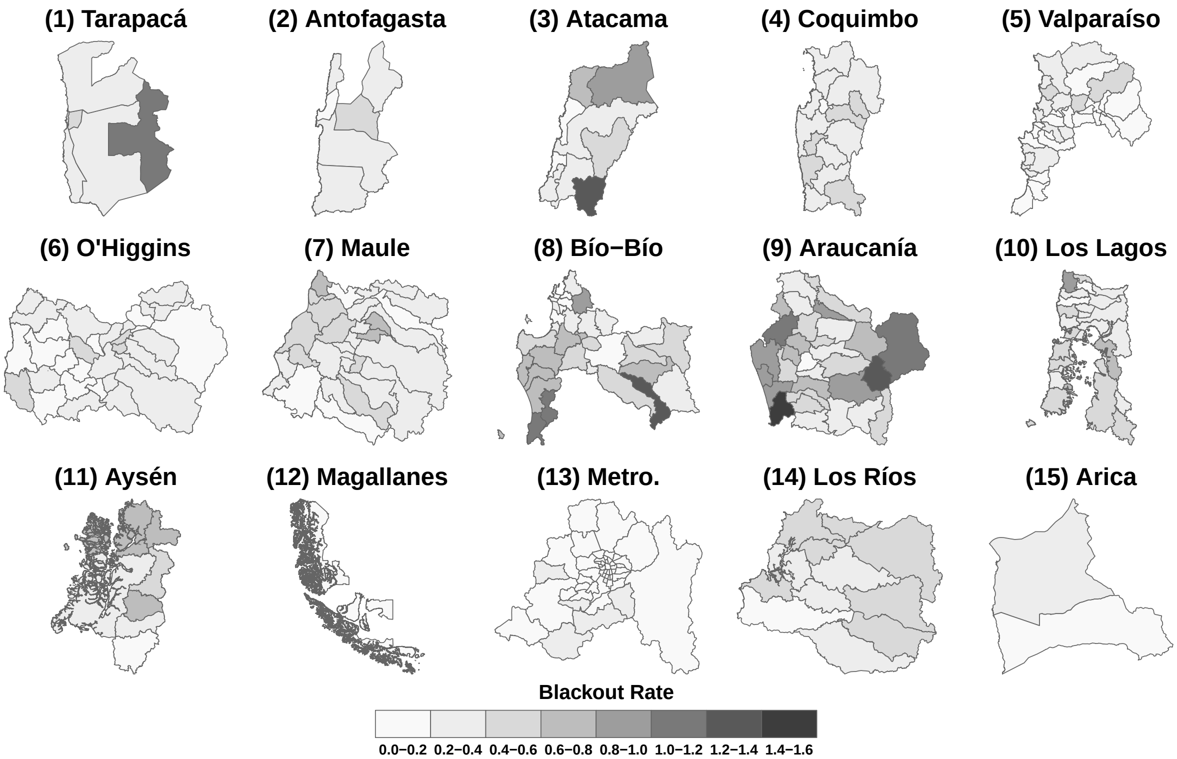
Notes: Table represents 36 separate regressions for each type of crime and treatment. Treatments are defined as blackouts which 1) affected more than 37 houses (40th percentile) in the 1st panel, 2) affected more than 0.25% of all houses (40th percentile) in the 2nd panel and 3) lasted more than 30 minutes in the 3rd panel. In the 4th panel we use all three criteria. We remove from our baseline 1) all daytime outages and 2) blackouts which do not meet the treatment criteria. The dependent variable is the inverse hyperbolic sine transformation of the crime rate per 1m people. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level. Data collapsed at the municipality-hour level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 16: Estimated Effect of Scheduled Blackouts on Crime: Municipality-Hour Level

	Property Crimes:				Violent Crimes:			
	(1) Total	(1.1) Burglary	(1.2) Robbery	(1.3) Theft	(2) Aggravated Assault	(3) Simple Assault	(4) Murder	(5) Rape
Blackout	0.0908*	0.0200	-0.00234	0.0732	-0.00487	-0.0109	-0.000946	0.00420
[>37 Houses]	(0.0460)	(0.0146)	(0.0151)	(0.0412)	(0.00575)	(0.00992)	(0.00132)	(0.00255)
N	5007709	5007709	5007709	5007709	5007709	5007709	5007709	5007709
Municipality Sample	293	293	293	293	293	293	293	293
R^2	0.242	0.134	0.152	0.265	0.120	0.128	0.117	0.119
Mean DV	3.064	0.709	0.414	1.941	0.0682	0.470	0.00359	0.0129
Blackout	0.00436	-0.0282	-0.0274	0.0600	-0.00749	0.0163	-0.000262	0.00316
[>0.25% Houses]	(0.0503)	(0.0196)	(0.0203)	(0.0444)	(0.00597)	(0.0189)	(0.00179)	(0.00370)
N	5075343	5075343	5075343	5075343	5075343	5075343	5075343	5075343
Municipality Sample	297	297	297	297	297	297	297	297
R^2	0.241	0.134	0.152	0.263	0.120	0.128	0.117	0.119
Mean DV	3.062	0.706	0.415	1.942	0.0680	0.470	0.00363	0.0130
Blackout	0.0893**	0.0181	0.00370	0.0675*	-0.00523	-0.00985	-0.00152	0.00224
[>30 Minutes]	(0.0329)	(0.0123)	(0.0123)	(0.0276)	(0.00508)	(0.00752)	(0.000929)	(0.00201)
N	5206073	5206073	5206073	5206073	5206073	5206073	5206073	5206073
Municipality Sample	303	303	303	303	303	303	303	303
R^2	0.243	0.134	0.151	0.267	0.120	0.127	0.116	0.118
Mean DV	3.095	0.716	0.417	1.962	0.0682	0.470	0.00356	0.0129
Blackout	0.0124	-0.0333	-0.0184	0.0641	-0.00397	0.0170	-0.0000352	0.00350
[>All]	(0.0493)	(0.0203)	(0.0206)	(0.0436)	(0.00643)	(0.0200)	(0.00194)	(0.00367)
N	4879041	4879041	4879041	4879041	4879041	4879041	4879041	4879041
Municipality Sample	286	286	286	286	286	286	286	286
R^2	0.243	0.134	0.152	0.265	0.121	0.128	0.118	0.119
Mean DV	3.072	0.707	0.413	1.951	0.0671	0.469	0.00351	0.0129

Notes: This table represents 32 separate regressions for each type of crime and treatment. Treatments are defined as scheduled blackouts which 1) affected more than 37 houses (40th percentile) in the first panel, 2) affected more than 0.25% of all houses (40th percentile) in the second panel and 3) lasted more than 30 minutes in the third panel. The fourth panel uses all three criteria. We remove from our baseline 1) all scheduled daytime outages and 2) scheduled blackouts which do not meet the treatment criteria defined in each panel. The dependent variable is the crime rate per municipality per 1m people. Each regression is weighted by the population of each municipality and includes: municipality-month-dow-hod fixed effects. Standard errors are clustered at the municipality level. Data collapsed at the municipality-hour level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 7: Municipal Blackout Rates by Region: 2014-2015



Notes: We estimate the blackout rate in municipality m as follows: $\frac{\sum_i \sum_m C_{i,m} * D_{i,m}}{N \sum HH_m}$ where $C_{i,m}$ represents the total number of houses affected by blackout i in municipality m, N represents the total number of hours of exposure from 2014-2015, and HH_m indicates the number of households in municipality m.