Crime During the Austin 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, 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, Hsu, Shah, and Taneja, 2021) although Vallejo, Wong, Buttorff, Olapade, Perez Arguelles, Pinto, and Sipole (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. Policy makers need to have an understanding of how crime patterns shift during these events in order to optimally plan and respond.

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

[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, whit indicates that less that 6% of people were without power.

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.

There is surprisingly little literature on the impact of power outages on crime rates. Instead, we rely on a three bodies of literature that explore some of the key consequences of power outages. Specifically, the impact of darkness, street lighting, and weather on crime have all been extensively researched. Darkness, for example, has been shown to increase crime (Doleac and Sanders, 2015; Domínguez and Asahi, 2019). Similarly, recent experimental evidence shows that the addition of street lights can reduce the crime rate in newly lit areas (Chalfin, Kaplan, and LaForest, 2020). On the other hand, the literature on weather and crime has consistently found a strong positive relationship between temperature and crime (Ranson, 2014; Baysan, Burke, González, Hsiang, and Miguel, 2019).

The totality of these three bodies of research paints a complicated predicted crime effect of the Austin power outages. The outages themselves negated street lights and otherwise darkened some neighborhoods, which would tend to increase crime. However, the cold temperatures, especially when combined with dangerous road conditions and business closures should be expected to reduce crime in the city. Moreover, power outages caused by severe weather events may have different impacts than what we might predict from the impact on temperature, darkness, and streetlights alone. For one thing, during severe weather that does not involve evacuations, people tend to stay home. This may reduce criminal opportunities. There may also be pro-social community effects that cause individuals to come together and look to help their neighbors instead of victimizing them. Finally, 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.

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, and when we limit the sample range of dates on either side of the outages. Finally, using local stoplight outages as a proxy for power outages, we disaggregate the data to the neighborhood level and find similar results to the ZIP Code level analysis.[2]

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

[2]There are a total of 38 ZIP Codes and 102 neighborhoods in Austin.

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.[3]

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, 2021b).[4] Unlike power outages due to a failure of a particular component, these outages were done systematically to relieve strain on the overburdened

[3]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).

[4]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.

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).[5]

Austin Energy General Manager Jaqueline Sargent has stated that the areas chosen for these rotating power outages were random but excluded critical infrastructure such as hospitals, fire stations, and water treatment facilities (Autullo, 2021). However, some consumers in Austin have claimed that the outages were in fact systematic with poor and minority neighborhoods experiencing more outages than wealthier, whiter areas and downtown Austin. 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 noted that a failure of the city in response to the power outages relate to inequity in who lost power. 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

[5]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.

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). Amin examines 6,000 manufacturing firms in Latin American countries to establish what causes a firm to experience crime. The author's major conclusion in that larger firms are more likely to experience crimes than a smaller firm. 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. Reaching a bit further, Chalfin, Kaplan, and LaForest (2020) estimates the effect of street lights on crime using almost 300,000 street light outages in Chicago. The authors find little evidence that street light outages impact crime at the location of the outage. However, the authors find that crime seems to spillover to nearby locations during the outages. 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 incidence of crime dates back to at least 1974, when Wright, Heilweil, Pelletier, and Dickinson (1974) found evidence that street lighting reduced crime. Painter (1996) finds 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), Welsh and Farrington (2008), and Chalfin, Hansen, Lerner, and Parker (2021). However, the link between street lighting and crime has often been at best inconclusive and at worst contradictory. For example, Atkins, Husain, and Storey (1991) find no conclusive evidence that street lights impact reported crimes. Farrington and Welsh (2002) ultimately conclude that street lights reduce crime, but 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) finds that the crime-reducing conclusion of Farrington and Welsh (2002) is unfounded.

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) find that the extra daylight during evening hours created by daylight savings time result in a reduction in crime.

Because our paper specifically examines power outages that largely 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. Field (1992) finds that increased temperatures increase crime in England and Wales, though rainfall and sunshine appear to have no impact on crime. Horrocks and Menclova (2011) find that increased temperatures increase violent and property crimes in New Zealand. They further find that increased precipitation reduces violent crimes. 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. Finally, Baysan, Burke, González, Hsiang, and Miguel (2019) go beyond the direct relationship between temperature and crime and study how psychological and physiological factors interact with temperature to cause violence.

Collectively, these three bodies of literature have a couple of key implications for our analysis. First, we expect that specifications that do not carefully control for weather will be biased towards finding that power outages reduce crime as both the low temperatures and precipitation are expected to cause decreases in crime. Second, if the only implication of power outages was a decrease in light, we would expect outages to increase crime at the margin. 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, this may cause crime to fall.

4 Data

To estimate the effect of the Austin Power Outages on the city's crime rate, we construct both a ZIP-Code-by-hour panel dataset and a neighborhood-by-hour panel dataset that consists of crime, weather, demographic, and power outage data. We also support our primary research question using policing and traffic data.

4.1 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.[6] These records, dating back to 2003, document the crime's latitude & longitude, the crime's clearance status, and the date and time that the crime occurred and was reported.[7] We aggregated these crime records to both the ZIP-Code-by-hour level and the neighborhood-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. Our crime data consists of hourly records for 38 ZIP Codes and 102 neighborhoods between January 1, 2020 and March

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

[7] 294 (1.8%) of the crimes in the data did not have latitude or longitude and were dropped from the analysis.

31, 2021.[8]

4.2 Weather Data

The weather controls come from the National Oceanic and Atmospheric Administration (NOAA)'s Local Climatological Dataset (LCD). 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 neighborhood, we 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 and neighborhood in our sample.

4.3 Power Outage Data

The power outage data, purchased from Bluefire Studios, LLC, reported hourly data 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 statistics to calculate the fraction of customers in a ZIP Code without power. We validated the Bluefire studios power outage data against stoplight outage data produced by the Austin Transportation Department. Data on

[8]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.

the stoplight outages come from the Advanced Traffic Management System's Communication Event Log, which recorded the start and stop time that stoplights lost connection to the central server between 11th and the 28th of February. Because the stoplights stop signaling during power outages, sudden stops in signals, especially during the week of February 15th to 21st, could signal power outages in that region. We aggregated the stoplight data in Austin to both the neighborhood-hour and ZIP-Code-hour level and calculated the proportion of stoplight minutes that were out in a given hour. Because we were not able to obtain neighborhood level power outage data from Bluefire Studios, all analysis at the neighborhood level uses this stoplight based measure of power outages. The correlation between the stoplight and Bluefire studio data is 0.20. This is perhaps unsurprising as power outages are not the only reason why a stoplight would go offline, particularly during a winter storm.[9]

4.4 Additional Data Sources

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 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.[10]

[9] 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)

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

To assess claims that the Austin Power Outages disparately impacted marginalized groups, we used the 2017 American Community Survey Profiles to compile demographic information for each of the 36 ZIP Codes in our sample.[11] These profiles described the racial, economic and social conditions for each of the ZIP Codes. We supplemented the demographic data with data on the location of critical infrastructure (water centers, police stations, fire stations and hospitals), as well as data on the location of warming centers and on the location where electricity dependent medicare beneficiaries reside.[12]

We also consider the potential for crime spillovers. To do this, we utilize traffic data compiled by the City of Austin's GRIDSMART optical traffic detectors and published in the camera traffic count dataset.[13] These traffic detectors record the number of vehicles passing the sensors every 15 minutes. 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.

Finally, we examine whether policing behavior changed during the power outages. For

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

[12] Note that because our demographic, critical infastructure, and warming center data do no vary over time, these variables are not included in our primary analysis. Instead, they are used only to establish whether outages were disproportionately targeted at certain groups. The locations of these buildings come from a variety of publicly available websites. 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. The location of warming centers was taken from Livengood (2021a). Finally, the locations of electricity dependent medicare beneficiaries was obtained from the US Department of Health and Human Services HHS emPOWER Map.*

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

this, we utilize data from the official records of the Austin Police Department to analyze police efficiency. These records, spanning the month of February, include information on the number of calls for service received by the police, as well as the police's response time. The data are broken up by the urgency of the call to service and were provided after a direct request to the Austin Police Department.

4.5 Baseline Characteristics

With the data complete, we next 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 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 affected 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.[14] Column 3 of Table 1 reports the results of a simple regression with the percentage households experiencing power outages as the independent variable and the descriptive statistic variables as the dependent variable.

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 ares 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 result 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. 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 is in the direction that would indicate systematic bias towards marginalized groups in which ZIP Codes experienced power outages. Neighborhoods 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, neighborhoods 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. Although the signs of all estimated coefficients would tend to tell a story of systemic bias in power outages, it is important to note that only the total population,

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

percentage foreign born, and percentage Hispanic are statistically significant. However, the demographic variables are collectively significant in explaining power outages as can be seen by the significant F-statistic value of 3.32.[15]

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 neighborhoods 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 neighborhoods during the times and days in which those neighborhood 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:

$$Crime_{zdt} = \beta Outage_{zdt} + X_{dt}^{\prime}\Gamma + \delta_{zwt} + \delta_d + \epsilon_{zdt}, \tag{1}$$

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

[15] 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.

$Outage_{zdt}$ 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, Magee, and Robb, 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.

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. 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%. In totality, Table 2 indicates that the power outages caused by the 2021 winter storm caused no significant crime changes in Austin.

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 without power, particularly in a stressful situation, may turn to illicit substances for comfort and entertainment, leading to an increase in drug crimes.

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, or violent crime. Only public order crimes have a statistically significant effect at the 10% level, but its coefficient indicates that a 10% increase in power outages decreased public order crime by just 0.01%.

Fears of crime increases during power outage typically focus on increases in property crime. We find no evidence that power outages cause any significant impact on property crime. Our results suggest that an increase in police resources used to prevent property crime during a power outage are wasted. Instead, those resources could be directed towards community outreach and responding to urgent calls for service.

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 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 significant difference in the impact of power outages on crime between day and night. Importantly, however, because the nights with the highest power outages also had snow, clear skies, and a half full 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. We find no impact on violent crimes at any time of day. For property crime, we find that power outages increase property crime during the day but not at night. A 10% increase in power outages increases property crime by 0.02% during the day. We find that for public order crimes, power outages have no impact on crime rates during the day, but that power outages decrease public order crimes at night. During the night, public order crimes decrease by 0.02% for every 10% increase in power outages. Due to the size of these estimated impacts, we once again conclude that power outages have no impact on crime, regardless of the time of day the outage occurs.

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 variables. 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 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. This implies the impact on crime of a 10% increase in power outages ranges from -0.13% to 0.14%.

Panels B through D of Figure 4 indicate the impact of scaling choice on our coefficient estimates by crime type. Public order and violent crime follow the same pattern our all crime estimates: coefficient estimates and 95% confidence intervals stabilize as the scaling factor increases, but no scaling factor ever results in an estimate that is statically significant at the 5% level. As property crime stabilizes, it results in a statistically significant positive coefficient; however, the magnitude of the coefficient estimate is still quite small. 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 nearly all possible 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 that include at least one month.[16]

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.

[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.

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 specification: Column 1 reports the linear regression results, Column 2 reports the log +1 results, Column 3 reports the extensive margin model, and Column 4 reports the Poisson estimates. 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 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 restrictions, 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 out 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 either in regular times or during an outage, 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.[17]

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.

6.4 Neighborhood Level Analysis

The results thus far have relied on ZIP Code level power outage data. While that data is reliable, the amount of geographical aggregation may be limiting our ability to fully understand the impacts of the outages at a local level. To alleviate this concern, in this section we introduce a different measure of the fraction of residents in a given area experiencing a power outage at any given time. Specifically, Austin records the location of every stoplight

[17] 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.

in the city along with precise times that each stoplight is not operating properly.[18] While there is no guarantee that a stoplight's failure is due to a power outage, particularly during a severe storm, power outages do trigger stoplight failures. Moreover, when aggregating stoplight outages to the ZIP Code level, we find that stoplight outages are correlated with official power outages.

Table 9 presents results similar to those in Table 2 but measures crime rates at the neighborhood-day-of-the-week-by-hour level and replaces all ZIP Code fixed effects with neighborhood fixed effects. Our neighborhood level results are consistent with basic findings at the ZIP Code level. Power outages do not have an effect on the overall crime rate.

Table 10 reports our neighborhood-level analysis broken out by crime type. While we do find a statistically significant decrease in property crimes, our results overall are consistent with those found in Table 4: there is no economically significant impact of power outages on crime.

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

[18] Unfortunately, the stoplight outage data is only available between February 11, 2021 and February 28, 2021. While this range is quite fortunate in that is overlaps the power outage event, it does force us to restrict the number of days on either side of the power outages relatively narrowly.

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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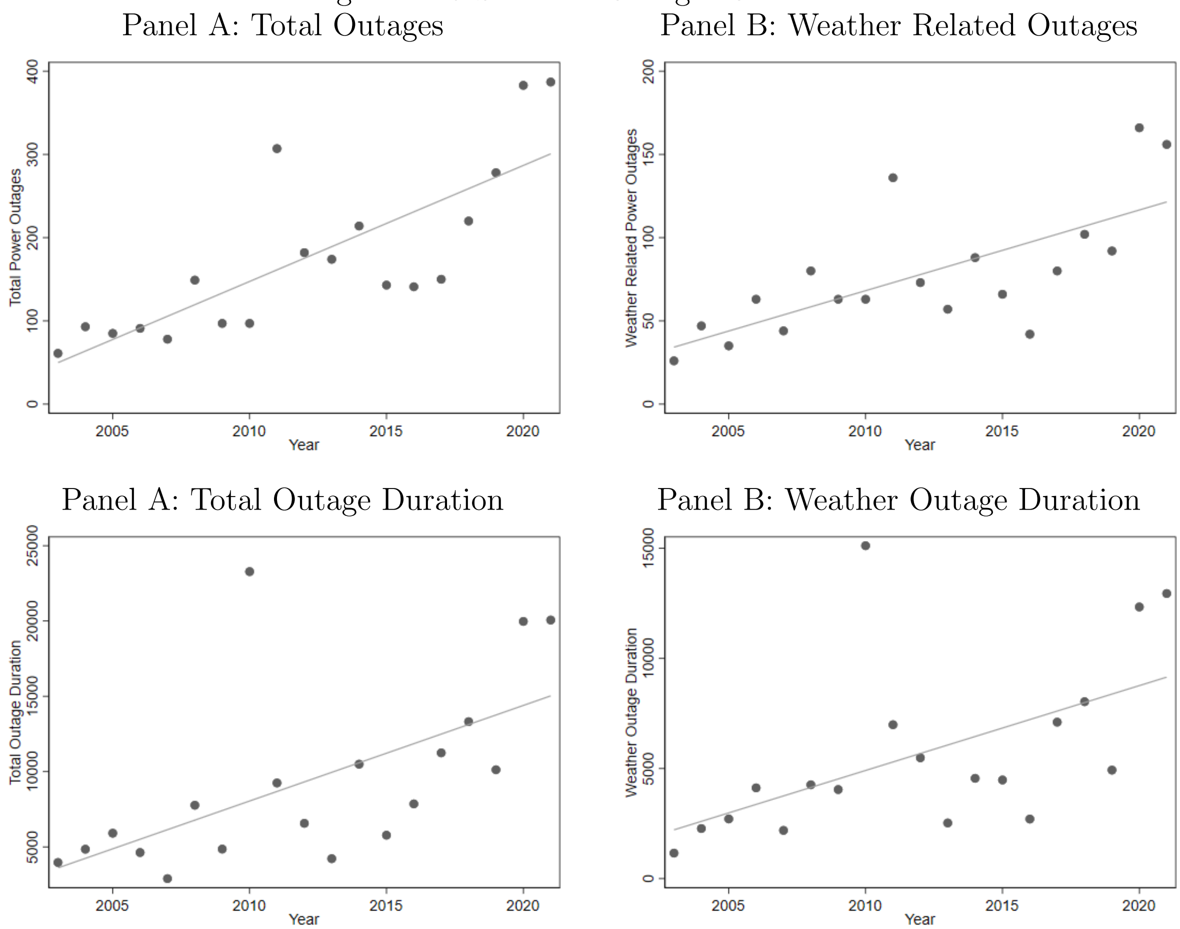
8 Tables and Figures

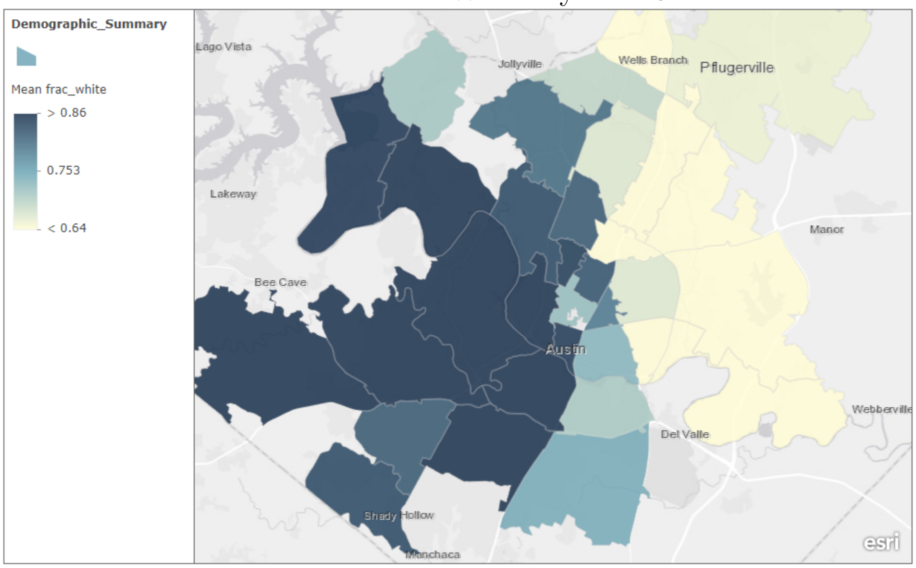
Figure 1: U.S. Power Outages Over Time



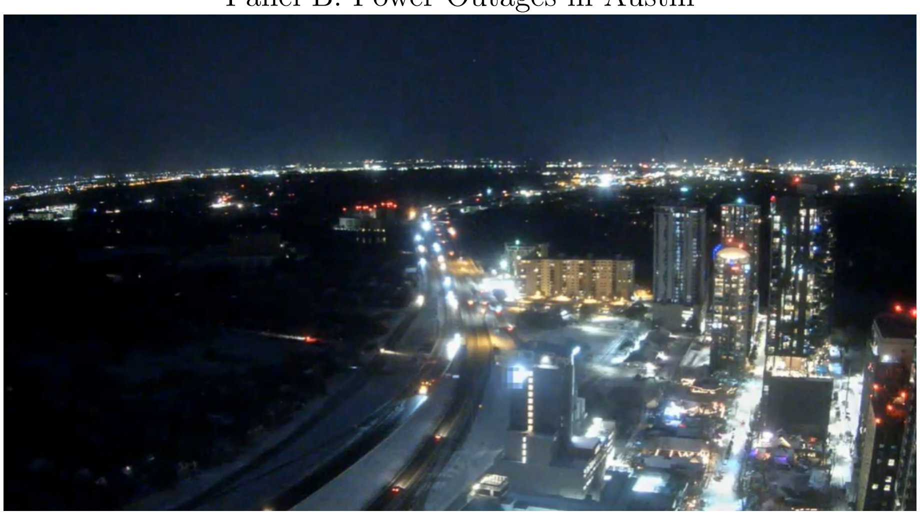
Notes: Panel A shows the number of Power Outages experienced in the US each year over time. Panel B shows the number of power outages due to weather. Panel C shows the total duration of power outages in hours and Panel D shows the total duration of weather related power outages in hours. Note that this 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



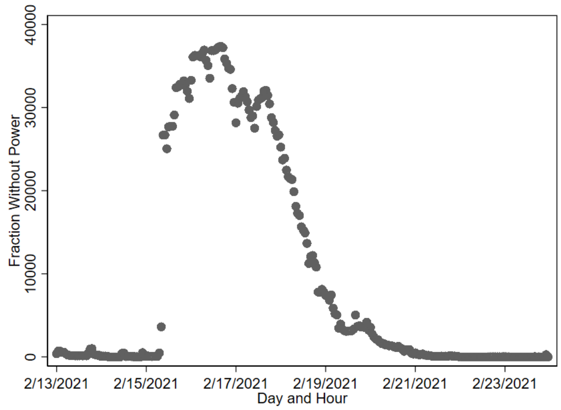
Panel B: Power Outages in Austin



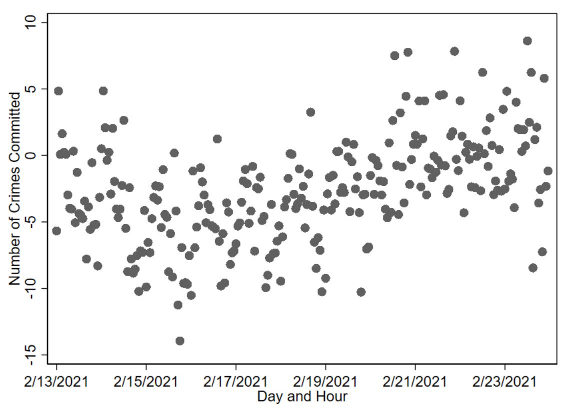
Notes: In Panel B, picture is taken looking South along Interstate 35. As such the left hand side of the picture roughly corresponds to the right hand side of the Figure in Panel A. The photograph in Panel B was taken and shared by local news station KVUE on February 16.

Figure 3: Power Outages and Crime Over Time

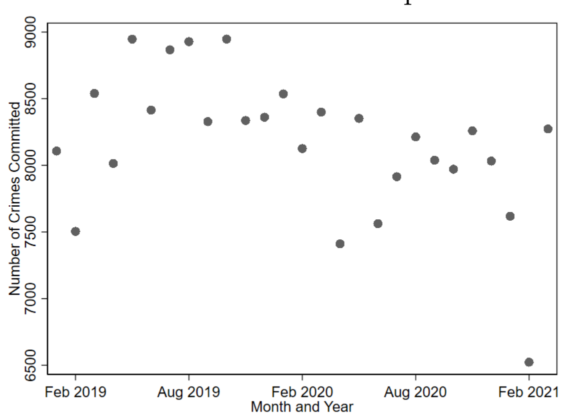
Panel A: Fraction of Households Without Power



Panel B: Number of Crimes per Hour

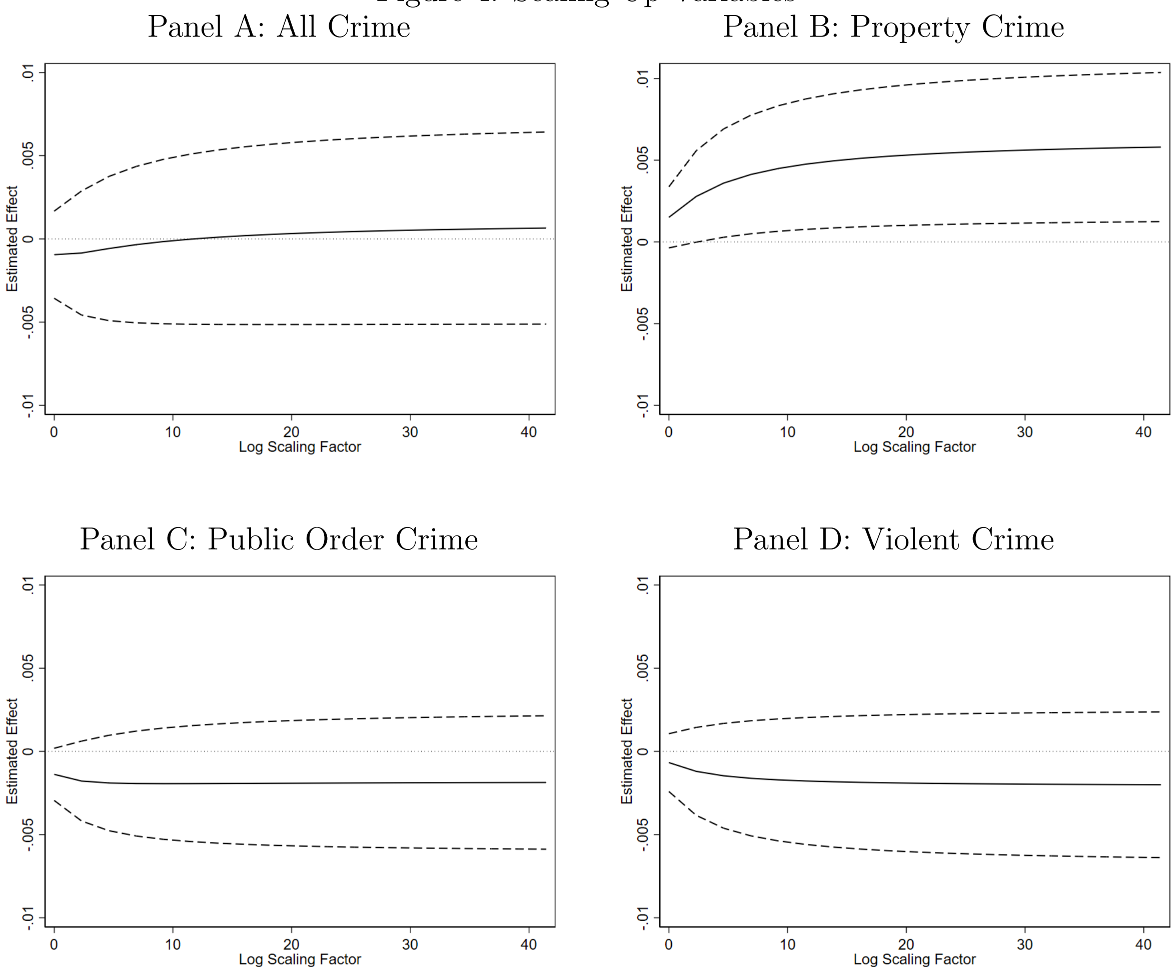


Panel C: Number of Crimes per Month



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.

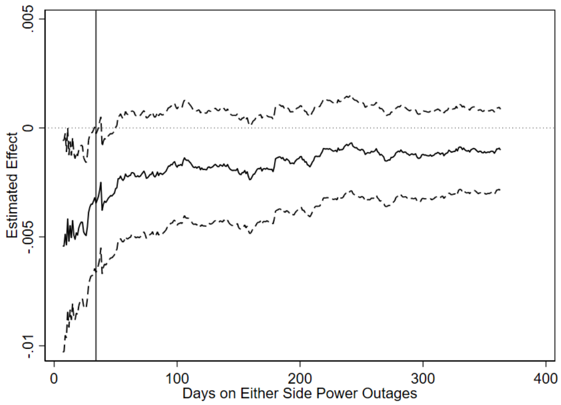
Figure 4: Scaling Up Variables



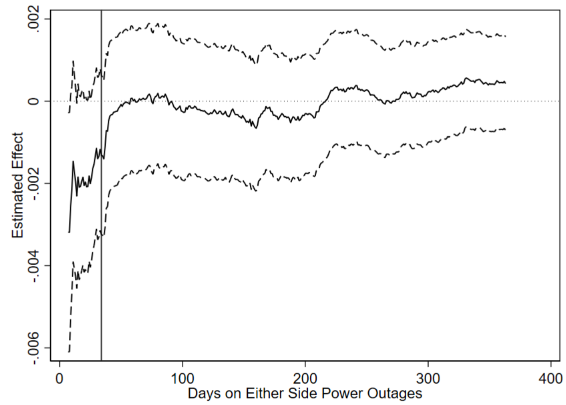
Notes: Figure shows the results of our preferred specification after scaling both the crime rate and the outage rate by the indicated value. The X-axis has been logged such that a value of 9 is approximately equivalent to multiplying both variables by 100,000. This would imply that we are measuring crimes (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

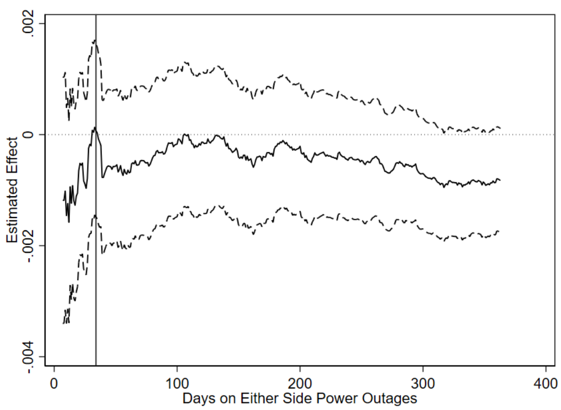
Panel A: All Crime



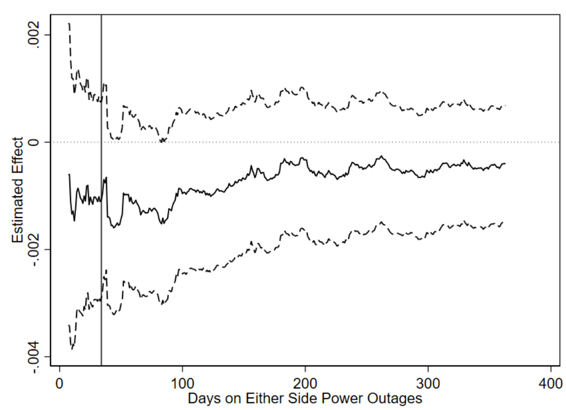
Panel B: Property Crime



Panel C: Public Order Crime

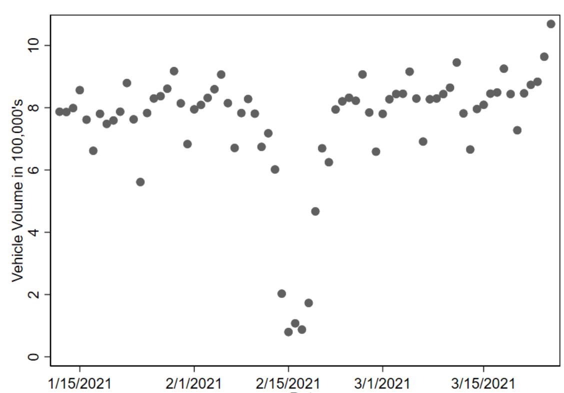


Panel D: Violent Crime



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.

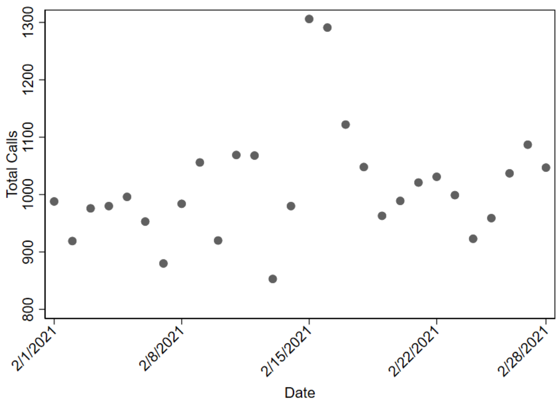
Figure 6: Impact of Outages on Traffic - Vehicles per Day



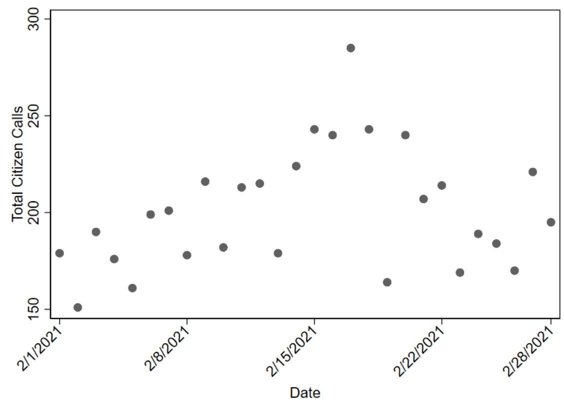
Notes: Figure shows the total number of vehicles driving past sensors distributed throughout Austin per day.

Figure 7: Policing During February 2021

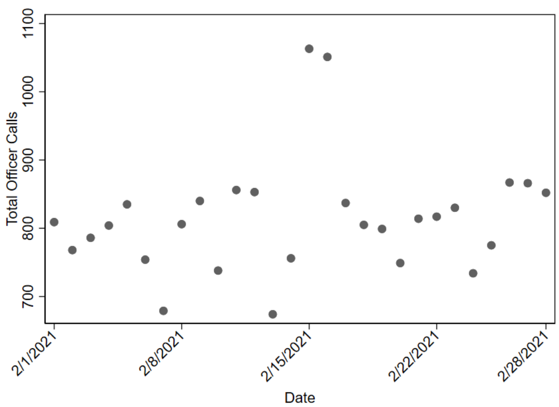
Panel A: Total Calls for Service



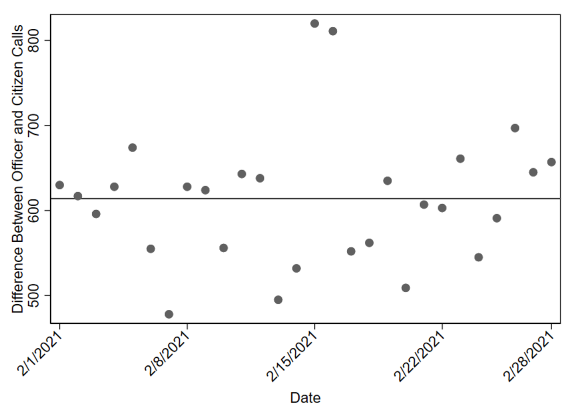
Panel B: Citizen Calls for Service



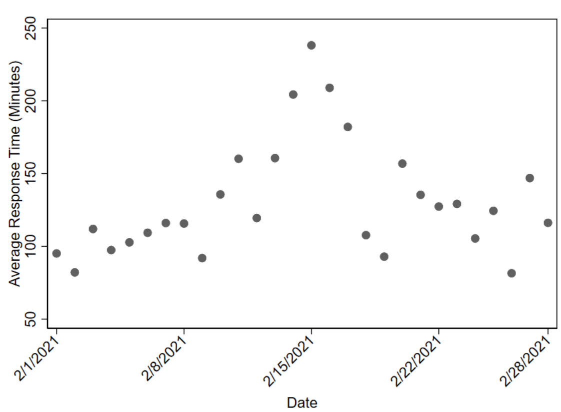
Panel C: Officer Calls for Service



Panel D: Call Difference

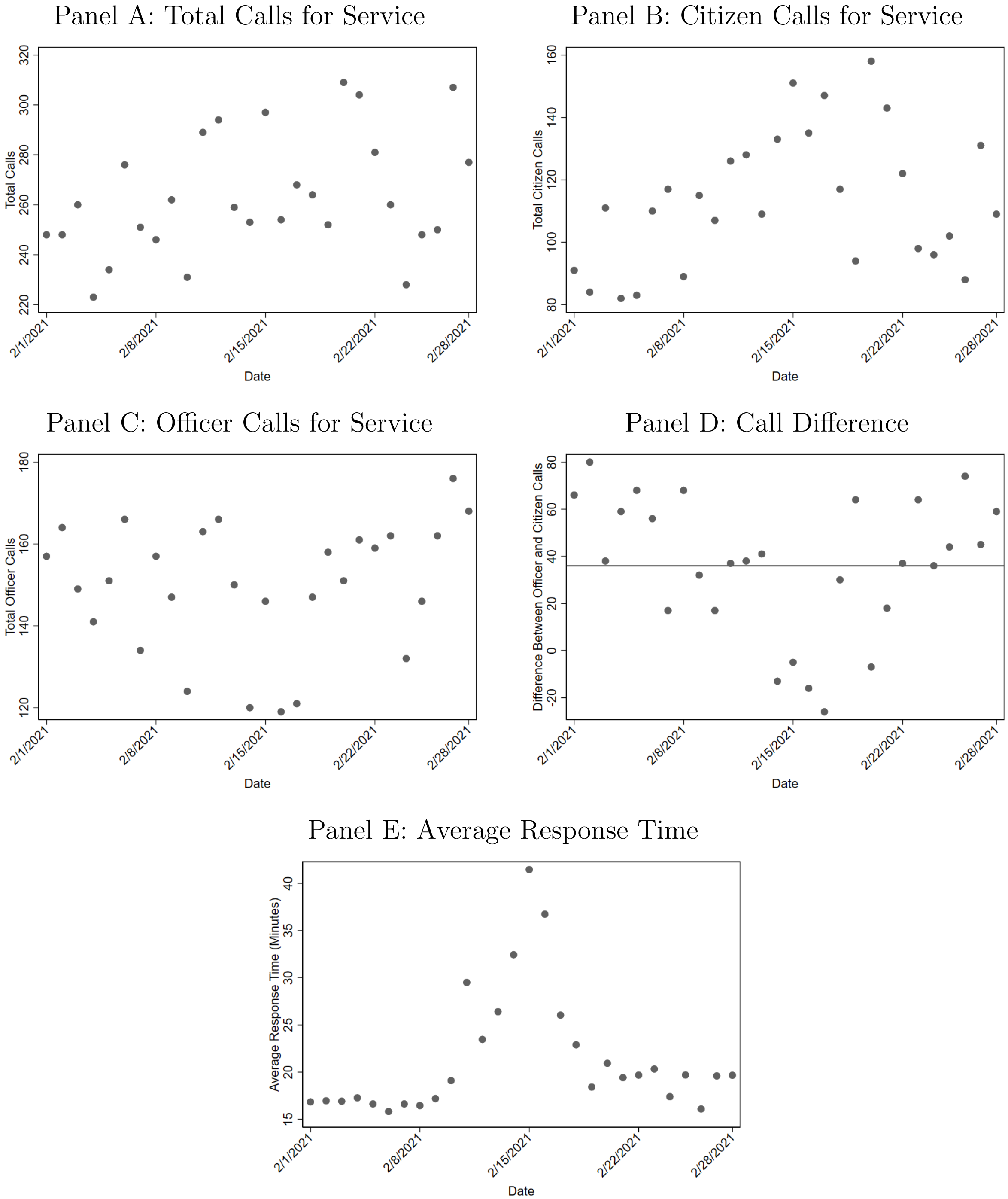


Panel E: Average Response Time



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) ≥ 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 ≥ 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
Outages per 100,000 Households	-0.001	0.002	-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)
Temperature	0.002**	0.001**	-0.000	0.000
	(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)
Precipitation	0.066	0.049	0.008	0.035
	(0.051)	(0.037)	(0.032)	(0.031)
Wind Speed	-0.000	0.000	-0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.424***	0.160***	0.137***	0.145***
	(0.034)	(0.024)	(0.020)	(0.021)
Observations	393944	393944	393944	393944
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. 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	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	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
	(0.002)	(0.002)	(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)
Temperature	0.001	-0.004**	0.001	-0.002	0.000	-0.001	0.000	-0.003**
	(0.001)	(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)	(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
	(0.076)	(0.077)	(0.057)	(0.052)	(0.047)	(0.046)	(0.044)	(0.049)
Wind Speed	0.000	-0.001	0.000	0.000	-0.000	-0.001*	0.000	-0.001
	(0.001)	(0.001)	(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***
	(0.056)	(0.061)	(0.041)	(0.041)	(0.032)	(0.039)	(0.034)	(0.039)
Observations	213408	180536	213408	180536	213408	180536	213408	180536
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ZIP Code×Hour×DOW FE	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. 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) Last 2 Hours	(2) Last 4 Hours	(3) Last 6 Hours	(4) Last 12 Hours
All Crimes				
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
Public Crimes				
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
Property Crimes				
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
Violent Crimes				
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
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.

Table 9: Neighborhood Level Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Frac Without Power	-0.080	-0.009	0.015	-0.021	-0.021	-0.100
	(0.065)	(0.071)	(0.072)	(0.074)	(0.075)	(0.107)
Temperature	0.023***	0.031***	0.007	0.007	0.007	0.013
	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)
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	-1.463	2.284*	0.345	0.289	0.289	2.314
	(0.915)	(1.184)	(1.208)	(1.189)	(1.194)	(1.493)
Wind Speed	0.006	0.016***	0.001	0.001	0.001	0.010
	(0.004)	(0.005)	(0.006)	(0.005)	(0.005)	(0.007)
Constant	0.306***	0.007	0.682***	0.687***	0.687***	0.481***
	(0.054)	(0.117)	(0.125)	(0.123)	(0.123)	(0.183)
Observations	42768	42768	42768	42768	42768	42768
Date FE	No	Yes	Yes	Yes	Yes	Yes
Hour FE	No	No	Yes	Yes	No	No
Neighborhood FE	No	No	No	Yes	No	No
Neighborhood×Hour FE	No	No	No	No	Yes	No
Neighborhood×Hour×DOW FE	No	No	No	No	No	Yes

Notes: Dependent variable is the crime rate per 100,000 people in a particular neighborhood during a particular hour. Outages are calculated by based on the number of stoplights that were not functional in each neighborhood in each hour per 100,000 stoplights. Because we only have stoplight data from February 11, 2021 through February 28, 2021, our analysis in this Table is limited to that short window around the outages. Standard errors allow for clustering within neighborhood-by-hour-by-day-of-the-week-bins and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Neighborhood Level - Crime Type

	(1) All	(2) Property	(3) Public Order	(4) Violent
Outages per 100,000 Households	-0.002	-0.002**	-0.001	0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Temperature	0.004	0.000	0.002	0.001
	(0.003)	(0.002)	(0.001)	(0.002)
Temperature Squared	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	0.752	0.531*	-0.075	-0.515**
	(0.490)	(0.312)	(0.238)	(0.258)
Wind Speed	0.004	0.002	0.001	0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Constant	0.158***	0.086**	0.026	0.059
	(0.060)	(0.035)	(0.032)	(0.038)
Observations	42768	42768	42768	42768
Date FE	Yes	Yes	Yes	Yes
Neighborhood×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 neighborhood during a particular hour. Outages are calculated by based on the number of stoplights that were not functional in each neighborhood in each hour per 100,000 stoplights. Because we only have stoplight data from February 11, 2021 through February 28, 2021, our analysis in this Table is limited to that short window around the outages. Standard errors allow for clustering within neighborhood-by-hour-by-day-of-the-week bins and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.