Crime During Power Outages.

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Abstract

In February of 2021, Texas experienced a winter storm that caused rolling blackouts throughout the state. We exploit the pseudo-random variation of blackouts in Austin to unravel the relationship between electrical power, light, and crime. Using hour by ZIP code level data and relying on fixed effects to absorb variation caused by cold temperatures or similar factors, we find that power outages do not impact crime and we rule out large effects in either direction. We estimate a 95% confidence interval of the elasticity of crime with respect to power outages of -0.004 to 0.002. We also explore the extent to which the "random" outages disproportionately affected poor and minority residents of Austin. We find that areas with more foreign and Hispanic residents experienced significantly more outages than other areas.

Keywords: Crime, Power Outage, Darkness, Weather

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1 Introduction

In February of 2021, a series of winter storms caused prolonged, state-wide power outages in Texas. Ostensibly rolling power outages left much of the state without power for prolonged periods of time during uncharacteristically cold weather. The winter storm and accompanying power outages even caused several deaths due to exposure and carbon monoxide poisoning. In addition to the inability to heat homes, the lack of power prevented people from lighting homes, powering streetlights, or operating home security systems. Neighborhoods were thus left completely dark and potentially vulnerable to crime. In this paper, we estimate the impact that the Austin power outages had on crime rates.

Officially, the power outages were randomly distributed throughout Austin excluding "critical" buildings like hospitals, fire stations, and water treatment plants. In practice, there have been a number of allegations that the outages, and the consequences they caused, were not random, but instead, disproportionately affected certain areas and certain groups of people. We briefly examine the question of whether these power outages were truly random and find evidence that residents were significantly more likely to experience power outages if they lived in a more populated ZIP Code, a ZIP Code with a higher percentage of foreign-born population, or a ZIP Code with higher percentage of Hispanic people. In addition to these significant differences, every demographic and socioeconomic variable we measure has a direction consistent with the claim that marginalized groups as defined by income, race, crime exposure, and age were more likely to experience power outages. This conclusion is further supported by other research (Carvallo et al., 2021), although Vallejo et al. (2021) argue that the differences can be explained by residents' willingness to pay for reliable energy.

Regardless of whether the outages in Austin were truly random, they represent a unique opportunity to explore the impact of power outages on crime. Specifically, these outages were rolled out in such a way that two similar people, living in different parts of Austin experienced very different outage patterns during the five day period in which the outages were most intense. The rolling nature of the outages implies that most residential areas were exposed to treatment at some point, but the exact timing and duration of those outages was both unpredictable and exogenous. During the five day outage event, roughly 20% of residents were "treated" with a power outage at any given time. This created an ideal natural experiment for understanding the extent to which relatively short power outages influence crime.[1]

Understanding the impacts of power outages is crucially important. This is especially true when those outages are a direct result of a severe weather event. Climate change models predict that severe weather events will become increasingly common in the coming decades, with power outages a common and often long lasting consequence. U.S. utility customers experienced an estimated 1.33 billion hours without electric power in 2020 alone, primarily due to weather related events including hurricanes, heatwaves, windstorms, and wildfires. This represented a 73% increase relative to 2019 and is part of a longer term upward trend in outages (Hering, 2021). As can be seen in Figure 1, both total and weather related power outages have steadily increased over the last 15 years.

There is also evidence that widespread power outages can lead to dramatic increases in crime. The 2023 blackouts in South Africa have been associated with "a crime pandemic" as homes' security systems fail and police mobility is limited in the absence of working traffic lights (Trenner, 2023). In the United States, local police departments and media outlets regularly warn citizens to take extra measures to protect themselves from crime during power outages (Smith-

[1]The variation in power outages by ZIP Code and hour can be visualized in Video 1 in the online appendix. The video displays a map of Austin, with Zip Codes boundaries clearly marked. In the video, each frame represents the fraction of customers without pour during a one hour. The video start at midnight on February 15 at Midnight on February 20. Darker areas on the map indicate more outages. Specifically, black indicates that at least 57% of customers in that zip code were without power during that hour, as the scale moves towards white, the subsequent ranges are 37-56% without power, 21-36% without power, 6-20% without power, and finally, **white** indicates that less that 6% of people were without power.

son, 2018; Lauren, 2022; James, 2023). Modern media articles also breathlessly recount a "crime rampage" that occurred during a severe power outage in New York in 1977 (Maxouris, 2019; Khalifeh and Rozon, 2023). Despite the narrative, there is little to no causal evidence demonstrating the link between power outages and crime. This is an important gap in the literature for a variety of reasons. Policymakers need to have an understanding of how crime patterns shift during these events in order to optimally plan and respond. Citizens need to know whether they need to prioritize crime prevention as they deal with the issues associated with an outage. Finally, police need information about whether, where, and what types crime may increase during widespread outages in order to position their officers optimally.

Of course, the details of each power outage event will be important in predicting the consequences of those outages. This reality, along with the unique nature of individual power outage events, may limit the extent to which we can predict the outcomes of future power outages using past power outages. On the other hand, the details in the outages we study, are perhaps not so unique. For example, Texas experienced another wave of rolling power outages during a similar severe winter storm in both 2022 and 2023 (Aguilar, 2022; Taylor and Diaz, 2023). In all three events, power outages were accompanied by icy roads that limited travel and business closures that can be expected to change crime patterns. Texas is not alone in experiencing this type of outage, in December of 2022 winter storm Elliott knocked out power for more than 6.3 million homes and businesses in the United States including particularly intense outages in North Carolina and Tennessee. As in Texas, these outages were accompanied by dangerous travel conditions and school and business closures (Arbaje, 2023). Said differently, our paper cannot speak clearly to the impacts of all power outages, but we can speak to outages caused by winter storms. Unfortunately, these appear to be a consistent and growing threat throughout the United States.

To examine the impact of power outages on crime in Austin during the 2021 winter storms, we obtained the hourly data on the number of households without power in each ZIP Code as well as the number of households being tracked. We combine this information with crime data from the Austin Police department, which lists the date, time, and address of every crime reported in the city of Austin. To isolate the effects of power outages from the impact of temperature, we employ a detailed set of fixed effects. In addition we control for weather using data from the National Oceanic and Atmospheric Administration. We also transform relevant variables using an inverse hyperbolic sine function to deal with the large number of zeros in our data.

We find that the power outages had no impact on crime rates in Austin, regardless of type of crime or time of day. This result is robust to a variety of specifications. Specifically, we show that our estimated impacts are consistent when aggregating to longer time periods, when using Poisson maximum likelihood, log +1, or linear estimators, when we limit the sample range of dates on either side of the outages, .

We go on to consider whether the lack of changes in crime reflect an increase in crime that is offset by changes in reporting rates. To do this, we estimate the effect of power outages on the fraction of crimes reported within one hour of the event occurring, the average time between the crime and the report, and the fraction of crimes that were successfully closed by the police department. We find suggestive evidence that the outages delayed crime reporting and reduced clearance rates although these reductions are very small in size.

In terms of policy, our results suggest that during severe weather events, optimal police officer deployment will likely involve many officers assigned to helping neighborhoods in ways not associated with crime. In the absence of increases in crime, officers can be useful in helping residents to deal with the emergency situation on the ground. In Austin, this would have included having police directing or even transferring citizens to warming centers or other buildings in which heat was available.[2]

The paper proceeds as follows. Section two provides background on the Austin power outages. Section three contains a review of the relevant literature. Section four describes the data used in the paper, including an examination of the randomness of power outages while section five details the empirical model we employ. Section six describes our results and in section seven we offer some concluding thoughts and discussion.

2 Background

Between February 15th and February 20th, 2021, the state of Texas, in the midst of a series of particularly severe winter storms, experienced state-wide electricity generation failures which lead to more than two hundred deaths in the state. Travis Country, which includes the city of Austin, experienced 28 deaths as a result of the winter storms and subsequent power outages (Livengood, 2021).[3] Unlike power outages due to a failure of a particular component, these outages were done systematically to relieve strain on the overburdened power grid. The power outages were supposed to be "rotating" and affect areas for roughly 15 to 45 minutes at a time. However, due to the enormous demand for power and a severely diminished supply, for many the power outages ended up not rotating, leaving some without power for periods exceeding twenty-four hours (Autullo, 2021).[4]

Austin Energy General Manager Jaqueline Sargent has stated that the areas chosen

[2] In anticipating the cold weather and subsequent outages, the city of Austin and other groups opened warming centers throughout the city. There were 22 warming centers scattered across Austin although most residents were discouraged from seeking them out. The city stated that the warming centers were "meant for vulnerable people, such as those with medical devices that rely on power" (Egan, 2021).

[3] While some of these deaths were the result of exposure, many were the result of carbon monoxide poisoning as people lit fires in there home or ran vehicles in their garages in an effort to keep warm.

[4] The supply side issues were caused by a number of factors. The largest was the freezing of a number of gas wellheads and pipelines which prevented natural gas power plants from operating.

for these rotating power outages were random but excluded critical infrastructure such as hospitals, fire stations, and water treatment facilities (Autullo, 2021). **Some consumers in Austin have claimed, however, that the outages disproportionately affected poor and minority neighborhoods while wealthier, whiter areas and downtown Austin largely retained power throughout the event.** Pictures were posted showing downtown Austin completely lit up while East Austin, an historically Black and Hispanic part of town, is completely without power (O'Donnell, 2021). **A report published by Austin's Winter Storm Review Task Force highlighted the inequity in power outages as a weak point in the city's response to the crisis.** One task force member, Jeffrey Clemmons, noted "there's a need to improve the equity in terms of our distribution of power in the city of Austin, since there were some communities that lost power for much longer than others. And the reasons for that likely go back to our equity in terms of infrastructure" (Charpentier, 2021). Figure 2 provides further anecdotal evidence of this claim. Panel A displays the majority race in each neighborhood in Austin. There is a clear divide along Interstate 35, with mostly majority white neighborhoods west of I-35 and mostly majority Hispanic and Black neighborhoods east of I-35. Panel B shows a photograph taken by local news station KVUE on February 16, the height of the outages, looking South above I-35. As in the race map, there is a clear disparity on either side of I-35 with the minority neighborhood in the east dark while the downtown area clearly has power.

Despite these challenges, the Austin power outages represent a unique opportunity to understand the impacts of power outages on crime. Typically, power outages effect either a few households or a large area. In this case, many people lost power at some point, but the pseudo random variation in both the timing of outages and affected areas created an opportunity to understand the ways in which crime is influenced by power outages. Specifically, because every ZIP Code in Austin had periods of outages interspersed with periods without outages during the five day storm event, we are able to include a robust set of fixed effects that isolate the variation caused by the power outages while controlling for potentially confounding factors such as weather and ZIP Code characteristics.

3 Literature review

There is very limited evidence in the literature on the impact of power outages on crime. To the best of our knowledge, the closest anyone has come to directly estimating the impact of power outages on crime is Amin (2009), **which examines data on 6,000 manufacturing firms in Latin America. While not the main focus of the paper,** a secondary result of Amin (2009) is that firms which experience a power outage are significantly more likely to experience an incident of crime, though this result is not robust to all specifications **and the author points out that power outages may be capturing other factors including the development level of neighborhoods which is an important predictor of crime**. Reaching a bit further, Chalfin et al. (2020) estimates the effect of street lights outages on crime. **Using nearly 300,000 unexpected streetlight outages as a natural experiment,** the authors find little evidence that street light outages impact crime at the location of the outage. **While streetlight outages can reasonably be expected to have different effects that power outages as a whole, Chalfin et al. (2020) does suggest that darkness alone, at least in outdoor settings, is not sufficient to cause large increases in crime, particularly when that darkness was unexpected.** In the absence of clear evidence on the relationship between power outages and crime, we turn to three related bodies of literature: street lighting and crime, darkness and crime, and weather and crime.

Research studying the impact of street lighting on crime dates back to at least 1974, when Wright et al. (1974) **used the upgrading of street lighting from incandescent to mercury and sodium-vapor lighting in Kansas City, Missouri, to show that** street lighting reduced crime. Painter (1996) **used before and after surveys to access the impacts of upgrading street lighting,** finding that streetlights reduce crime and disorder, though "most of the reductions reported relate more to threatening and disorderly incidents than to crime." Other papers finding that streetlights reduce crime include Painter and Farrington (1999), **which used victimization surveys to access the impact of improved lighting** and Welsh and Farrington (2008), **which finds that improved lighting decreases both nighttime and daytime crime, which may indicate that street lighting reduces crime through a sense of community pride rather than through any observation deterrence. The role of community pride is particularly important in our context. During the winter storms, proud Austinites may have chosen to pull together while taking care of and watching out for each other. All else equal, we would expect this type of behavior to reduce crime during storm generally and perhaps during outages in particular. On the other hand, studies looking for a link between street lighting and crime have often been at best inconclusive. For example, Atkins et al. (1991), using lighting data from two years in London, find no conclusive evidence that street lights impact reported crimes. Farrington and Welsh (2002) reviewed studies on street lighting and crime, and ultimately concluded that street lights reduce crime; however, the authors note that half of the American studies used in the paper concluded that street lights had no crime-reducing effect. Further, Marchant (2004), find that the crime-reducing conclusion of Farrington and Welsh (2002) is unfounded.**

More recently, Chalfin et al. (2021), randomly allocated 40 temporary street lights in New York City and found that street lights reduce nighttime crime. They also find a significant reduction in arrests, which may indicate that street lights reduce crime through deterrence. This deterrence effect of streetlights is particularly important when considering the impact of power outages during winter storms. The direct impact, less light during the outages, would be expected to cause an increase in crime. On the other hand, the limited mobility of the police during and immediately after the storm, if widely known or predicted,

may have undermined the deterrence effect of street lights as well as other types of lighting and security systems. In that case, we would expect to find that power outages did not significantly impact crime as most of the benefits of the lighting and security systems still operating had already been rendered moot by the inability of police to respond to any crimes that occurred. A related body of literature studies the effect of ambient light on crime, using daylight savings time as an exogenous shock to daylight. Both Doleac and Sanders (2015) and Domínguez and Asahi (2019) **exploit exogenous variation in daylight caused by switching to daylight savings,** and find that extra daylight results in a reduction in crime.

Because our paper specifically examines power outages that occurred during a massive winter storm in Texas, it is important that we also note the extensive literature relating weather to crime. Cohn (1990) serves as an effective literature review of the link between weather and crime prior to the 1990s. **The paper argues for a U-shaped temperature crime curve with individuals exposed to very cold weather exhibiting increased aggression when angry.** Field (1992) finds that increased temperatures increase crime in England and Wales, though rainfall and sunshine appear to have no impact on crime. **The author concludes that increased temperatures increase crime because more people are out in public, which leads to more victimization.** Horrocks and Menclova (2011) similarly find that increased temperatures increase violent and property crimes in New Zealand while precipitation reduces violent crimes.[5] **Together, these papers lead us to believe that the winter storms likely drove people indoors where they had relatively little interaction with people outside of their immediate families. This should be expected to reduce crime overall although if the cold temperatures**

[5]Ranson (2014) finds a strong relationship between temperature and crime in the U.S., which the author uses to calculate the impact of climate change on crime. Baysan et al. (2019) go beyond the direct relationship between temperature and crime and study how psychological and physiological factors interact with temperature to cause violence.

are increasing aggression, domestic crimes may reasonably be expected to increase. Of course, careful temperature and precipitation controls, along with the assumption that the weather was similar throughout Austin at any given time should allow us to estimate the impact of power outages during winter weather without our estimates suffering from weather related biases.

Collectively, these three bodies of literature have a few important implications for our analysis. **First, the winter weather should be expected to cause crime to fall everywhere in Austin, regardless of whether a power outage occurs, primarily because individuals will stay indoors. On the other hand, if cold temperatures cause increased aggression, we may see increases in crime, especially domestic crimes.** Second, if the only implication of power outages was a decrease in light, we would expect outages to increase crime overall. In practice, however, power outages have implications other than darkness that likely reduce crime. For example, if people are more likely to stay home during power outages **or tend to rally together in the face of a difficult situation**, this may cause crime to fall. Finally, it is important to keep in minds that even in the absence of real changes in crime, crime reporting may change as people are either unable to report crimes or too busy dealing with the difficult circumstances imposed by the weather and outages.

4 Data

To estimate the effect of the Austin Power Outages on the city's crime rate, we construct a ZIP-Code-by-hour panel dataset that consists of crime, weather, demographic, and power outage data. **We also explore potential mechanisms using policing and traffic data.**

Our crime data consists of hourly records for 38 ZIP-Codes between January 1, 2020 and March 31, 2021. The data include every crime reported by or to Austin Police during this period and are available through the Austin Crime

Reports database.[6,7]

Weather controls come from four weather stations stations distributed throughout Austin. The data from each station were combined to create a weighted average for each zip code, based on the distance between the center of that zip code and each station. The power outage data includes hourly counts of the total number of power customers and the number of customers without power for each of Austin's 38 unique ZIP Codes. The power outage data were purchased from Bluefire Studios, LLC.[8]

In addition to studying the relationship between power outages and crime, we examined national trends on the frequency of power outage incidents, investigated the demographics of the communities hit hardest by the Austin Power Outages, and explored potential mechanisms behind a power outage-crime relationship. Data on the frequency of power outages is taken from all power outages reported to the Department of Energy. Using these records, we estimate the total number of power outages, as well as the number of weather-induced power outages, that arise every year from 2003 to 2022.

To assess claims that the Austin power outages disparately impacted marginalized groups,

[6]**Complete details for all data sources can be found in the data appendix.**

[7]There are 38 ZIP Codes in which a majority of the land area falls within Austin city limits and the jurisdiction of the Austin Police Department. Throughout our analysis, we include 36 of these ZIP Codes. We exclude ZIP Code 78712, which is entirely comprised of the University of Texas at Austin, and ZIP Code 78719, which encompasses Austin's international airport. Neither of these ZIP Codes had demographic information available. **Our crime results are all robust to their inclusion in regressions without demographic controls.**

[8]We attempted to use NASA satellite data to further verify our power outage data and to evaluate the impact of darkness on crime directly. Unfortunately, the data are measured at most once per day and, due to cloud cover, snow, and other factors, are unreliable during the key period of our analysis (February 15, 2021 to February 20, 2021)

we use the 2017 American Community Survey to compile demographic information for each of the 36 ZIP Codes in our sample. These profiles described the racial, economic and social conditions for each ZIP-Code. **We supplemented the demographic data with information on the location of critical infrastructure (water centers, police stations, fire stations and hospitals), warming centers, and electricity dependent medicare beneficiaries.**

We also consider the potential for crime spillovers. To do this, we utilize traffic data compiled by optical traffic detectors in Austin. These traffic detectors record the number of vehicles passing **each sensor**. Finally, we examine whether policing behavior changed during the power outages. For this, we utilize data from the official records of the Austin Police Department. These records, spanning the month of February, 2021, include information on the number of calls for service received by the police, as well as police response times. The data **include** the urgency of the call and were provided after a direct request to the Austin Police Department. **Unfortunately, the data do not include any information about the location of the call for service.**

4.1 Baseline Characteristics

Next we establish the crime and outage patterns during the winter storms. Panel A of Figure 3 shows the number of households without power per 100,000 people in each hour between February 13th and February 23rd. Widespread power outages in Austin were first reported on February 15th and had largely stopped by February 20th. In Panel B, we plot the number of crimes per hour occurring in Austin during this same period after demeaning the data to account for the wide variation in the average number of crimes committed during each hour of the day. Panel B indicates that **reported** crime fell by about 5 crimes per hour during the outages although this result is likely driven at least partially by the extremely low temperatures experienced in Austin during this period. In Panel C, we plot the number of crimes per month. Here, we see a large reduction in the number of crimes during February

2021, with more than 1,000 fewer crimes reported in in that month than in any other month.

The data also allow us to examine whether the outages were truly random or if they were instead targeted at particular areas. Given the demographic segregation that exists in Austin, such a pattern would likely disproportionately effect some groups of people while affecting other groups less. To more deeply explore the extent to which racial and socioeconomic **factors are correlated with outages**, in Table 1 we present summary statistics among the ZIP Codes that were most and least affected by the outages. Column 1 shows the summary statistics of ZIP Codes where less than 17.5% of households experienced power outages. Column 2 shows summary statistics for ZIP Codes with at least 17.5% of households experiencing power outages.[9] **Column 3 of Table 1 reports the results of a series of simple regressions. In each row, we estimate a unique regression with the row variable as the dependent variable and an indicator for whether the outage level is above or below 17.5% as the only independent variable. Using this method, every coefficient returns the difference between columns 1 and 2 and the standard error can be used to determine whether the difference is statistically significant.**

As described above, Austin Energy explicitly kept power on to critical infrastructure buildings like hospitals, fire stations, and water treatment plants. Before considering discrimination, then, we must first establish the locations of these important buildings. If, for example, critical buildings are overwhelmingly located in rich, white areas, these areas may be expected to experience fewer outages on average even in the absence of discrimination. Instead, as can be seen in the first row of Table 1, we find that households in ZIP Codes with more critical buildings did not experience fewer power outages. In fact, the point estimate actually suggests that these ZIP Codes experienced more power outages on average. While this may seem surprising, note that power companies have the ability to turn off power in highly localized areas, especially relative to the size of a ZIP Code. In any case, this re-

[9] **The value of 17.5% was chosen to ensure that an equal number of ZIP Codes fell into each group.**

sult is a clear signal that any differences we observe in the types of individuals more likely to experience outages can not be explained away by the existence of critical infrastructure buildings in that area.[10] A similar result holds true for the presence of warming centers in a ZIP Code.

Turning now to the demographic variables in Table 1, we note that **the sign on every difference in Table 1 suggests that marginalized groups experienced more extensive power outages. ZIP-Codes which had a higher percentage of foreign-born population, had a higher percentage of Hispanic population, had a higher percentage of people below the poverty line, and which had higher population density all were more likely to experience power outages. Meanwhile, ZIP-Codes which had a higher percentage of White population, which had a higher percentage of people over the age of 65, and which had a higher median household income all were less likely to experience a power outage. Importantly, however, only the total population, percentage foreign born, and percentage Hispanic are statistically significant and two of these are only significant at a 90% confidence level. On the other hand, the demographic variables are collectively significant in explaining power outages as can be seen by the significant F-statistic value of 3.32. Even if we restrict the set of variables to those most likely to be associated with marginalized groups (crime rate per 100,000, percent foreign born, percent Hispanic, and percent below the poverty line), we still estimate an F-statistic of 2.96.** [11]

[10]**It is possible that many critical buildings have their own backup power generation systems in case of power failure. As long as these systems are not providing power to households beyond the critical building itself, this should not influence our estimates.**

[11]The F-statistic reported in Table 1 is estimated using the fraction of households without power as the dependent variable and all of the indicated demographic variables as the independent variables. Standard errors throughout Table 1 are robust to heteroskedasticity.

5 Empirical Model

If outages were truly random, a simple OLS regression should return causal estimates of the impact of power outages on crime after controlling for temperature and date. However, as demonstrated in the previous section, there is significant evidence that outages were not truly random, with some communities experiencing more widespread and longer lasting outages than others. To overcome this challenge, we use a comprehensive set of fixed effects in order to isolate only the variation that can be considered plausibly exogenous. Specifically, our preferred model includes two sets of fixed effects: date fixed effects and ZIP-Code-by-day-of-the-week-by-time-of-day fixed effects. If, for example, certain areas tend to have higher crime rates and happened to experience more power outages, the ZIP-Code fixed effect will net that out. Even if the power outages happened to occur primarily in high crime areas during the times and days in which those areas experience the highest or lowest crime rates, the ZIP-Code-by-day-of-the-week-by-time-of-day fixed effects will absorb that effect. Finally, the date fixed effect acts as an important control for temperature. Specifically, we estimate:

$$Crime_{zdt} = \beta Outage_{zdt} + X'_{dt}\Gamma + \delta_{zwt} + \delta_d + \epsilon_{zdt}, \tag{1}$$

where $Crime_{zdt}$ is the crime rate per 100,000 people in ZIP-Code z on day d in hour t and $Outage_{zdt}$ measures the number of outages per 100,000 households. Both $Crime_{zdt}$ and $Outage_{zdt}$ are transformed using an inverse hyperbolic sine transformation. We do this because both variables include a high number of zero observations and both have a rightward skew. Inverse hyperbolic sine transformations have been shown to appropriately deal with these issues (Burbidge et al., 1988; MacKinnon and Magee, 1990; Pence, 2006). Moreover, because both the dependent and independent variables are undergoing the transformation, the resulting coefficient estimates are directly interpretable as elasticities for large values of x and y (Bellemare and Wichman, 2020).

X'_{dt} is a vector of weather controls which includes the existence of snow on the ground, temperature, temperature squared, amount of precipitation, humidity, and wind speed. In δ_{zwt} we include ZIP-Code-by-day-of-the-week-by-hour fixed effects while δ_d represents the date fixed effect. If losing power decreases crime, $\hat{\beta}$ will be negative in Equation 1. In all specifications, we report robust standard-error estimates, allowing for clustering within ZIP-Code-by-day-of-the-week-by-hour, zwt.

6 Results

Our results are presented in Table 2. In Column 1, we present the simplest possible specification, explaining crime with only power outages and weather controls. In subsequent columns, we add fixed effects to isolate the variation which we believe offers causal identification. Specifically, in Column 2, we add date fixed effects. In Column 3, we also include an hour-of-the-day fixed effect. Column 4 adds a ZIP Code fixed effect, while Column 5 interacts this ZIP Code fixed effect with the time fixed effect to create a ZIP-Code-by-hour fixed effect in addition to the date fixed effect. Finally, Column 6 shows the results for our preferred specification, which includes both the date fixed effect as well as a ZIP-Code-by-hour-by-day-of-the-week fixed effect.[12]

When no ZIP Code fixed effects are included, we find a statistically significant positive correlation between power outages and crime: a 10% increase in outages leads to a 0.13% to 0.22% increase in crime. However, for all specification in Table 2 which include ZIP Code controls (Columns 4-6), we find no statistically significant impact of power outages on crime.

[12] **There may be significant correlation among unobservable variables across ZIP-Codes that are not fully accounted for when clustering at the ZIP-Code-by-hour-by-day-of-the-week level. As a robustness test, in Table A1 we replicate Table 2 but allow for clustering at the ZIP-Code level. Because there are only 36 Zip-Codes in our data, we calculate the standard errors using the wild cluster bootstrap technique (Cameron et al., 2008). We find that the estimated standard errors are nearly identical using this method.**

In our preferred specification, Column 6, the point estimates suggest that a 10% increase in power outages causes crime to fall by 0.01% with a 95% confidence interval that ranges from -0.04% to 0.02%.

6.1 Heterogeneity

While our results show that power outages had no impact on crime rates overall, there may still be important effects among certain types of crime. For example, we might expect that the outages would cause people to be at home, reducing opportunities for property crime. **On the other hand, individuals stuck at home, particularly in a stressful situation, may lead to an increase in domestic violence (Leslie and Wilson, 2020).**

In Table 3, we replicate our estimates for the total change in crime before breaking that into more specific categories. Our results show that power outages have no economically significant impact on property crime, public order crime, violent crime. **We also find no impact of power outages on domestic violence, a subset of violent crime that one might reasonably expect to be more responsive to power outages than other types of violent crime. Fears of crime increases during power outage typically focus on increases in property crime. We find no evidence that power outages have an economically significant impact on property or any other type of crime.**[13]

An additional source of heterogeneity in the impact of power outages on crime could be the time of day that the outage occurs. It may be the case that power outages during daylight have different effects than power outages at night. This would be consistent with the literature on the role of darkness in causing crime (Doleac and Sanders, 2015). In

[13]**The null finding here may be masking variation across the city. For example, it could be the case that property crime increases in residential areas during outages, but falls in other parts of the Zip-Code. To address this concern, in Table A2 we separately consider total and property crimes in residential and non-residential areas. We find no evidence that crime changes in either residential or non-residential areas.**

Table 4, we explore this by estimating our preferred regression after separating the data between daytime and nighttime. The first two columns of Table 4 report the results for all crime. Our results show no impact of power outages on crime during either day or night night. **Moreover, we test whether the coefficient estimates on day and night are statistically distinguishable for each type of crime. As can be seen from the F-stat values at the bottom of the table, we find no evidence of differences between day and night.** Importantly, however, because the nights with the highest power outages also had snow, clear skies, and a **quarter moon**, it is possible that the streets were not all that dark, even in the absence of streetlights.

The remaining columns of Table 4 report the daytime/nighttime heterogeneity by crime type. **Using a 95% confidence level, none of the four crime types we consider are impacted by power outages in statistically significant way during either the day or the night. Moreover, the point estimates remain small with relatively precise standard errors. For example, the 95% confidence interval suggests that a 10% increase in power outages will cause property crime to increase by, at most, 0.05%.**[14]

6.2 Robustness

Unlike other non-linear estimators, Aihounton and Henningsen (2021) shows that the use of the inverse hyperbolic sign transformation is sensitive the scale chosen for the transformed

[14]**We also considered the possibility of criminal learning during the outages. That is, it's possible that, over time, individuals on the margin of committing crimes figured out how to take advantage of the outages and the changed police presence. This could cause crime to stay stagnant or even fall at the beginning of the outages, but increase over time. To test this theory, we replicate our base results (Table 2) but include a term that interacts the outages with a dummy variable equal to one if the date is on or after February 17, 2021. The results are presented in Table A3 in the Results Appendix. We find no evidence of learning over time.**

variables.[15] Specifically, larger values improve the stability of elasticity estimates in inverse hyperbolic sine models. Because we are using ratios, it is easy to scale our variables to essentially any value. To demonstrate robustness to this scaling, results using a variety of scaling of both $Crime_{zdt}$ and $Outage_{zdt}$ can be found in Figure 4. As expected, the results and 95% confidence interval stabilize for larger scaling factors of outages and crimes. Though the confidence interval does widen slightly with higher scaling, even when scaling our variables to be reported in terms of crimes (outages) per $1e^{24}$ people, the confidence interval is still quite narrow and ranges from -0.013 to 0.014 for total crimes.

Panels B through D of Figure 4 indicate the impact of scaling choice on our coefficient estimates by crime type. **In general, this exercise indicates that our results are not sensitive to scaling. The one possible exception is property crime. As property crime stabilizes, it results in a statistically significant positive coefficient; however, the magnitude of the coefficient estimate is still quite small. Even using a log scaling factor of 40, the coefficient estimate of property crimes suggests that a 10% increase in power outages would cause just a 0.05% increase in property crimes.** As such, all scaling factors lead to the same conclusion: power outages have no economically significant impact on crime

As described in section four, the above estimates include dates between January 1, 2020 and March 31, 2021. In Panel A of Figure 5 we present the results of our preferred specification with every possible range of dates, down to a minimum of ten days on either side of the power outage event. For most bandwidths, we find no evidence that the power outages significantly influenced crime rates overall or for any particular crime type. Moreover, the estimated effect of the outages is relatively stable over time, particularly among bandwidths

[15] **For a complete characterization of the scale sensitivity of transformation in linear regression models, see Thakral and Tô (2023).**

that include at least one month.[16,17]

Another potential confounding factor when estimating the impact of power outages on crime is the duration of the outage. While the official policy was that power outages were supposed to last 45 minutes before rotating elsewhere, some citizens of Austin experienced outages that lasted several hours. Table 5 reports the results on crime of outages lasting two, four, six, and twelve hours. The results are reported for all crimes as well as public crimes, property crimes, and violent crimes. Once again, we find no statistically or economically significant impacts of power outages on crime.

As a final robustness check, we explore alternatives to the OLS model with IHS transformations on both the dependent and independent variables. Specifically, we explore using a log + 1 transformation, a model that focuses only on the extensive margin of outages, a linear regression model, and a Poisson pseudo-maximum likelihood estimator. Table 6 reports the results for each of these specifications. As has been the case throughout this paper, we find no evidence that power outages impact crime rates. Unsurprisingly, the IHS model, which is able to leverage both the extensive and intensive margins, while incorporating the prepoderance of observations in which no crimes were committed is much more precise than

[16]Because our data end on March 31, 2021, bandwidths greater than 40 days are imbalanced with more observations before the power outage event than after it. In addition, each subsequent day after the forty day bandwidth is adding only half as many observations to the sample.

[17]**Some readers may be concerned about the significant negative effects that we find when restricting our sample to observations right around the outage event. These effects are largely an artifact of our inability to properly estimate the Zip-Code-by-hour-by-day-of-the-week fixed effects when we significantly restrict the number of days included on each side of the outages. In Appendix Table A4, we estimate the effect of outages on crime rates as well as on specific crime types while include Zip-Code, Hour, and Date Fixed effects. We also bootstrap standard errors and allow for clustering by Zip-Code. As in our primary results, we find that the outages did not impact either crime overall or any specific type of crime.**

the linear OLS models.

Collectively, these results indicate that power outages do not cause large changes in overall crime rates. The lack of an increase in crime may be surprising, given the darkness and lack of reliable security systems during outages. On the other hand, one might have also expected decrease in crime, given that many Austinites likely just hunkered down and tried to survive the storm. In fact, these two conflicting priors may have offset each other nearly perfectly. Alternatively, it may be the the case that crime is simply not responsive to relatively brief power outages.

6.3 Mechanisms

One possible explanation why we do not find impacts from the power outages is that people systematically left areas experiencing outages and went to places that had power. Recall, outages were not long lasting but were also relatively localized making staying in powered areas a possibility if one was willing to travel often. On the other hand, Figure 6 demonstrates that the storms associated with the outages dramatically reduced car travel. This reduces the likelihood of large scale migration causing problems for our estimates.

A related possibility is that the warming centers drew in large groups of people and became susceptible to crime during outages. Recall, we find no evidence that power outages were less prevalent in areas with warming centers and warming centers were not explicitly protected from rolling blackouts (though many had generators). We explore this possibility in Table 7 which breaks out our results by ZIP-Codes with and without warming centers. We find a small increase in crime in areas with warming centers and small decreases in other areas but we hesitate to make too much of this result for a number of reasons. First, warming centers were not randomly distributed throughout Austin. Second, we have no temporal variation in warming centers. Finally, the number of people who actually used a warming center was sufficiently small that it is unlikely they could have caused a significant increase in observed crimes. Foy (2022) reported that the warming centers collectively had space for just 330 people during the storms.

Another possible explanation for our results is that crime increased during the outages, but crime reporting fell such that we are unable to observe increases in reported crime. To further explore this possibility, in Table 8, we estimate the impact of the outages on three reporting related outcomes. Specifically, in Column 1 we estimate the impact of outages on the number of days it took to report a crime. Similarly, in Column 2 we estimate the impact of outages on the fraction of all crimes that were reported within one hour. Column 3 looks at implications of delayed reporting and the challenging policing conditions during the outages by estimating the impact of the outages on the fraction of reported crimes that were eventually closed. Throughout this table, we limit our analysis to ZIP Code hours in which at least one crime was reported. Given this data restriction, we modify our primary specification slightly to include only ZIP-Code-by-hour fixed effects rather than ZIP-Code-by-hour-by-day-of-the-week fixed effects as presented elsewhere in the paper. In addition, because **our** outcome variables are not right skewed, we do not employ the inverse hyperbolic sine transformation and report the fraction of all household in the ZIP Code without power as the primary explanatory variable.

Unfortunately, our estimates are quite noisy and none of the outcomes measured in Table 8 are significantly impacted by outages. That being said, the point estimates are consistent with outages slowing down reporting and reducing clearance rates and the magnitudes, particularly on days to report, are large. Though we are unable to speak directly to the number of crimes that go unreported, the extra time between the crime being committed and reported on average is consistent with people continuing to report crimes at a similar rate, but waiting until the outages have passed.[18]

[18] An alternative explanation for the reduced clearance rates is that the crimes being committed changed in ways that we do not pick up with our broad crime categories. For example Goldstein (2022) documents that burglaries that included a forced entry generated more thorough police investigations and had higher clearance rates.

One additional aspect that may have influenced reporting rates is the ability of police officers to respond to calls in a timely manner. In Figures 7 and 8 we plot police behavior for total and urgent calls for service respectively. In each figure, Panel A shows the total number of calls, Panel B shows the number of calls reported by citizens, Panel C shows the number of calls reported by officers, Panel D shows the difference between officer and citizen calls, and Panel E shows the average response time among calls for service. A key takeaway from these figures is that the winter storm and power outages significantly increased both the total calls for service and police response times during this period. Moreover, there is some evidence that, relative to the number of officer reports, citizens were less likely to place non-urgent calls for service but more likely to place urgent calls for service during the storm.

7 Conclusion

In this paper we leverage the February 2021 winter storm in Texas, and the subsequent power outages it caused, to estimate the causal effect of power outages on crime. We first examine the claim the that power outages were randomly distributed throughout Austin. Our data suggests that the outages disproportionately affected already marginalized populations. Specifically, we find evidence that individuals were more likely to experience a power outage if they lived in a ZIP Code with a higher percentage of foreign-born population, a higher percentage of Hispanic population, or a higher total population.

After carefully controlling for the impact of the winter storm itself and for the potential non-random assignment of outages across ZIP Codes, our results suggest that power outages do not affect crime rates. We demonstrate that this result is quite robust across a number of dimensions, include type of crime, time of day, and duration of the power outage.

Climate models predict that the number and intensity of winter storms will continue to increase going forward. The existing literature offers surprisingly little evidence on the relationship between power outages and crime, especially power outages caused by severe weather events. Our results offer an important first step in understanding the ways in which cities and police forces should prepare for and respond to widespread power outages. Specifically, we find that fears of dramatic increases in violent and property crimes during outages are overstated. Similarly, while many might expect that crime would fall dramatically as everyone simply stays home, our results suggest that crime should be expected to continue during this difficult period although the nature of the crimes committed is likely to change.

Given the scarcity of research in this literature, there is an abundance of room for future projects in this area. Of particular interest would be studies that can speak to the impact of power outages in cases where temperatures were not dangerously low and travel was relatively unrestricted. If the number of power outages continues to increase at a dramatic pace, opportunities for this type of research will likely present themselves in the near future.

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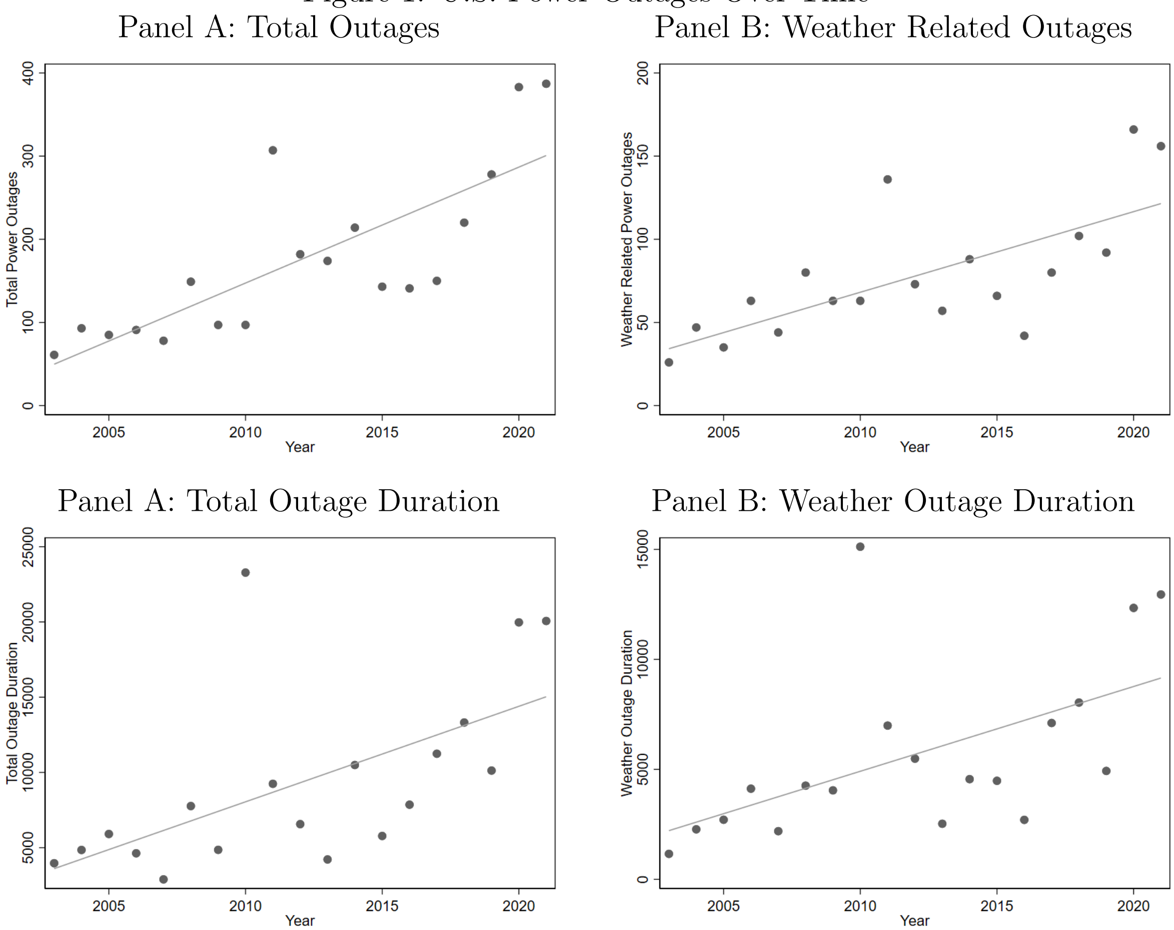
8 Tables and Figures

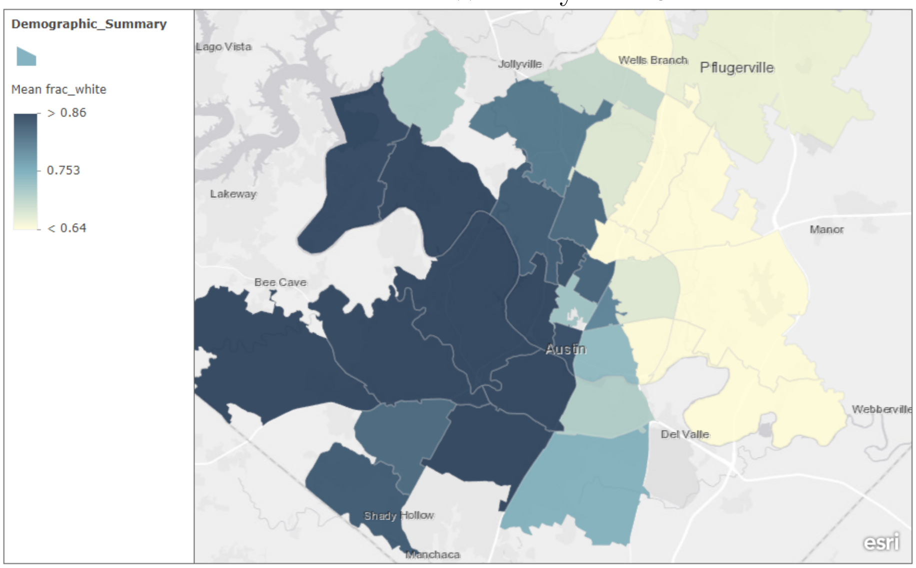
Figure 1: U.S. Power Outages Over Time



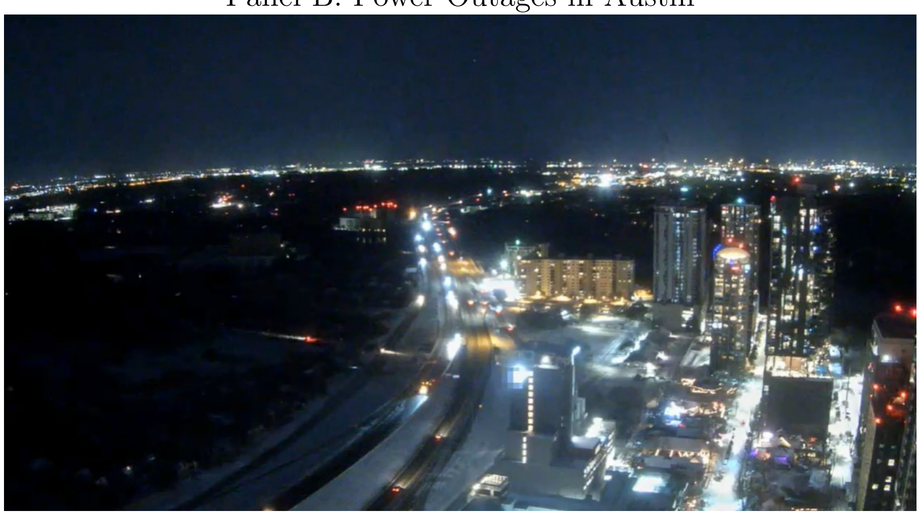
Notes: Panel A shows the number of Power Outages experienced in the US each year over time. Panel B shows the number of power outages due to weather. Panel C shows the total duration of power outages in hours and Panel D shows the total duration of weather related power outages in hours. Note that this data does not include information about the number of people affected by each outage. As such, the hourly outage data does not reflect the number of people affected by these outages. Data for all four panels come from Department of Energy's Electric Disturbance Events Annual summaries (OE-417)

Figure 2: Race and Outages in Austin

Panel A: Fraction White by ZIP Code



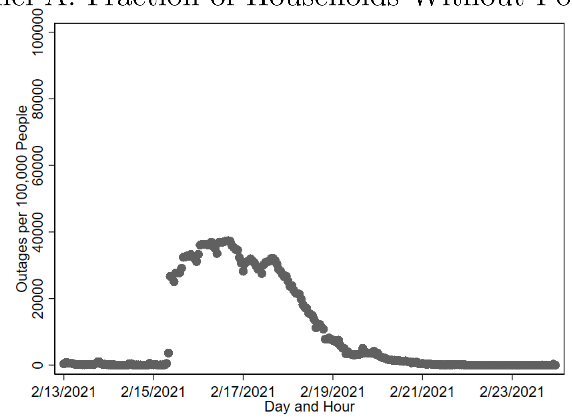
Panel B: Power Outages in Austin



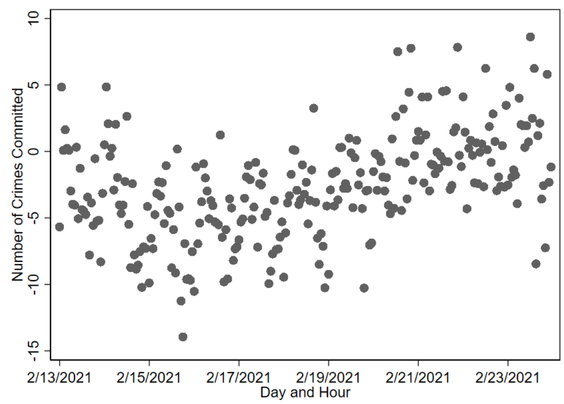
Notes: In Panel B, picture is taken looking South along Interstate 35. As such the left hand side of the picture roughly corresponds to the right hand side of the Figure in Panel A. The photograph in Panel B was taken and shared by local news station KVUE on February 16.

Figure 3: Power Outages and Crime Over Time

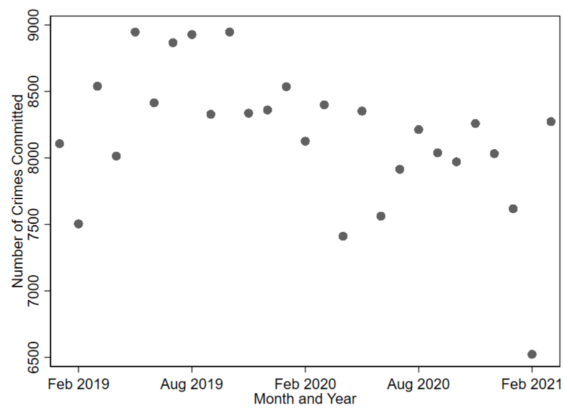
Panel A: Fraction of Households Without Power



Panel B: Number of Crimes per Hour



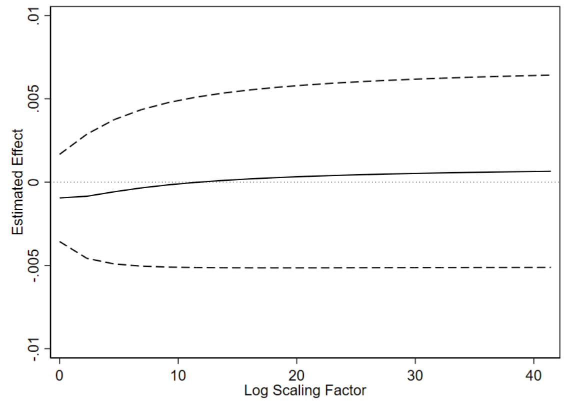
Panel C: Number of Crimes per Month



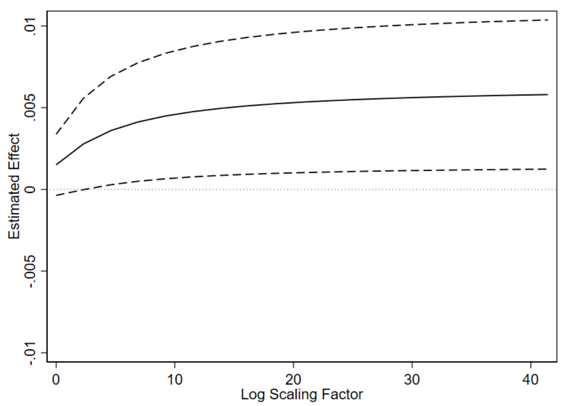
Notes: Panel A displays the fraction of households in Austin Texas without power during each hour between February 13, 2021 and February 23, 2021. Panel B displays the total number of crimes committed in Austin during each hour over this same period. Number of crimes has been scaled to absorb variation based on hour of the day and day of the week. Panel C displays the total number of crimes in Austin in each month in our data.

Figure 4: Scaling Up Variables

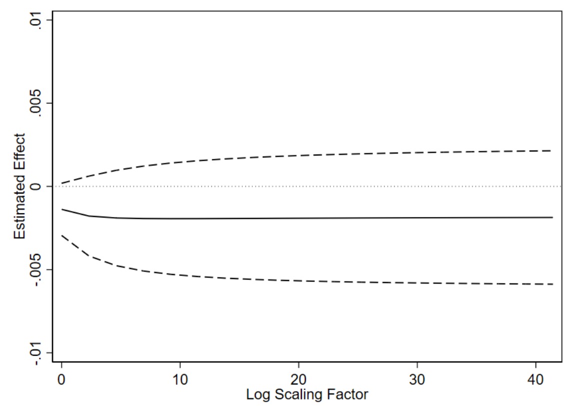
Panel A: All Crime



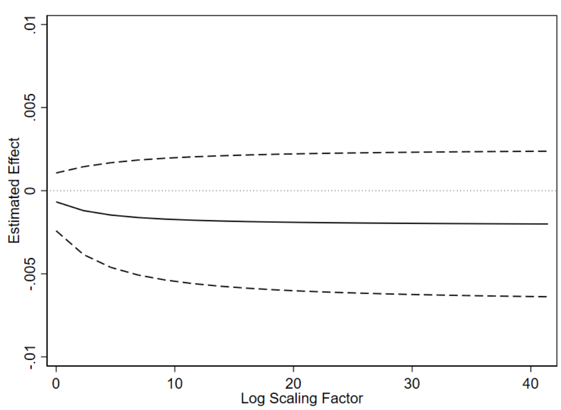
Panel B: Property Crime



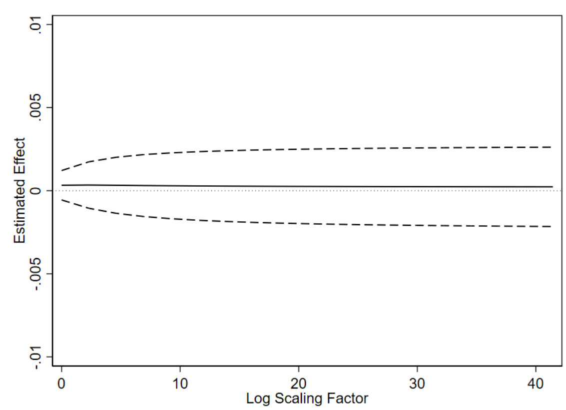
Panel C: Public Order Crime



Panel D: Violent Crime

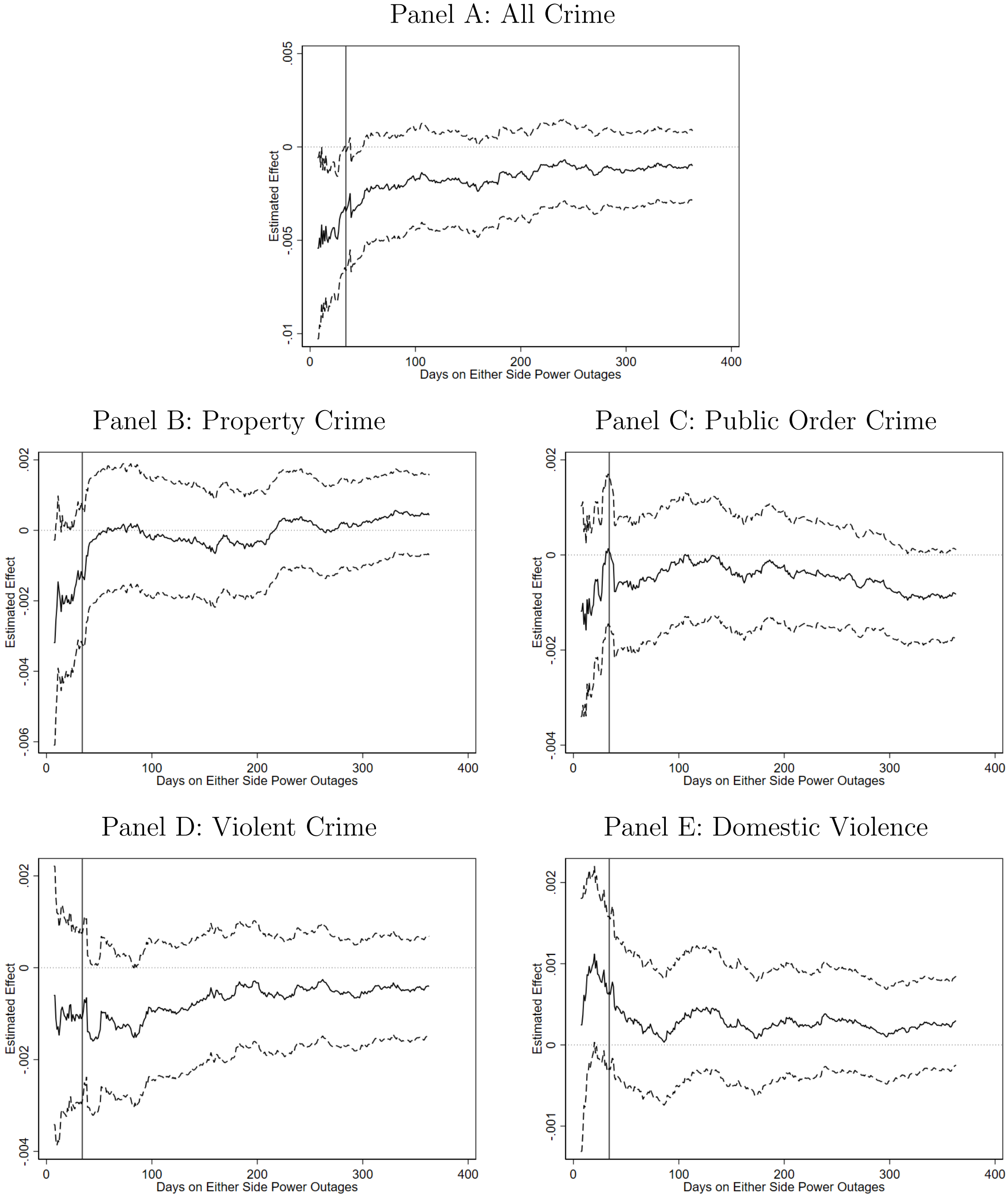


Panel E: Domestic Violence



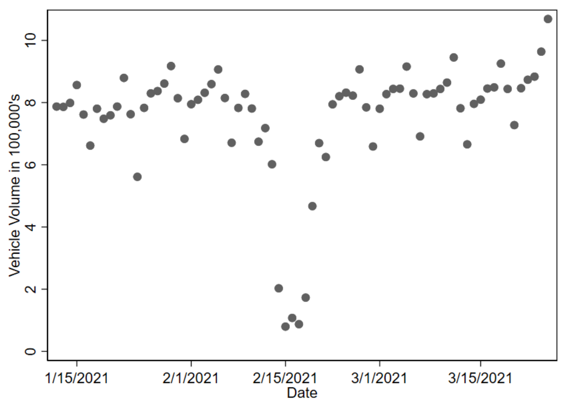
Notes: Figure shows the results of our preferred specification after scaling both the crime rate and the outage rate by the indicated value. The X-axis has been logged such that a value of 9 is approximately equivalent to multiplying both variables by 100,000. This would imply that we are measuring crimes (outages) per 10 billion people (households). At the extreme right side of the graph, we are measuring crimes (outages) per $1e^{22}$ people (households).

Figure 5: Estimated Impact by Date Bandwidth



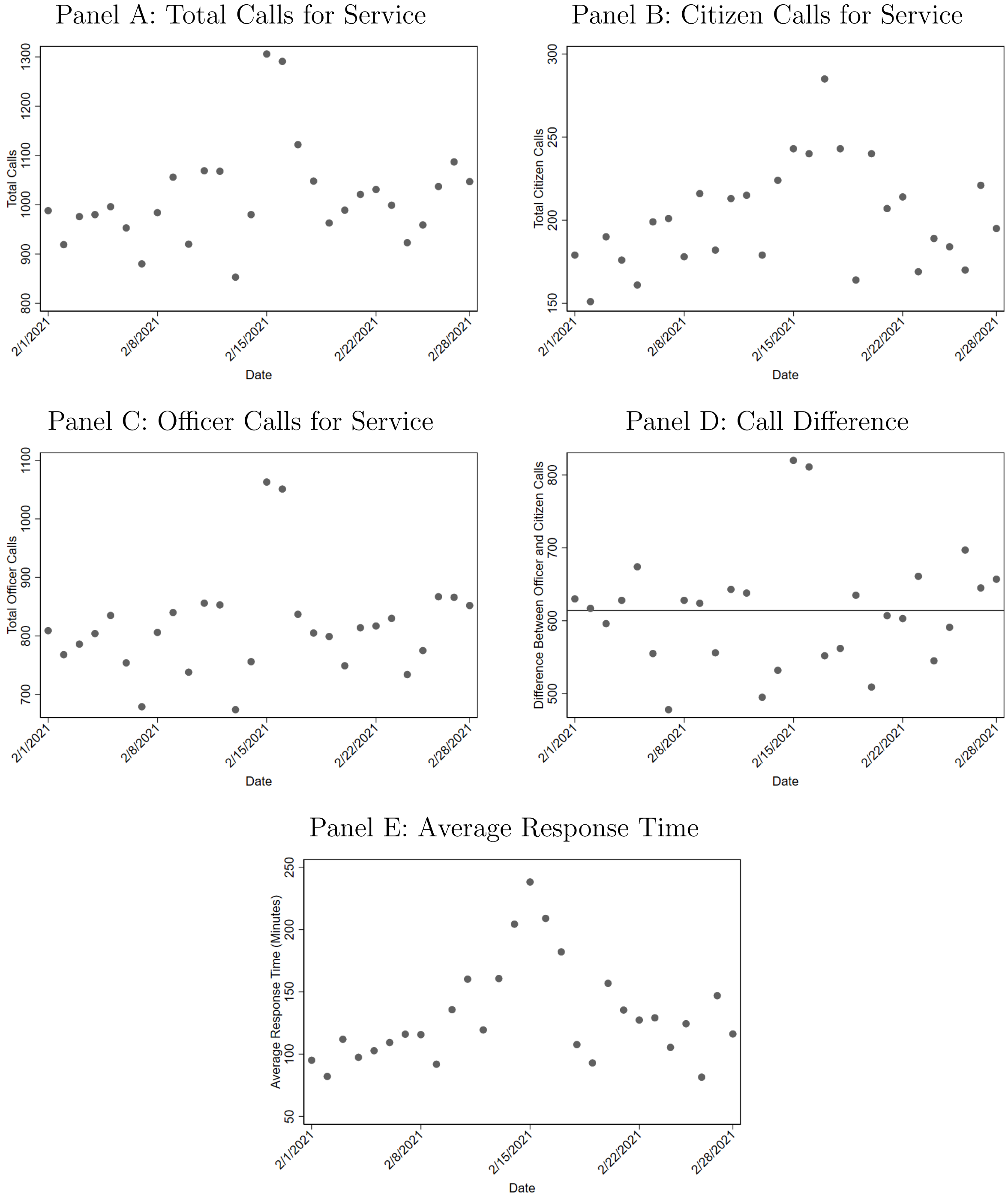
Notes: Each figure shows the results of our preferred specification as described in Equation 1 for a variety of different bandwidths. the dashed lines represent the 95% confidence interval. The vertical line indicates the point at which we reach the end of our sample in the post-treatment period. As such, further increases in bandwidth beyond this point only increase the number of days we observe before the outages began.

Figure 6: Impact of Outages on Traffic - Vehicles per Day



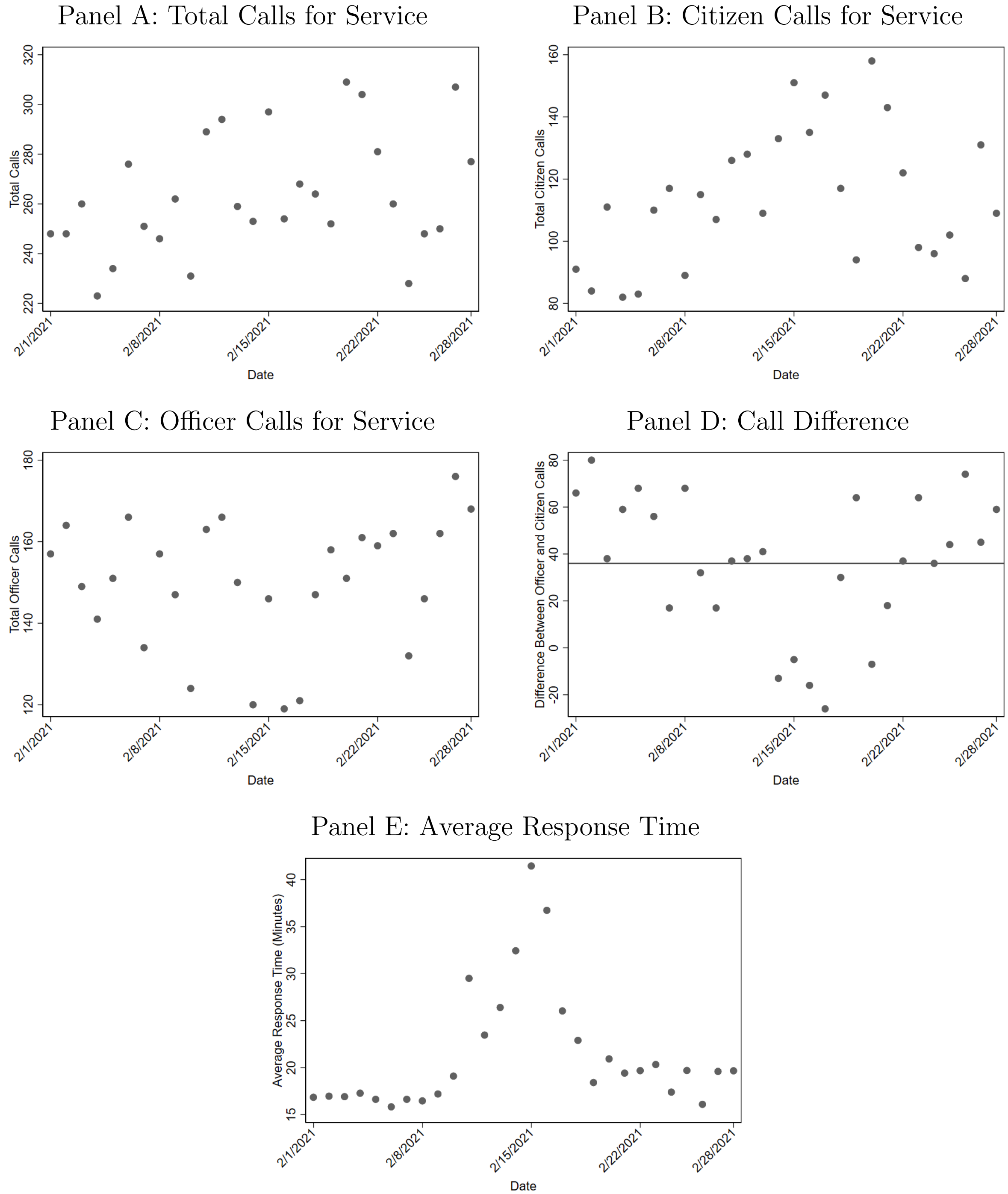
Notes: Figure shows the total number of vehicles driving past sensors distributed throughout Austin per day.

Figure 7: Policing During February 2021



Notes: All data from this figure comes from the official records of the Austin Police Department. Panel A indicates the total number of service calls received by the Austin Police Department on each day during the month of February. Panel B repeats Panel A, but includes only calls made by citizens. Panel C replicates Panel B, but instead includes only calls initiated by police officers. Panel D plots the difference between officer and citizen calls. The horizontal line shows the average difference. That is, on an average day in our sample, police place 612 more calls for service than citizens. Finally, Panel E plots the average police response time in minutes.

Figure 8: Policing During February 2021 - Urgent Calls



Notes: All data from this figure comes from the official records of the Austin Police Department. Panel A indicates the number of urgent service calls received by the Austin Police Department on each day during the month of February. Panel B repeats Panel A, but includes only calls made by citizens. Panel C replicates Panel B, but instead includes only calls initiated by police officers. Panel D plots the difference between urgent officer and citizen calls. The horizontal line shows the average difference. That is, on an average day in our sample, police place 37 more urgent calls for service than citizens. Finally, Panel E plots the average police response time in minutes among urgent calls for service.

Table 1: Descriptive Statistics - Pre-Assignment Characteristics

	(1) < 17.5% Outages	(2) $\geq$ 17.5% Outages	(3) Difference
Number of Critical Buildings	1.39	1.78	0.39
	[1.20]	[1.35]	(0.43)
Number of Warming Centers	0.33	0.33	0.00
	[0.59]	[0.49]	(0.18)
Crime Rate per 100,000	1.09	1.06	-0.02
	[1.49]	[0.65]	(0.383)
Total Population	22612	34943	12,331**
	[15101]	[19089]	(5,735)
Percent Foreign Born	14.48	19.00	4.53*
	[4.93]	[8.62]	(2.34)
Percent White	57.11	47.88	-9.23
	[19.50]	[23.36]	(7.17)
Percent Hispanic	24.21	36.38	12.16*
	[15.60]	[21.11]	(6.19)
Percent Below Poverty	11.71	14.76	3.05
	[10.42]	[8.28]	(3.14)
Population Density	3.60	3.68	0.08
	[3.91]	[1.98]	(1.03)
Percent $\geq$ 65	12.53	11.47	-1.05
	[4.04]	[4.27]	(1.39)
Median Household Income	80.56	69.12	-11.44
	[34.89]	[24.52]	(10.05)
Percent Medicare Beneficiaries	12.14	11.52	-0.63
	[4.44]	[3.74]	(1.37)
Percent Requiring Electricity	0.34	0.36	0.02
	[0.11]	[0.09]	(0.34)
Observations	18	18	36
Joint Significance F-Test			3.32***

Notes: Columns 1 and 2 report mean values for the indicated groups and standard deviations in square brackets. Column 3 presents estimates of the difference between high and low crime areas. In Column 3, robust standard errors are reported in parentheses. Column 3 also reports the results of an F-test of joint significance from a regression that includes all listed variables. The Number of Critical Buildings and Number of Warming Centers variable are excluded from the F-test to isolate the impact of variables that were not supposed to influence outage frequency or duration. In all three columns, crime rate is calculated during the pretreatment period. Population density is measured per 1,000 residents and Median Household income is measured in \$1,000. Percent Requiring Electricity is the percent of all residents that are on medicare and have a documented medical condition that requires constant electricity to treat. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Base Results

	(1)	(2)	(3)	(4)	(5)	(6)
Outages per 100,000 Households	0.013***	0.022***	0.017***	0.001	-0.001	-0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Humidity	-0.003***	-0.003***	0.001***	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature	0.011***	0.011***	0.001	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature Squared	-0.000***	-0.000***	0.000	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	0.099*	0.095*	0.049	0.069	0.069	0.066
	(0.054)	(0.056)	(0.054)	(0.051)	(0.051)	(0.051)
Wind Speed	0.005***	0.003***	0.004***	-0.000	-0.001	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Constant	0.237***	0.118***	0.304***	0.427***	0.432***	0.424***
	(0.019)	(0.037)	(0.036)	(0.034)	(0.034)	(0.034)
Observations	393944	393944	393944	393944	393944	393944
Date FE	No	Yes	Yes	Yes	Yes	Yes
Hour FE	No	No	Yes	Yes	No	No
ZIP Code FE	No	No	No	Yes	No	No
ZIP Code×Hour FE	No	No	No	No	Yes	No
ZIP Code×Hour×DOW FE	No	No	No	No	No	Yes

Notes: Dependent variable is the crime rate per 100,000 people in a particular ZIP Code during a particular hour. Standard errors allow for clustering within ZIP-Code-by-hour-by-day-of-the-week bins and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Results By Crime Type

	(1) All	(2) Property	(3) Public Order	(4) Violent	(5) Domestic Violence
Outages per 100,000 Households	-0.001	0.002	-0.001*	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Humidity	-0.000	-0.000	0.000	0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature	0.002**	0.001**	-0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Temperature Squared	-0.000**	-0.000**	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	0.066	0.049	0.008	0.035	0.000
	(0.051)	(0.037)	(0.032)	(0.031)	(0.015)
Wind Speed	-0.000	0.000	-0.001**	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.424***	0.160***	0.137***	0.145***	0.034***
	(0.034)	(0.024)	(0.020)	(0.021)	(0.011)
Observations	393944	393944	393944	393944	393944
Date FE	Yes	Yes	Yes	Yes	Yes
ZIP Code×Hour×DOW FE	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the crime rate for the indicated type of crime per 100,000 people in a particular ZIP Code during a particular hour. Standard errors allow for clustering within ZIP-Code-by-hour-by-day-of-the-week bins and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Results By Day/Night and Crime Type

	All		**Property**		**Public Order**		**Violent**		**Domestic Violence**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night
Outages per 100,000 Households	0.001	-0.002	0.002*	0.001	-0.001	-0.002*	-0.000	-0.001	0.001	0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Humidity	0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature	0.001	-0.004**	0.001	-0.002	0.000	-0.001	0.000	-0.003**	-0.000	-0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Temperature Squared	-0.000	0.000**	-0.000	0.000	0.000	0.000	-0.000	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	0.029	0.047	0.064	-0.010	0.024	-0.030	-0.018	0.072	-0.029*	0.011
	(0.076)	(0.077)	(0.057)	(0.052)	(0.047)	(0.046)	(0.044)	(0.049)	(0.018)	(0.026)
Wind Speed	0.000	-0.001	0.000	0.000	-0.000	-0.001*	0.000	-0.001	0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.453***	0.563***	0.150***	0.226***	0.109***	0.166***	0.167***	0.243***	0.038**	0.063***
	(0.056)	(0.061)	(0.041)	(0.041)	(0.032)	(0.039)	(0.034)	(0.039)	(0.017)	(0.019)
Observations	213408	180536	213408	180536	213408	180536	213408	180536	213408	180536
F-stat		0.82		0.65		0.45		0.36		0.14
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ZIP Code×Hour×DOW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the crime rate for the indicated type of crime per 100,000 people in a particular ZIP Code during a particular hour. "Day" results includes crimes committed between 7:01 AM and 6:59 PM while "Night" includes crimes committed between 7:00 PM and 6:59 AM. This corresponds to the periods of light and dark during February in Austin. The F-stat in Columns 2, 4, 6, 8, and 10 tests whether the coefficients on Outages per 100,000 Households are equal across Day and Night for each type of crime. Standard errors allow for clustering within ZIP-Code-by-hour-by-day-of-the-week bins and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Cumulative Outage Results

	(1)	(2)	(3)	(4)
All Crimes				
	Last 2 Hours	Last 4 Hours	Last 6 Hours	Last 12 Hours
Outages per 100,000 - 2 hours	-0.001			
	(0.001)			
Outages per 100,000 - 4 hours		-0.001		
		(0.001)		
Outages per 100,000 - 6 hours			-0.000	
			(0.001)	
Outages per 100,000 - 12 hours				-0.002
				(0.001)
Observations	393908	393836	393764	393548
Chi-squared				2.59
Public Crimes				
	(1)	(2)	(3)	(4)
	Last 2 Hours	Last 4 Hours	Last 6 Hours	Last 12 Hours
Outages per 100,000 - 2 hours	-0.001			
	(0.001)			
Outages per 100,000 - 4 hours		-0.000		
		(0.001)		
Outages per 100,000 - 6 hours			-0.000	
			(0.001)	
Outages per 100,000 - 12 hours				-0.000
				(0.001)
Observations	393908	393836	393764	393548
Chi-squared				2.42
Property Crimes				
	(1)	(2)	(3)	(4)
	Last 2 Hours	Last 4 Hours	Last 6 Hours	Last 12 Hours
Outages per 100,000 - 2 hours	0.001			
	(0.001)			
Outages per 100,000 - 4 hours		0.001		
		(0.001)		
Outages per 100,000 - 6 hours			0.001	
			(0.001)	
Outages per 100,000 - 12 hours				-0.000
				(0.001)
Observations	393908	393836	393764	393548
Chi-squared				3.81
Violent Crimes				
	(1)	(2)	(3)	(4)
	Last 2 Hours	Last 4 Hours	Last 6 Hours	Last 12 Hours
Outages per 100,000 - 2 hours	-0.001			
	(0.001)			
Outages per 100,000 - 4 hours		-0.001		
		(0.001)		
Outages per 100,000 - 6 hours			-0.001	
			(0.001)	
Outages per 100,000 - 12 hours				-0.001
				(0.001)
Observations	393908	393836	393764	393548
Chi-squared				0.31
Date FE	Yes	Yes	Yes	Yes
ZIP Code×Hour×DOW FE	Yes	Yes	Yes	Yes

Notes: Dependent variable is the crime rate for the indicated type of crime per 100,000 people in a particular ZIP Code during a particular hour. Outages now measure the cumulative time spent without power over the last 2, 4, 6,or 12 hours. Standard errors allow for clustering within ZIP Code-by-hour-by-day-of-the-week bins and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Alternative Model Results

	(1) Linear	(2) Log +1	(3) Extensive Margin	(4) Possion
Power Outages	-0.023	-0.001	0.006	0.000
	(0.152)	(0.001)	(0.019)	(0.000)
Humidity	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.000)	(0.001)	(0.000)
Temperature	0.001	0.002**	0.001	0.005**
	(0.003)	(0.001)	(0.003)	(0.002)
Temperature Squared	0.000	-0.000**	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	0.211	0.052	0.212	0.168
	(0.181)	(0.040)	(0.181)	(0.112)
Wind Speed	-0.002	-0.000	-0.002	-0.000
	(0.002)	(0.000)	(0.002)	(0.001)
Observations	393944	393944	393944	364696
Dependent Variable Mean	1.142		1.142	
Date FE	Yes	Yes	Yes	Yes
ZIP Code×Hour×DOW FE	Yes	Yes	Yes	Yes

Notes: Dependent variable is the crime rate per 100,000 people in a particular ZIP Code during a particular hour. Column 1 shows the results from a simple linear model where neither the independent nor the dependent variable have been transformed. For ease of interpretation, in this model fraction of households without power is not scaled per 100,000 households. Column 2 shows the results of a log-log model in which 1 has been added to the values of both the dependent and independent variables so that observations with a value of 0 can be included in the estimation. The results of this specification can thus be interpreted as an elasticity estimate. Column 3 presents the results of a linear specification where power outages are measured exclusively on the extensive margin. That is, the independent variable can only take on values of 0 or 1. Column 4 presents the results of a Poisson model. In Column 4, crimes are measured as a simple count of the number of crimes in each ZIP Code in each hour. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Zip Codes With and Without Warming Centers

	(1) Warming Center	(2) No Warming Center
Outages per 100,000 Households	0.005*	-0.003**
	(0.002)	(0.002)
Humidity	-0.000	-0.000
	(0.000)	(0.000)
Temperature	0.004**	0.001
	(0.002)	(0.001)
Temperature Squared	-0.000*	-0.000*
	(0.000)	(0.000)
Precipitation	0.258**	-0.017
	(0.116)	(0.053)
Wind Speed	-0.001	0.000
	(0.001)	(0.001)
Constant	0.608***	0.342***
	(0.071)	(0.037)
Observations	120,371	273,573
Date FE	Yes	Yes
ZIP Code×Hour×DOW FE	Yes	Yes

Notes: Dependent variable is the crime rate for per 100,000 people in a particular ZIP Code during a particular hour. Twenty-five ZIP Codes did not have a warming center. Of the remaining eleven ZIP Codes, ten had a single warming center and one had a single warming center. Standard errors allow for clustering within ZIP-Code-by-hour-by-day-of-the-week bins and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Crime Reporting and Case Closures

	(1) Days to Report	(2) Reported within Hour	(3) Cleared
Frac Without Power	8.348	-0.010	-0.016
	(7.771)	(0.107)	(0.063)
Humidity	-0.008	0.000	0.000
	(0.010)	(0.000)	(0.000)
Temperature	-0.071	-0.001	-0.003***
	(0.051)	(0.001)	(0.001)
Temperature Squared	0.000	0.000	0.000***
	(0.000)	(0.000)	(0.000)
Precipitation	-0.159	-0.006	-0.060*
	(3.397)	(0.063)	(0.036)
Wind Speed	0.048*	-0.001	-0.000
	(0.026)	(0.001)	(0.000)
Constant	7.158***	0.500***	0.214***
	(1.894)	(0.043)	(0.033)
Observations	88591	88591	88591
Dependent Variable Mean	4.485	0.494	.153
Percent Change	186.13%	-2.02%	-10.46%
Date FE	Yes	Yes	Yes
ZIP Code×Hour	Yes	Yes	Yes

Notes: Each column estimates an equation similar to Equation 1 but replaces ZIP-Code-by-hour-by-day-of-the-week fixed effects with ZIP-Code-by-hour fixed effects. The dependent variable in each specification is indicated in the column heading. Note that variables in this table are the original values and have not been transformed using an inverse hyperbolic sine. ZIP Code hours in which no crime were reported are dropped from the analysis. Standard errors allow for clustering within ZIP-Code-by-hour bins and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

9 Data Appendix

This appendix contains complete details on data sources. It also describes the process used to construct our data set.

9.1 Crime Data

The City of Austin releases weekly updates on the crimes that were reported to the Austin Police Department via the Crime Reports dataset.[19] These records, dating back to 2003, document the crime's latitude and longitude, the crime's clearance status, and the date and time that the crime occurred and was reported.[20] We aggregated these crime records to the ZIP-Code-by-hour level and generated hourly counts of the number of crimes committed by crime type, the number of cleared crimes, and the average report time for crimes committed during that period. We have hourly records for 38 ZIP Codes between January 1, 2020 and March 31, 2021.

9.2 Weather Data

The weather controls come from the National Oceanic and Atmospheric Administration's Local Climatological Dataset. We restricted our sample of weather stations to those within 15 miles of Austin, Texas leaving four stations: the Austin Bergstrom International Airport, the Austin Camp Marbry, the Austin Executive Airport and the Taylor Municipal Airport. To assign weather condition estimates to observations, we found the central point for each ZIP Code and calculated the distance between that center and the weather station, and used second power inverse distance weighting to calculate weather values. These stations report weather data at irregular intervals, typically multiple times per hour. We averaged the reports within each hour to estimate the values for temperature, wind, humidity, and precipitation for each ZIP Code in our sample. **Because most of the variation we observe in weather is over time rather than across the various weather stations, our results are not sensitive to the methodology used to calculate weather for each zip code.**

9.3 Power Outage Data

The power outage data was purchased from Bluefire Studios, LLC. **The data contain hourly information on the total number of power customers and the number of customers without power for each of Austin's 36 unique ZIP Codes. We utilized these two variables to calculate the fraction of customers in a ZIP Code without power in each hour.**

[19] The crime reports can be found at *https://data.austintexas.gov/Public-Safety/Crime-Reports/fdj4-gpfu.*

[20] 294 (1.8%) of the crimes in the data did not have latitude or longitude and were dropped from the analysis.

9.4 Additional Data Sources

Data on the frequency of power outages come from the Department of Energy's Electric Disturbance Events Annual summaries (OE-417). These summaries document information on all power outages reported to the Department of Energy. Using these records, we estimate the total number of power outages, as well as the number of weather-induced power outages, that arise every year from 2003 to 2022.[21]

Demographic information comes from the 2017 American Community Survey Profiles, which we used to compile demographic information for each of the 36 ZIP Codes in our sample.[22] These profiles described the racial, economic and social conditions for each of the ZIP-Codes.

We also use data on the location of critical infrastructure (water centers, police stations, fire stations and hospitals), warming centers, and electricity dependent medicare beneficiaries.[23] **The locations of these buildings come from a variety of publicly available websites.**[24] The location of warming centers was taken from Livengood et al. (2021). Finally, the locations of electricity dependent medicare beneficiaries was obtained from the US Department of Health and Human Services HHS emPOWER Map.

Finally, we also utilize traffic data compiled by the City of Austin's GRIDSMART optical traffic detectors and published in the camera traffic count dataset.[25] We aggregated these traffic records to the ZIP-Code-by-day level to holistically evaluate whether spillovers occurred across ZIP Codes. Specifically, these data allowed us to evaluate whether individuals in areas experiencing outages migrated in significant numbers to areas that were not experiencing outages.

[21] This data can be found at *https://www.oe.netl.doe.gov/OE417_annual_summary.aspx.*

[22] This data can be found at *https://www.austintexas.gov/page/data-library.*

[23] Note that because our demographic, critical infrastructure, and warming center data do not vary over time, these variables are not included **in our estimates of the impact of the power outages on crime**. Instead, they are used only to establish whether outages were disproportionately targeted at certain groups.

[24] Specifically, locations of wastewater management plants are available at *https://www.austintexas.gov/edims/document.cfm?id=133821, police station locations at https://data.austintexas.gov/Public-Safety/Map-of-Austin-Police-Stations/fsgj-5xyt, fire stations at https://data.austintexas.gov/Public-Safety/Austin-Fire-Stations/64cq-wf5u/data, and hospitals at https://www.austintenantadvisors.com/blog/map-list-of-all-austin-tx-hospitals.*

[25] This data can be found at *https://data.austintexas.gov/Transportation-and-Mobility/Camera-Traffic-Counts/sh59-i6y9.*

10 Results Appendix

Table A1: ZIP-Code Level Clustering

	(1)	(2)	(3)	(4)	(5)	(6)
Outages per 100,000 Households	0.013**	0.022***	0.017**	0.001	-0.001	-0.001
	(0.005)	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)
Humidity	-0.003***	-0.003***	0.001	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Temperature	0.011***	0.011***	0.001	0.002*	0.002**	0.002**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature Squared	-0.000***	-0.000**	0.000	-0.000*	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	0.099*	0.095*	0.049	0.069	0.069	0.066
	(0.058)	(0.054)	(0.057)	(0.049)	(0.049)	(0.048)
Wind Speed	0.005***	-0.003	0.004	-0.000	-0.001	-0.000
	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Constant	0.237***	0.118***	0.304***	0.778***	0.572***	0.332***
	(0.050)	(0.060)	(0.036)	(0.083)	(0.067)	(0.030)
Observations	393944	393944	393944	393944	393944	393944
Date FE	No	Yes	Yes	Yes	Yes	Yes
Hour FE	No	No	Yes	Yes	No	No
ZIP Code FE	No	No	No	Yes	No	No
ZIP Code×Hour FE	No	No	No	No	Yes	No
ZIP Code×Hour×DOW FE	No	No	No	No	No	Yes

Notes: Dependent variable is the crime rate per 100,000 people in a particular ZIP Code during a particular hour. Standard errors allow for clustering within ZIP-Code-by-hour-by-day-of-the-week bins and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Residential and Non-Residential Areas

	All Crime		Property Crime	
	(1)	(2)	(3)	(4)
	Residential	Other	Residential	Other
Outages per 100,000 Households	-0.000	-0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Humidity	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Temperature	0.001	0.002**	0.000	0.001*
	(0.001)	(0.001)	(0.000)	(0.001)
Temperature Squared	-0.000	-0.000**	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	0.049	0.055	0.037	0.018
	(0.044)	(0.042)	(0.025)	(0.032)
Wind Speed	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.301***	0.236***	0.064***	0.100***
	(0.028)	(0.028)	(0.015)	(0.021)
Observations	393944	393944	372058	372058
Dependent Variable Mean	0.674	0.683	0.131	0.283
Date FE	Yes	Yes	Yes	Yes
ZIP Code×Hour	Yes	Yes	Yes	Yes

Notes: Dependent variable is either the crime rate or property crime rate per 100,000 people in a particular ZIP Code during a particular hour. Standard errors allow for clustering within ZIP-Code-by-hour-by-day-of-the-week bins and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Criminal Learning During the Outages

	(1)	(2)	(3)	(4)	(5)	(6)
Outages per 100,000 Households	0.016***	0.021***	0.017***	0.000	-0.001	-0.002
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Dates after 2/16/2021	-0.008					
	(0.005)					
Outages X Dates after 2/16/2021	-0.010***	0.001	0.002	0.003	0.003	0.004
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Humidity	-0.003***	-0.003***	0.001***	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature	0.011***	0.011***	0.001	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature Squared	-0.000***	-0.000***	0.000	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	0.104*	0.095*	0.048	0.069	0.069	0.066
	(0.054)	(0.056)	(0.054)	(0.051)	(0.051)	(0.051)
Wind Speed	0.005***	0.003***	0.004***	-0.000	-0.001	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Constant	0.237***	0.118***	0.304***	0.427***	0.431***	0.423***
	(0.019)	(0.037)	(0.036)	(0.034)	(0.034)	(0.034)
Observations	393944	393944	393944	393944	393944	393944
Date FE	No	Yes	Yes	Yes	Yes	Yes
Hour FE	No	No	Yes	Yes	No	No
ZIP Code FE	No	No	No	Yes	No	No
ZIP Code×Hour FE	No	No	No	No	Yes	No
ZIP Code×Hour×DOW FE	No	No	No	No	No	Yes

Notes: Dependent variable is the crime rate per 100,000 people in a particular ZIP Code during a particular hour. Standard errors allow for clustering within ZIP-Code-by-hour-by-day-of-the-week bins and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Results By Crime Type - Narrow Bandwidth

	(1) All	(2) Property	(3) Public Order	(4) Violent	(5) Domestic Violence
Outages per 100,000 Households	-0.003	0.000	-0.001	-0.002	0.000
	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)
Humidity	-0.001	-0.001	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Temperature	0.003	-0.000	0.002	0.004	-0.001
	(0.004)	(0.003)	(0.002)	(0.003)	(0.001)
Temperature Squared	0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-1.342	-0.153	-0.781*	-0.783*	-0.381**
	(0.826)	(0.481)	(0.422)	(0.447)	(0.153)
Wind Speed	-0.001	-0.001	-0.001	-0.000	-0.002*
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Constant	0.198	0.139*	0.115	-0.060	0.073
	(0.143)	(0.078)	(0.090)	(0.111)	(0.055)
Observations	9500	9500	9500	9500	9500
Dependent Variable Mean	0.831	0.287	0.191	0.296	0.072
Date FE	Yes	Yes	Yes	Yes	Yes
ZIP Code FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the crime rate for the indicated type of crime per 100,000 people in a particular ZIP Code during a particular hour. Standard errors allow for bootstrap clustering within ZIP-Codes and are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.