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Extreme Weather Events, Blackouts, and Household Adaptation

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Extreme weather events, blackouts, and household adaptation

Working Paper

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Abstract

Extreme weather events are becoming more frequent with climate change, yet cold stress events remain understudied. I use the 2021 Texas freeze to examine household adaptation to extreme weather-induced blackouts, focusing on (1) adaptation uptake, (2) socio-economic disparities in adaptive capacity, and (3) salience spillovers. Using an event study design, I analyze the time-varying effects of a one-off dosage treatment, defined as blackout exposure. I leverage novel data on installation permits for home generators and rooftop-solar-battery systems as adaptation measures. Results show a significant, robust response peaking in the second calendar quarter post-treatment, where a 10 percentage point increase in outages leads to 16.4 (8) additional quarterly permits per 10,000 households for generators (solar-battery systems). Google search data suggests the 2021 freeze was widely associated with climate change for the first time, possibly explaining the adaptation response absent in earlier events. Notably, in addition to finding weaker responses for lower-income, less-educated, and high-minority neighborhoods, I also identify a one-quarter delay in their response, highlighting disparities in both adaptive capacity and promptness. Salience spillovers further reinforce adaptation, which can be explained both by social connectedness and geographic proximity. My findings underscore the need for public outage resiliency investments and regulation to decrease unequal future exposure and policies that address inequities in climate resilience.

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Keywords: Extreme weather, Adaptation, Outage, Climate change, Event study, Dosage treatment

JEL Classification: D12, Q54, L94

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Declaration of interests. The author declares that they have no known competing conflict of interest or financial interests that could have appeared to influence the work reported in this paper.

1. Introduction

Reports from the current IPCC assessment cycle have emphasized that climate change is well underway and the world is on track to exceed the 1.5°C target from the Paris Agreement (IPCC Working Group II, 2022, IPCC Synthesis Report, 2023, Paris Agreement, 2015). While mitigation strategies for carbon abatement remain important, it will, however, also become relevant to understand and optimally use adaptation potentials to dampen the impacts of climate change. With climate change, adverse weather events and extreme temperatures become more frequent (IPCC Synthesis Report, 2023) – and go beyond heat and drought-related events. Natural scientists forecast breakouts of the polar vortex to happen more frequently, causing extreme cold waves in North America and Europe (Cohen et al., 2018) – hitting also historically mild regions further south. Extreme weather events are known to cause substantial damages and experiencing natural disasters has an impact on households’ investment choices, such as home ownership (Sheldon and Zhan, 2019). Most prolonged outages in the U.S. are caused by extreme weather (Do et al., 2023) and Rubin and Rogers (2019) reveal that many studies find preparedness to play a key role in household resilience against major blackouts. Understanding the investments (or lack thereof) of households into adaptation and resilience is therefore vital, if policymakers want to incentivize appropriate adaptation under equity considerations and choose optimal public investment.

In this study, I analyze the aftermath of the Texas freeze in February of 2021. This cold wave led to extreme negative °Celsius temperatures in a state that is used to mild winters. This caused severe outages for multiple days, leaving millions of Texans without electricity during already challenging weather conditions.¹

Hence, I use the Texas case study to analyze adaptation behavior at the ZIP code level in the city of Austin after this extreme weather event in order to understand (1) if and to what extent households took up adaptive resiliency measures, (2) if there are socio-economic disparities in adaptive capacity, and (3) if there are salience spillovers to adaptation behavior. In an event study design, I analyze the causal treatment effect of an absorbing one-off dosage treatment on adaptation investments, allowing for varying treatment effects over time. The treatment is defined as exposure to the outages during the freeze event. As a measure of adaptation I use a novel type of granular data collected on mandatory installation permits for home electricity stand-by generators, an intervention type not studied so far, and rooftop-solar-battery systems. These permits are required for any permanent building and electrical construction modifications to building structures and

¹See a report by the University of Texas at Austin (2021) on the timeline of events.

granted by the city or county. My identification strategy relies on an unanticipated treatment event with parallel pre-trends, and on variation in treatment dosage via the outages. The causal identification is supported by the assumption that the blackout treatment was as good as random, as it is uncorrelated with relevant observables. The treatment intensity (dosage) is a continuous variable in terms of hours and customers blacked-out per ZIP code over the course of the outage event. This allows a rich analysis of dosage effects instead of simple binary treatments.

My findings show a significant, prolonged treatment response, which peaks in the second calendar quarter post-treatment, where a 10 percentage point increase in electricity service disruption leads to 16.4 (8) additional quarterly permits per 10,000 households for generators (solar-battery systems). Sample splits by socio-economic characteristics show policy-relevant heterogeneity in treatment responses. Notably, besides finding weaker responses for lower-income, less university-educated, and high-minority neighborhoods, I also show a consistent one-quarter delay in their response, informing on disparities in both adaptive capacity and promptness. In the context of Brehm et al. (2024), who find that private investments in grid substitutes decrease the optimal level of public outage prevention and resilience investments, my findings have large distributional implications for low(er) public adaptation investments. Salience spillovers further reinforce adaptation, which can be explained both by social connectedness and geographic proximity.

The case of the Texas freeze with its subsequent blackouts is especially interesting to study for three reasons. First, it is known that cold-stress causes damages and seems to induce adaptation behavior (Yu et al., 2019). However, the literature on unanticipated cold-stress events is scarce, even though multiple regions are seeing unusual cold events (Europe cold snap 2018, Texas freeze 2021, Spanish snowstorm 2021), which can be associated with climate change (Cohen et al., 2018). Second, I study a case, where the baseline level of cold-stress adaptation can be assumed to be very low, such that the treatment effect can be cleanly measured. Despite two prior cold-stress events in 1989 and 2011, the permits for electricity generators in my sample had been consistently low prior to the 2021 event, while adequate public investments were missing, too. Google searches around the 2011 event did not show a systematic association with climate change and historical permit data also does not show a relevant investment response after this event, which speaks to the unpreparedness of households. In contrast, Google searches during the 2021 event indicate a systematic association with climate change and coincide with significant treatment effects found in this study. This suggests that the recent response is likely motivated by adaptive resilience. Third, the adaptation interventions of cold-stress and related blackouts have large policy relevance. For instance, household interventions against blackouts from cold-stress (e.g. generators) also lead to

benefits in the common case of heat-stress-related blackouts, which are also amplified by climate change. Further, interventions against weather-related blackouts are highly relevant for energy policy and low-carbon transitions. For instance, investments into fossil-fuel-based home electricity generators can be regarded as maladaptation from a climate policy perspective, while investments into rooftop-solar-battery systems can be viewed as clean adaptation. Last, Texas is currently discussing public policies of extreme weather-related outage prevention and resilience, which should consider household adaptation needs and capacity.

My research complements increasing efforts in the literature to study the potentials, instruments, and issues of households' investments into outage resilience and adaptation to climate change. There is evidence for adaptation via mortality associated with temperature extremes (Barreca et al., 2016), where rural households exhibit less adaptive investments than urban households (Yu et al., 2019). This indicates the relevance of equity aspects of adaptation but provides no further differentiation of disparities. Noll et al. (2021) provide evidence on how household characteristics influence household adaptation efforts but are constrained to survey data. Furthermore, households' previous experience of natural disasters also influences their housing investments (Sheldon and Zhan, 2019), and survey-based salience of climate change and risk perception (Demski et al., 2016). This aligns with a study on hurricanes, where Beatty et al. (2019) find systematic differences in ex-post disaster response regarding bottled water, batteries, and flashlights as emergency supplies.

My work is most similar to very recently published studies that used blackouts and solar-PV-battery installations mostly in California to analyze the value of lost load (VOLL) (Brown and Muehlenbachs, 2024), the technological complementarity of solar PV and storage (Bollinger et al., 2023), and the welfare effects of these private substitutes for grid reliability via a calibrated theory model (Brehm et al., 2024). These studies focus primarily on California, which is known for wildfire-related outages, and, importantly, do not take into account investments into home electricity generators in the empirical analysis.² Hence, the VOLL from Brown and Muehlenbachs (2024) and investments into private grid substitutes in Brehm et al. (2024) can be expected to be lower bound estimates, as important alternatives to PV with storage, namely generators, are not considered.

To the best of my knowledge, this study is the first to look at causal adaptive responses to

²Brehm et al. (2024) present survey data on the general stock of generators as motivating empirical facts. However, their causal estimation of treatment responses is based only on battery storage.

electricity infrastructure disruptions during cold-stress events and, notably, to work with actual archive data for stand-by electricity generators. I also focus on a state other than the well explored Californian market. Combining this with data on PV-battery-systems from the same data source, I am the first, to my knowledge, to estimate causal responses for both types of investment alternatives, hence providing an opportunity to compare them and uncovering the extent of underestimation of studies considering only PV-battery-systems as grid substitutes. I further present a novel argument that responses are of adaptive nature not only with regards to grid independency but also to climate change being a significant risk factor for outages. This is supported by Google search data associating the extreme weather event with climate change. My findings contribute to filling the literature gap on private adaptive resilience responses to cold-stress related disruptions of critical infrastructure services, in light of dirty and clean intervention measures and socio-economic inequities in adaptive capacity, which underline the distributional implications of public underinvestment.

The remainder of this paper is organized as follows. Section 2 describes the treatment event and provides some context, section 3 introduces the data, section 4 develops the empirical strategy, section 5 presents results, section 6 discusses them, and section 7 concludes.

2. The treatment event and background

Weather. In February 2021, Texas was hit by an unusual, largely unanticipated cold wave that caused two-digit negative °C temperatures in a region that usually experiences mild winters (e.g. in Austin in February the average maximum temperature is +19°C and average minimum temperature is +7°C).³ The responsible winter storm lasted from February 13 to February 20 and its severity was largely unanticipated by both the Electric Reliability Council of Texas (ERCOT) and the public. The University of Texas at Austin (2021) report summarizes that by end of January, the expert community on meteorology did indeed forecast a polar vortex event. However, weather models had issues predicting the extent and severity of the temperature impacts at the regional level. As a consequence, the weather model employed by ERCOT underestimated the temperature drop even shortly before its arrival. Due to temperature being an important predictor of electricity demand, ERCOT’s demand projections were also underestimated for the freeze event (University of Texas at Austin, 2021).

³See <https://weather-and-climate.com>.

Electricity generation failures. Despite some irregular previous cold wave events e.g. in 1989 and 2011, the Texas power system was significantly impacted by the winter storm of 2021. In particular, already on February 13, first major generation capacity began to fail and by February 14, first supply shortages began to occur and cause grid instability. At the peak, about 40% of the ERCOT generation capacity (thermal and renewable capacity being both affected) was out, mainly directly due to not being able to operate under the weather conditions, due to fuel or equipment issues or due to being taken off-grid to avoid damages at the generation unit from low grid frequencies (ERCOT, 2021). The situation in Texas is special, as the power system is largely independent and hardly connected to any neighboring power systems, which could have dampened the impact of regional generation outages through cross-border transmission. In response to the severe supply shortage, ERCOT set electricity prices to the system price cap of \$ 9,000 per MWh for multiple days, which particularly harmed a minority of customers on real-time pricing plans (University of Texas at Austin, 2021).

Electricity outages. The combination of generation failures, high demand, and lack of grid interconnection with other states, led to severe outages over the course of multiple days from February 15 to February 18 (University of Texas at Austin, 2021), marking the outage treatment event period. Starting on February 15, ERCOT had to order load shedding, i.e. controlled partial blackouts, so-called brownouts⁴, to avoid a complete grid collapse. The procedure was as follows. ERCOT gave ad-hoc load shedding quotas for the next 15 minutes to the transmission network⁵ operators, who then had to fulfill these quotas by in return giving quotas to their distribution network⁶ operators. It was the responsibility of the distribution network operators to finally decide ad-hoc, which circuits to cut-off in real-time in their area of operation. The majority of service disruption occurred in this partially controlled but unsystematic manual manner and was complemented by automatic load shedding. This refers to circuits being automatically cut-off by installed grid switches, when local grid frequencies deviate beyond a certain threshold (University of Texas at Austin, 2021). Combined, this led to quite some variation in outage patterns and fluctuations in the hourly share of blacked-out customers across ZIP codes over the event window (Appendix A, Figure A.1). Overall, it was, hence, for customers not possible to anticipate the timing, duration, and location of outages.

⁴For simplicity here and in the following I will continue to refer to these outage events as blackouts.

⁵high-voltage, long-range grid

⁶lower-voltage, shorter-range grid

Precedence. Texas had experienced two similar, major cold events with subsequent blackouts in 1989 and in 2011. There are some notable similarities and differences between the three events: In terms of temperature lows, the cold spell in 1989 was comparable to the 2021 event, but lasted only for three days. The week long cold spell in 2011 was similarly long as in 2021 but milder. Looking at the extent of generation failures, both preceding events fall short of the 40 % generation failure in 2021 (FERC and NERC, 2011). Controlled outages in 1989 lasted for up to 10 hours at maximum (differing by region) and for about 8 hours in 2011. While the market structure in 1989 consisted of vertically integrated utilities without a joint market, the 2011 market structure was roughly the same as in 2021. System price caps were reached for multiple hours in 2011, which were at the time set at \$ 3,000 per MWh (University of Texas at Austin, 2021). In summary, both events preceding the 2021 freeze fall slightly behind in terms of outages and economic impacts, however, both constitute major preceding electricity supply disruptions. Some policy intervention efforts were undertaken after 2011, relating to weatherization of generation units and emergency planning, but they were largely unsuccessful or not properly put into action (University of Texas at Austin, 2021).

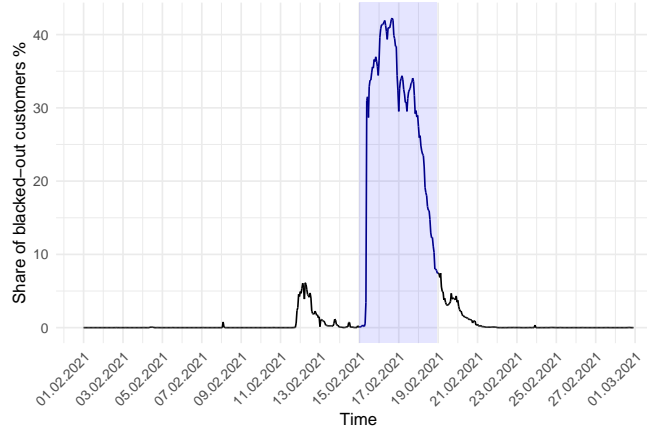
3. Data

3.1. Electricity outages data

The relevant time frame for the blackout event is February of 2021, in particular, the main event time being the outages in the Texan power grid from February 15 to February 18. Data for outages is collected and published by electricity providers and tracked and aggregated by the data service provider Bluefire Studios LLC (2023) on PowerOutage.US. I acquired historical outage data on the event month of February 2021 from this source at the hourly level for the state of Texas. In particular, the data contains the hourly number of tracked customers and customers with interrupted service per tracked location. Even if not the whole population is observed, this allows to keep track of how large the share of observed population is and to control for possible data quality issues here. The granularity level of tracked locations depends on the tracking level of electricity providers, such that the most granular location can be at the county, city, or ZIP code level. Generally, the more densely populated an area, the more granular the tracking level. As I need sufficient variation in outages, I constrain the data to locations tracked at the ZIP code level. The resulting data set is ZIP code-based panel data, not household panel data, meaning that the total number of blacked-out customers is tracked without being able to trace household-specific durations of outages.

Figure 1 provides insights into the extent of outages aggregated for the city of Austin. On the vertical axis customers with interrupted service are plotted in the aggregate for all Austin ZIP codes as a percentage share of total tracked customers. The event period from February 15 to February 18 is indicated in blue.

Figure 1: Share of hourly outages in percent for the City of Austin



Event period Feb 15 - Feb 18 2021 marked in blue.

As the ZIP code-based treatment variation is lost in the aggregate plot in Figure 1, Table 1 presents the summary statistics for the ZIP code-specific outage shares for the whole event period and Figure 5 plots the spatial variation. For ZIP code-specific timeseries of the outage intensity during the event, refer to Figure A.1 in Appendix A.

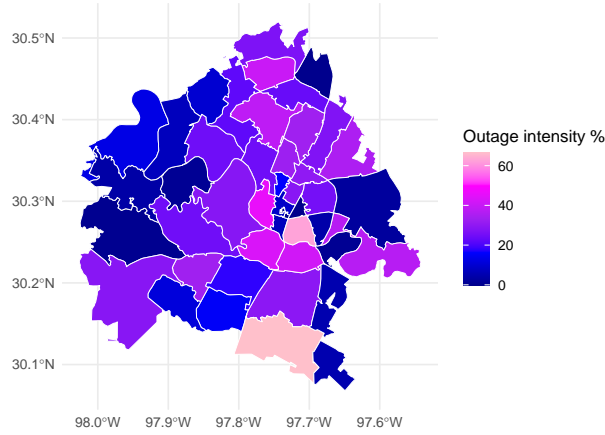
Table 1: Summary statistics of the ZIP code-specific outage share over the course of Feb 15 - Feb 18, 2021

Min.	1st Qu.	Median	Mean	3rd Qu.	Max	N=
0.000	7.412	24.760	22.450	32.830	66.730	44

3.2. Permit data

I use novel data on grid electricity substitutes. In particular, I have collected rich permit data from city archive records for the City of Austin, Texas (2023). Specifically, I use permits for stand-by generators, rooftop solar PV, and battery storage installations. I concentrate on Austin for my study as both the outages data and permit data exhibit high quality. All permits track the exact street address, permit type, exact application and issue dates of the permit, the permit status, and some even state an expected dollar amount for the whole work planned for the project.

Figure 2: Spatial variation of treatment intensity



The permit data is available not only for years 2021 and 2022 following the blackout event but also dates back multiple decades. This provides a rich basis to analyze pre-trends. The request or even the granting of an installation permit is not a guarantee that the respective household will actually have a generator installed. Instead, the permit data only records an intent and permission to take up this adaptation intervention. However, given that households have to invest time, effort, and a permit fee to go through the complex permitting process, which is often even done by an already contracted electric installation company, it is highly likely that the work has already been planned and commissioned and that some type of binding agreement already exists between the household and a contractor. It can therefore be assumed that the permits constitute a credible commitment and hence a good proxy for the installation of this adaptation measure. It should be noted that permits are mandatory for permanently installed electrical modifications such as stand-by generators, rooftop solar PV, and battery storage in this case – but not for portable generators. The latter are hence not covered by the permit data but also do not represent a reliable substitute for grid electricity due to low power and lack of weatherization compared to stand-by generators. A comparison of both generator types and battery systems for rooftop solar PV, including their potential to bridge prolonged outages, is provided in Appendix A, Table A.1. On a general note, the permit application itself is a complex bureaucratic process. It involves identifying the appropriate permit type(s) among many, checking for any permit exemptions, investigating if the application should be submitted by the homeowner or a contractor, and gathering all necessary information to fill the respective web application forms. The process may also involve appointments with service units from the City of Austin Permitting and Development Center to receive support

on the permitting process.

3.3. Socio-economic data

In order to control for socio-economic and socio-demographic characteristics of the population in the empirical setting, I employ U.S. Census Bureau (2023) data from the American Community Survey (ACS) at the ZIP code level. This pertains most importantly to population size but also includes data on income, race, education, dwelling characteristics like owner-occupancy versus renter occupancy, etc.

4. Empirical strategy

I develop my empirical design tailored to the characteristics of the study setting as follows.

Treatment is simultaneous, one-time, absorbing, with no/few never-treated units. I use the last pre-treatment period as the omitted category,⁷ which is supported by the following identifying assumptions; (a) I assume that there are no relevant determinants of the outcome that are correlated with time, as the pre-trend of generator permits is flat at virtually 0 and therefore a credible counterfactual (Miller, 2023). This is further supported by the lack of anticipation of the event (along the lines of Borusyak et al., 2023); (b) I assume that there are no confounders that change abruptly with treatment. Exploiting such a discontinuity introduces some regression discontinuity design in time (RDiT) properties to my study. However, as Hausman and Rapson (2018) point out, RDiT designs do not handle time-varying effects well, which typically leads to bias in the treatment effect estimates. This brings me to the next point.

Treatment effects likely fade over time. This is due to salience fading over time and due to long-run saturation effects (intuitively, once a household has acquired a generator, they will be saturated over the medium-term). In order to allow for time-varying treatment effects, I finally decide to use an event study set-up with time period dummies.

Treatment is continuous (non-binary). Units receive treatment in different intensities, i.e., there is continuous variation in treatment dosage. This presents an opportunity for richer insights from dosage response effects. For identification, I further use the supporting assumption that the

⁷Neither never-treated unit as in a DiD design, nor not-yet-treated units as in staggered adoption designs can be used as a control group.

blackout treatment dosage is as good as random due to the ad-hoc nature and institutional set-up of the rolling brown-outs (see section 2).

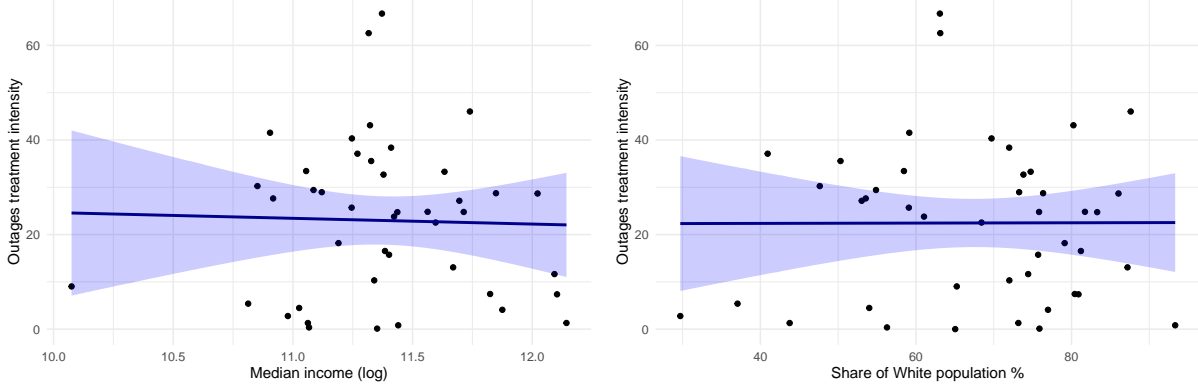
4.1. Threats to identification

Sample selection bias. My sample is restricted by the availability of outage (i.e. the treatment) data at the ZIP code level. This data is collected from electricity retail providers and aggregated by a third party – however, not all electricity retailers are covered. It would be a concern if the outage treatments were systematically correlated with the participation in outage statistics. This, however, is not possible as it was up to the distribution system operators (DSO) to take final decisions on load shedding, not electricity retail companies, and DSOs further do not share the same business operation areas as retailers. For instance, the same retail company may be active in multiple DSO areas and multiple retail companies can operate in the same DSO area.

Treatment selection bias. When analyzing dosage treatment effects, the most relevant threat to identification is possible endogeneity with regard to the treatment intensity. Two arguments, one anecdotal and one empirical, support the assumption that the outages were as good as random. (1) The institutional set-up. Remember that the rolling blackouts were decided upon by DSOs, who received load shed quotas from the transmission system operators, who in turn received quotas from ERCOT (University of Texas at Austin, 2021). This means that the decision process of the DSOs was significantly constrained due to the multi-layered quota cascade and the very short-term decision-making. (2) Descriptive empirics. The biggest concern would be if the treatment intensity were somewhat correlated with relevant predictors for permit applications. I therefore run regressions of the treatment intensity on logged median income and the share of White population (two major inequality indicators and likely determinants of permit applications) and find no correlation (see Figure 3).

Parallel trends assumption and lack of anticipation. Intuitively, the parallel trends assumption is likely to hold due to the seemingly random nature of treatment discussed previously. Due to the random treatment and the short-term forecast of the weather phenomenon, it is also unlikely that households could anticipate treatment. Both of these intuitions are supported by the raw time series data for permit applications. Even if aggregated for the whole city of Austin, in the 10 years prior to treatment, the monthly total generator permit applications are between 0 and 10. For most months the number is below 5. For reference, in this time frame the number of inhabitants in Austin ranged between 800,000 and 1,000,000. A placebo test for the parallel trends assumption and lack of anticipation is incorporated into the regression design and outlaid in Section 4.2.1.

Figure 3: Tests for selection into treatment (intensity)



Regression of outage treatment intensity on logged median income (left panel) and on the share of white population (right panel) for Austin ZIP codes (without controls) with 95 % confidence bands.

Average dosage response effects. As part of the most recent DiD and event study literature, Callaway et al. (2024) have pointed out some issues when measuring dosage treatment effects in TWFE event studies. Some of their concerns relating to selection bias and variation in treatment timing are alleviated in my study, as treatment seems as good as random and is simultaneous. Further, Callaway et al. (2024) emphasize that the measured dosage treatment effect is mainly driven by the treatment effect around the average dosage, i.e. in my case the effect of a percentage point dosage increase around the average dose. This has two implications; (1) any non-linear dosage response effects are lost, and (2) high weight on the dosage response makes the interpretation of the results more difficult, if the treatment dosage is not normally distributed around the average dose or if the distribution has fat tails. Due to the small sample size, it is unlikely that the outage intensity is normally distributed. In fact, a density plot (Appendix B, Figure B.2) reveals high weight especially to the left tail of the distribution and slight bimodality. However, there is still substantial weight of the distribution around the mean, rendering the dosage effect still informative, while being cautious about the above-named limitations.

4.2. Baseline model

4.2.1. Adoption of generators

I start out with an event study fixed-effects design with continuous treatment:

$$Gen_{it} = \alpha + \sum_{k \leq -2} \beta_k Out_i * I_{pre}\{k = t\} + \sum_{k \geq 0} \gamma_k Out_i * I_{post}\{k = t\} + \delta_i + \epsilon_{it} \quad (1)$$

where indices i and t represent the ZIP code area and time period in quarters (treatment in $t = 0$), Out is the treatment intensity, I_{pre} and I_{post} are indicator functions for the pre- and post-treatment time period dummies, δ are unit fixed effects.⁸ The omitted category for the treatment effect is the last period before treatment, $t = -1$. Further, Out is a continuous treatment intensity in percentage share of blacked-out customer×hours in the event period and the main variable of interest. Customer×hours is a measure jointly capturing the number of hours, in which a ZIP code experienced outages (extensive margin) and the number of households affected in each hour (intensive margin). I provide more detail on how this variable is constructed in Appendix B. Finally, Gen is the continuous outcome variable, measuring the generator permit applications per 10,000 households.⁹

As stated in my previous assumptions, the treatment is unanticipated and exhibits parallel pre-trends such that all pre-treatment coefficients (β_k) should be zero. In essence, I could therefore also reduce equation (1) to

$$Gen_{it} = \alpha + \sum_{k \geq 0} \gamma_k Out_i * I_{post}\{k = t\} + \delta_i + \epsilon_{it} \quad \forall (t \geq -1) \quad (2)$$

where $t - 1$ remains the omitted category. However, I can exploit equation (1) with the pre-period treatment dummies included as a placebo test for parallel trends and lack of anticipation (as discussed in de Chaisemartin and D'Haultfœuille, 2023). Given that the results are robust to the placebo test, I can proceed by using the simplified model in equation (2).

To shed light on linearity of treatment effects, I also estimate a model where the continuous treatment variable is categorized into tertile bins:

$$Gen_{it} = \alpha + \sum_{k \geq 0} \gamma_k Tertile_i * I_{post}\{k = t\} + \delta_i + \epsilon_{it} \quad \forall (t \geq -1) \quad (3)$$

4.2.2. Adoption of rooftop solar PV with storage

The permit application data likewise contains data for PV with storage. This presents an opportunity to use this as a second outcome measure, as both options can be set-up in a way to

⁸I opt to not use time fixed effects, as the pre-treatment data shows generator permit applications quite stable throughout, i.e. being very robust to time-varying external factors (e.g. macroeconomic environment). Furthermore, I aim to capture time-varying treatment effects. These would otherwise be absorbed by time fixed effects, as there is no variation in treatment timing (see Borusyak et al., 2023, for a related discussion).

⁹Note that I have aggregated the analysis at the quarterly level due to noisiness of the monthly data.

provide back-up power during a multi-day outage. One could argue that generators, however, leave households vulnerable to fuel shortages (and price spikes), which can be expected to occur during such extreme events. PV with storage, meanwhile, also serves an additional benefit beyond outage resilience thanks to possible usage throughout the year – not just during outages. In addition, considering decarbonization and air pollution abatement efforts of current policies, generators may be seen as a maladaptation intervention compared to clean and regularly employable rooftop-solar-battery systems.

I hence run a similar specification, where I change the outcome variable to permits mentioning PV in combination with storage capacity (*PVStor*). This covers both new installations of combined solar-battery-systems as well as retrofits of already existing PV installations through the addition or expansion of battery capacity.

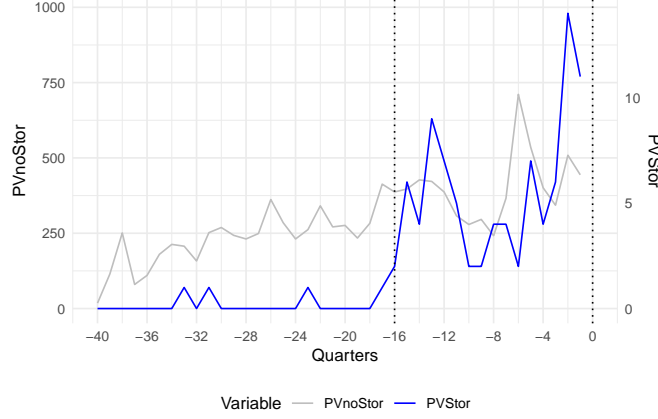
I also add a control variable for permits for PV-only systems, i.e. without any mention of storage, to control for general PV adoption trends, incentive policies, and investment incentives from electricity price signals. By measuring the net effect between PV-only and PV-battery investments, I capture the grid independence incentive, because PV-only installations are not a viable grid electricity substitute for two reasons. Without a battery, PV can only provide electricity during sunny hours – which, even for sunny weather, leaves evening and night-time hours uncovered. Second, in Austin, electricity generated from PV installations is usually fed back into the grid, for which the household is remunerated, while the household gets charged for the gross electricity consumed. In this case, the household physically consumes grid electricity even in hours in which the PV installation generates more electricity than the household consumes. Hence, such a PV-only installation would not grant grid independence in the case of an outage. Only combined systems with batteries provide an option for actual self-sufficiency, which is the effect I aim to capture. Figure 4 graphically illustrates how, since the arrival of battery adoption in the Austin market (around quarter -16), permits for combined PV-storage systems follow similar trends as permits for PV-only. This is further supported by a simple OLS estimation, ZIP-code-wise regressing *PVStor* on *PVnoStor* for quarters -16 to -1 (Appendix B, Table B.2). I hence add permits for PV-only systems as a control *PVnoStor* and obtain

$$PVStor_{it} = \alpha + \sum_{k \leq -2} \beta_k Out_i * I_{pre}\{k = t\} + \sum_{k \geq 0} \gamma_k Out_i * I_{post}\{k = t\} + PVnoStor_{it} + \delta_i + \epsilon_{it} \quad (4)$$

I refrain from adding additional controls or fixed effects, as *PVnoStor* and *PVStor* are driven

by essentially the same conditions (high electricity prices, PV incentive policies, etc.).

Figure 4: Parallel trends of permits for PV with and without storage



Permits for PV-only systems on the left axis. Permits for combined PV-storage on the right axis. Since the start of battery adoption in the Austin PV market (around quarter -16), both exhibit similar overall trends in the 4 years preceding the event.

4.3. Model extensions

4.3.1. Socio-economic heterogeneity

In order to understand the dynamics behind treatment effects and possible disparities, I develop an additional analysis with regard to socio-economic heterogeneity in treatment effects. Even if socio-economic characteristics seem to have not played a relevant role in treatment assignment, they may have an impact of the adaptive capacity of households. This would have distributional implications on the resilience and future disaster preparedness of households and can lead to systematic differences in vulnerability during future events. I therefore test for heterogeneous treatment effects with regard to socio-economic aspects. I extend the baseline models for generators and PV with storage by adding a dummy for the ZIP code being above the sample median for a socio-economic characteristic. This is essentially performing a sample split by a socio-economic characteristic. This approach does not provide any causal inference and some of these characteristics are likely correlated. However, it does provide valuable insights into systematic differences in treatment effects based on policy-relevant characteristics, while keeping statistical power with a relatively small sample size. For the example of generators, the regression equation becomes:

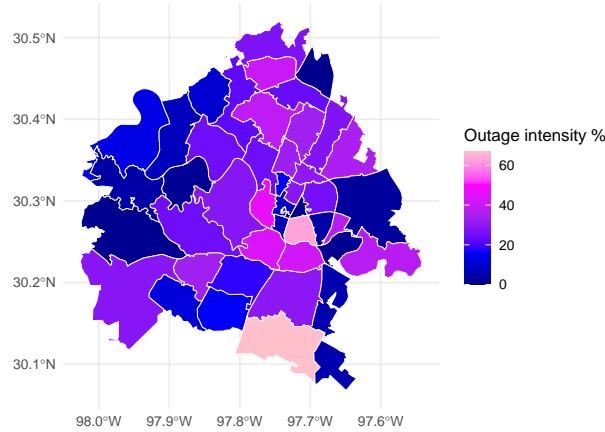
$$Gen_{it} = \alpha + \sum_{k \leq -2} (\beta_k + \vartheta_k D_i) * Out_i * I_{pre}\{k = t\} + \sum_{k \geq 0} (\gamma_k + \zeta_k D_i) * Out_i * I_{post}\{k = t\} + \delta_i + \epsilon_{it} \quad (5)$$

where D is a dummy variable for a socio-economic characteristic, such as income, the share of White population, education attainment, etc. It is equal to 1 for ZIP codes above the sample median and 0 otherwise. The main treatment effect coefficients γ (and the placebo coefficients β), now represent the treatment effect for the bottom half of the sample split, while ζ is the additional effect for the top half (and their placebo coefficient ϑ). Consequently, the total treatment effect for the top half is given by the sum of γ and ζ .

4.3.2. Treatment effect spillovers

Since salience is a relevant factor for household adaptive responses, there is a possibility that this mechanism is intensified by how affected the social environment of a household was by treatment. Measuring spillovers is particularly relevant in contexts with variation in treatment without systematic clustering. Section 4.1 has already laid out the absence of systematic clustering of outages by income and the share of White population of neighborhoods. Mapping out the outage intensity across ZIP codes in Figure 5 shows that also spatial clustering is limited. Often, spillovers are measured via the geographical proximity of two households. However, the social interactions through which experiences are shared, play a major role in how spillovers happen. I therefore use the social connectedness index at the ZIP code level, as introduced by Bailey et al. (2020) to measure spillovers between two ZIP codes.

Figure 5: Spatial variation of treatment intensity



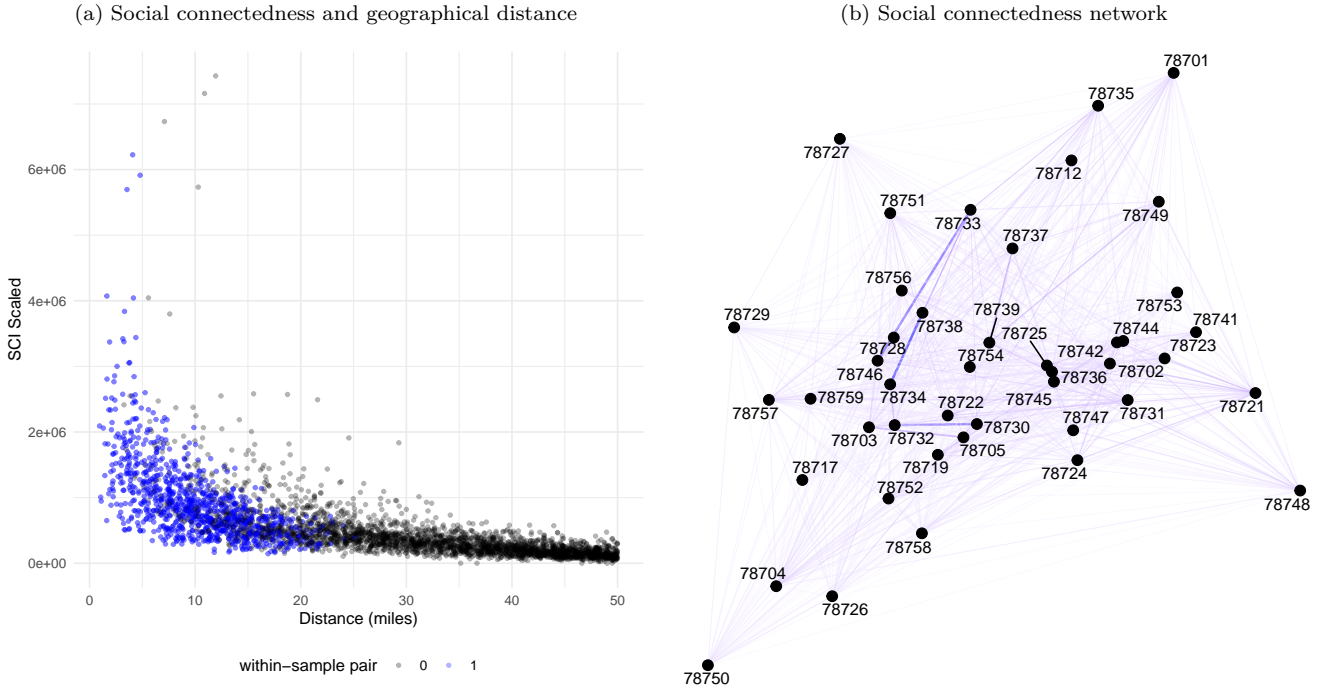
The social connectedness index (SCI) measures the number of friend connections on Facebook between two geographical areas, weighted by the product of total Facebook users in each of the two areas, scaled to range from 0 to 1,000,000 (equation 6). Conceptually, the SCI therefore measures

the likelihood that two given users from the two areas are friends on Facebook.¹⁰ Hence, the SCI proxies how socially intertwined two regions are.¹¹

$$SCI_{nm} = \frac{connections_{nm}}{users_n * users_m} \quad (6)$$

Figure 6a shows that the within-sample pairs in my data are not particularly sampled in terms of the relationship of distance and SCI (except for all being in Austin), compared to pairs with out-of-sample ZIP codes. It also illustrates that while, generally, the SCI and distance are inversely correlated, there are some outliers where the SCI is higher or lower than would be predicted by distance (holds both for within and out-of-sample pairs) – i.e. SCI is a spillover measure that can only imperfectly be proxied by distance, especially for very low distances.

Figure 6: Social connectedness across Austin



Left panel: Scatterplot of Austin ZIP codes and their distance and social connectedness to other ZIP codes up to 50 miles distance. Blue scatter points mark pairs where both ZIP codes are within this study's sample.

Right panel: Network graph of social connections between within-sample ZIP codes. Darker and thicker connections represent higher social connectedness.

¹⁰Hence, the index is robust to different levels of social media penetration.

¹¹The SCI is calculated based on October 2021 data and is not available as a time series. However, studies suggest that social networks change little over time (Bailey et al., 2021, Kuchler et al., 2022).

I adjust my empirical model to consider the treatment intensity of all other ZIP codes in the same city, weighted by the SCI with ZIP code i and interact it with a dummy indicating whether $t > 0$, i.e. simply whether after the treatment period. To avoid collinearity with the ZIP code FE, instead of estimating a fixed effects model, I perform a simple OLS estimation with a vector \mathbf{X} of socio-economic and dwelling controls:

$$Gen_{it} = \alpha + \sum_{k \geq 0} \gamma_k Out_i * I_{post}\{k = t\} + \eta \sum_{j \neq i} SCI_{ij} * Out_j * Post_t + \mathbf{X}_i + \epsilon_{it} \quad \forall (t \geq -1) \quad (7)$$

For comparison, I run the same specification with inverted log distance as the spillover weighting:

$$Gen_{it} = \alpha + \sum_{k \geq 0} \gamma_k Out_i * I_{post}\{k = t\} + \eta \sum_{j \neq i} \frac{1}{\log(Distance_{ij})} * Out_j * Post_t + \mathbf{X}_i + \epsilon_{it} \quad \forall (t \geq -1) \quad (8)$$

5. Results

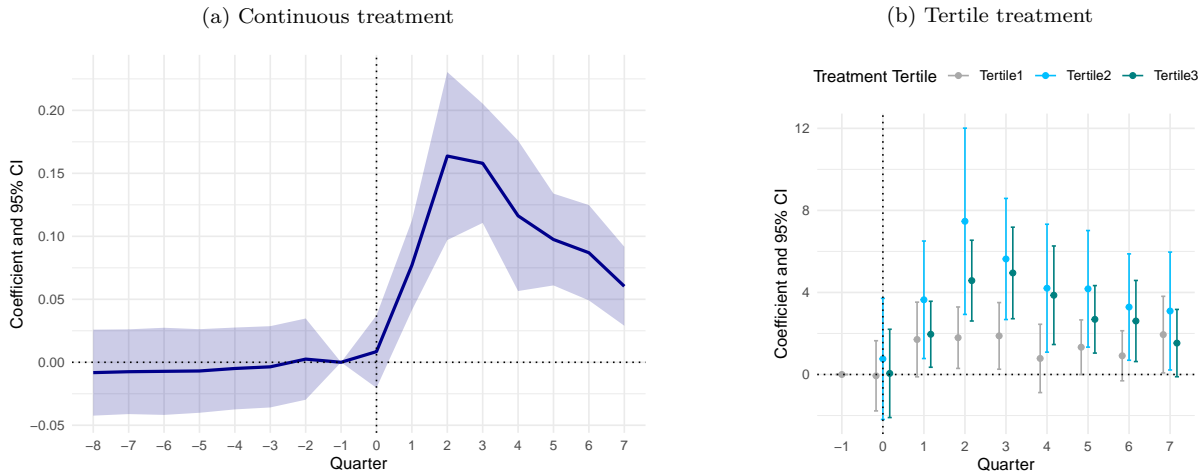
5.1. Treatment effect for generators

Continuous treatment intensity. I begin my estimating the baseline model for generators from equation (1). Here and in all following reported results, I use HC1 cluster-robust standard errors and adjust significance thresholds for a t-distribution, both to account for small numbers of clusters.¹² As expected, pre-treatment effect coefficients are not statistically different from zero. This confirms the parallel trends assumption and provides justification to simplify the model for further analyses without the placebo coefficients (see also Table 2). The results of the event study are graphically reported in Figure 7a. It can be observed that in the treatment period itself ($t = 0$) treatment shows no statistical effect yet. This is not surprising, as t is measured in calendar quarters, such that the treatment event falls in the middle of the $t = 0$ period. Figure 7a also graphically illustrates the importance of allowing for time-varying effects, as the treatment ramps up to full effect by quarters 2-3 and then begins to fade out. An intuitive mechanism behind this would be a lag in households' investment response (e.g. due to other ad-hoc disaster issues, time-consuming collection of information, decision processes, and bureaucratic procedures) but

¹²All results are, however, very robust to using conventional p-values, for which sets of results are reported in Appendix G.

also salience of the experienced treatment fading out over time and possibly saturation. As the outcome variable is measured in permit applications per 10,000 households, the interpretation of the coefficient is as follows. An increase in one percentage point¹³ of disrupted supply service¹⁴ led to 0.077 additional generator permit applications per 10,000 households in quarter 1, 0.164 in quarter 2, etc. Or in more intuitive magnitudes, an increase of 10 percentage points in service disruptions led to 16.4 additional generator permit applications per 10,000 households at the peak in quarter 2 after treatment. For comparison, in the 10 years prior to the event, the median (mean) number of quarterly permit applications for generators per 10,000 households was around 3.5 (4.3) in Austin. Although the effect is likely not linear, a treatment effect of 16.4 additional permits for a 10 percentage point increase of outages, when average outages were recorded at 22.4 %, speaks to the order of response magnitude. Even around two years later, in quarter 7 after treatment, generator permit applications per 10,000 households still remain higher by 6 applications.

Figure 7: Treatment effect coefficients for generator-related permits



The period preceding the treatment period is omitted ($t = -1$).

Treatment intensity tertiles. I now move to a decomposition by treatment intensities, where I assign units to tertiles of treatment intensity. *Tertile1* is assigned to the ZIP codes that were in the lowest tertile of treatment intensity, *Tertile3* to the ones in the highest. Since I can exploit

¹³around the average dosage and not ruling out non-linear dosage effects. See the discussion in Callaway et al. (2024).

¹⁴Perfect service equals 0 % outage intensity.

Table 2: Treatment effect coefficients for generator-related permits with continuous treatment

	<i>Dependent variable:</i>	
	Gen_per10kHH	
	Continuous/FE	Continuous/FE
	(1)	(2)
Out:'T-8'	-0.008 (0.017)	
Out:'T-7'	-0.007 (0.017)	
Out:'T-6'	-0.007 (0.017)	
Out:'T-5'	-0.007 (0.016)	
Out:'T-4'	-0.005 (0.016)	
Out:'T-3'	-0.004 (0.016)	
Out:'T-2'	0.003 (0.016)	
Out:T0	0.008 (0.014)	0.008 (0.027)
Out:T1	0.077*** (0.018)	0.077*** (0.022)
Out:T2	0.164*** (0.033)	0.164*** (0.032)
Out:T3	0.158*** (0.023)	0.158*** (0.026)
Out:T4	0.116*** (0.030)	0.116*** (0.030)
Out:T5	0.097*** (0.018)	0.097*** (0.022)
Out:T6	0.087*** (0.019)	0.087*** (0.026)
Out:T7	0.060*** (0.016)	0.060*** (0.022)
FE	ZIP	ZIP
clust-rob. SE	ZIP	ZIP
Observations	688	387
R ²	0.521	0.702
Adjusted R ²	0.477	0.657
Residual Std. Error	2.760 (df = 630)	2.804 (df = 336)
F Statistic	12.002*** (df = 57; 630)	15.819*** (df = 50; 336)
<i>Note:</i> Based on t-distribution: *p<0.1; **p<0.05; ***p<0.01		

the fact that up to treatment, the outcome variable was virtually constant, the treatment effect of *Tertile1* also provides an idea of the magnitude of the salience effect, as this group was hardly treated. The results are plotted in Figure 7b.¹⁵ For *Tertile1* the point estimates of the treatment effect show a distinct discontinuity between pre-treatment and the treatment period versus post-treatment periods. This effect, which is likely to a high degree driven by salience, is only small but quite persistent. However, the effect is only statistically significant at the 5 % level in quarters 2 and 3.

In contrast, treatment effect coefficients of *Tertile2* and *Tertile3* are much stronger and significant at the 5 % or 1 % level from quarter 1 on, which are intuitive results. However, it is surprising that in all periods, despite being not statistically different from each other, point estimates for *Tertile2* exceed the ones of *Tertile3*, particularly in early periods. This suggests that the treatment effects are not at all linear in dosage. Concretely, the treatment effect of *Tertile2* peaks at 7.47 additional generator permit applications per 10,000 households in quarter 2, while for *Tertile3* the peak is achieved one period later, in quarter 3, at only 4.95 additional permit applications. This general pattern is also confirmed by a robustness check dividing treatment groups by quartiles (Appendix C, Figure C.3). These results may seem unintuitive at first sight but a possible mechanism is the following. Neighborhoods that experienced the most outages, have likely experienced not just minor inconvenience and discomfort, but more severe structural damages and disruptions caused by the outages (e.g. burst pipes due to electric heating failure) and may have even temporarily relocated.¹⁶ Hence, heavily affected households may have prioritized time, effort, and income investment in repairing these damages and returning to daily routines, over investing into long-term resilience measures – which would explain both the weaker and slower response. More generally, results suggest that for investments into generators, it matters whether to have been substantially hit by outages or not – but experience of very extreme outages does not translate to even stronger investment responses.

Overall, the magnitude of treatment effects may not seem immense in absolute numbers at first sight. However, compared to the median 3.5 quarterly permits per 10,000 households in

¹⁵Regression table in Appendix C, Table C.3.

¹⁶The City of Austin, Texas (2025) reports, e.g., 381 public water pipeline damages, 200 housing complexes without water access due to damages in private plumbing infrastructure, 1,500 emergency water shut-offs, 164 hours with negative °C temperatures in Austin and Travis County. In a survey by Jones et al. (2024) Texans were most likely to report difficulties in food/ grocery supply, loss of internet service, loss of electricity service, and loss of access to drinkable and running water; 18 % of Texans who lost power at home, sought shelter elsewhere.

Austin in the 10 years preceding the event, the treatment effects are indeed substantial. It should also be considered that for the stock of generators in a population, the treatment effects need to be accumulated over time. For instance, for the ZIP codes in *Tertile2* on average this led to a cumulative additional 31.5 generator permit applications per 10,000 households¹⁷ in the 2 years after treatment. Generally, it can be assumed that the found estimates are a lower bound of generator-related investment responses to the outage event, as my data does not cover lower-cost portable generators. It should be noted, however, that portable generators are unweatherized and less powerful. They are, hence, usually not suited for powering entire homes during extreme weather conditions. With my estimates I therefore capture the type of generators that represent viable grid electricity substitutes.

5.2. Treatment effect for rooftop solar PV with storage

Continuous treatment intensity. Analogous to the analysis of generator permit applications, the placebo coefficients before treatment also confirm the parallel trends assumption for PV with storage permit applications (Figure 8a), allowing me to concentrate on the post-treatment period coefficients in subsequent analyses. The event study for PV with storage shows a similar pattern as for generators, with statistically significant treatment effects building up until about quarter 3 and then starting to fade out again. The magnitude of effects, however, is smaller. At the peak in quarter 3, a 10 percentage point increase in electricity supply disruption led to 8 additional permit applications for (retrofits of) rooftop PV with storage per 10,000 households.

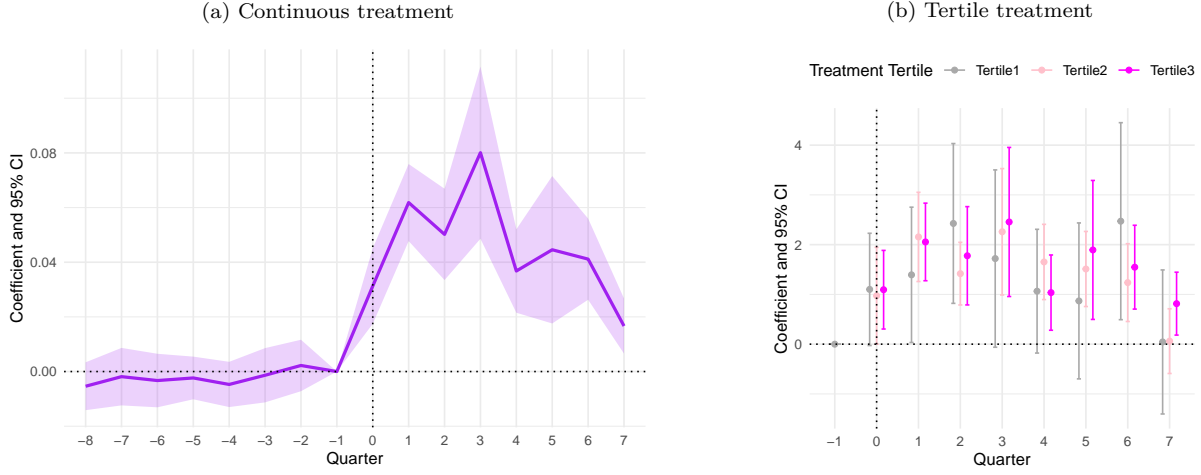
Treatment intensity tertiles. The analysis by treatment intensity tertiles is presented in Figure 8b. *Tertile2* and *Tertile3* exhibit significant treatment effects in virtually all post-treatment periods. However, a linear treatment effect that is systematically lowest for *Tertile1* and highest for *Tertile3*, cannot be confirmed. A possible intuition behind this could be that PV with storage seems a reasonable measure to all treatment groups, as it can be employed throughout the year and not only as a back-up option – i.e. treatment intensity possibly mattering relatively less here than in the generator analysis to justify investment.

5.3. Socio-economic disparities in adaptive capacity

I now turn to the heterogeneity analysis of adaptive capacity by socio-economic characteristics of neighborhoods. Figure 9 plots the treatment effects for generators (Figure 9a) and PV with

¹⁷counting only significant effect coefficients.

Figure 8: Treatment effect coefficients for PV with storage-related permits



The period preceding the treatment period is omitted ($t = -1$).

storage (Figure 9b) for repeated sample splits of the ZIP codes based on 7 socio-economic and dwelling characteristics; namely median household income, the share of White population, the share of Black population, the share of population aged 25 years or older holding a Bachelor or higher degree, the share of population aged 65 years or older, the share of owner-occupied (as opposed to renter-occupied) housing, and the share of single-unit buildings. Each plot shows the main effect for the bottom half of the sample split and the total effect for the top half of the sample split (main effect + interaction effect).¹⁸

For generators, population characteristics seem to be more relevant to reinforced treatment responses than dwelling characteristics. Neighborhoods with higher income, higher share of White population, higher education, and older population exhibit stronger responses to increased treatment intensity, while neighborhoods with higher shares of Black population exhibit weaker treatment responses. The most striking heterogeneity is found for income, racial composition, and high education attainment of ZIP codes – characteristics, which can be correlated. Possible mechanisms driving this could be higher financial means for investments, better understanding of the recurrence risk and the bureaucratic procedures for permit applications, and systemic privileges. It is interesting that ZIP codes with a high share of population of retirement age show a reinforced response to treatment intensity. A possible reason could be that elderly people are more

¹⁸The same set of plots showing only the interaction effects is presented in Appendix E, Figure E.5.

vulnerable to outages, e.g. due to lower mobility exacerbated by loss of indoor lighting, fewer social contacts providing community support, higher dependence on electric household or medical appliances, or decreased tolerance of low room temperatures during loss of heating. Regarding dwelling characteristics, it could be expected that owning your home and living in an independent 1-unit building could increase your ability and liberty to install a generator. Notably, I find no evidence that these dwelling characteristics are associated with a statistically significant increase of the treatment response. One notable, heterogeneous pattern in the timing of treatment responses can be observed across all sample splits. Not only do the ZIP codes in the bottom half of the sample split (top half for the share of Black population) react more weakly to treatment, but they also consistently react more slowly. Note how the above-median sub-samples all peak in quarter 2, while all the below-median sub-samples peak in quarter 3 (inversely for the share of Black population). This underlines the advantages of estimating time-varying effects. This observation would be consistent with the earlier suggestion that adaptive capacity is constrained in magnitude and also promptness, due to hurdles like financial constraints and completing bureaucratic procedures – exacerbated by systemic under-privileges.

The results for PV with storage are less clear-cut. Point estimates for the interaction effects are generally positive (negative for the share of Black population), this suggests that disparities exist also in the treatment response for PV with storage. However, magnitudes are smaller and in most cases the interaction effects are not statistically different from zero. Nonetheless, this could be routed in the overall very small numbers of permit applications for PV with storage per ZIP code and quarter, possibly leading to noisy estimates.

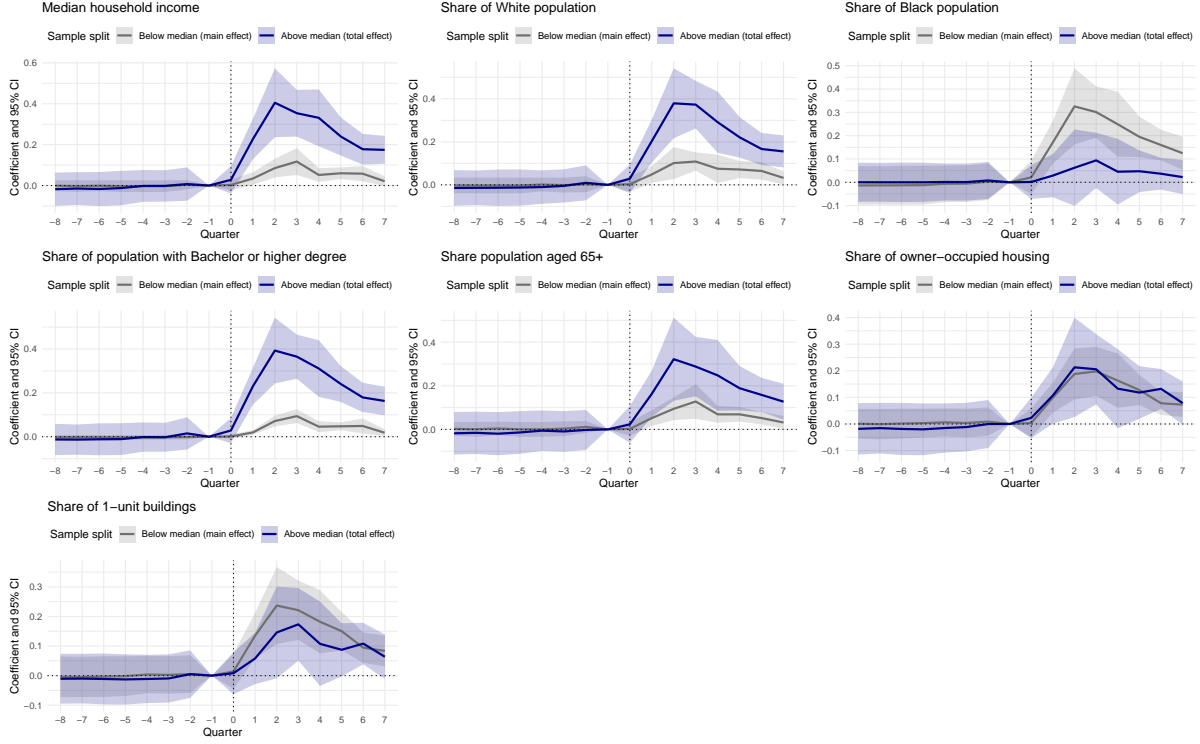
5.4. *Salience spillovers*

Table F.6 in Appendix F reports the results from the analysis of salience spillovers based on distance (column 1) and based on social connectedness (column 2). Both spillover measures exhibit a highly significant coefficient for the interaction with a post-treatment dummy. This highlights the important role that salience plays in adaptive responses, where salience can be increased through interaction with affected population groups. While coefficient sizes cannot be compared between the two measures because they are in different units, the coefficient and standard errors suggest that social connectedness explains salience spillovers even slightly better than geographic proximity.

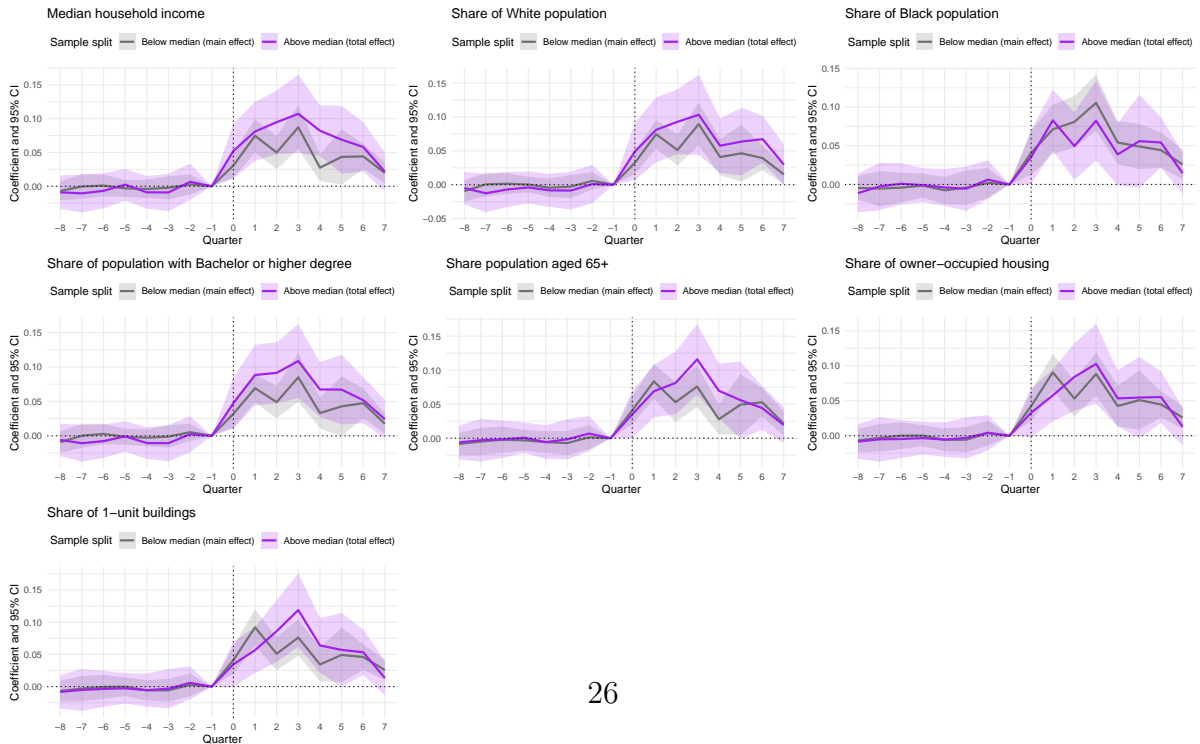
Figure 9: Heterogenous treatment effects by socio-economic characteristics

The period preceding the treatment period is omitted ($t = -1$).
Above median (total effect) is plotted as the sum of the main effect point estimate and the interaction effect.

(a) Generator-related permits



(b) PV with storage-related permits



6. Discussion and policy implications

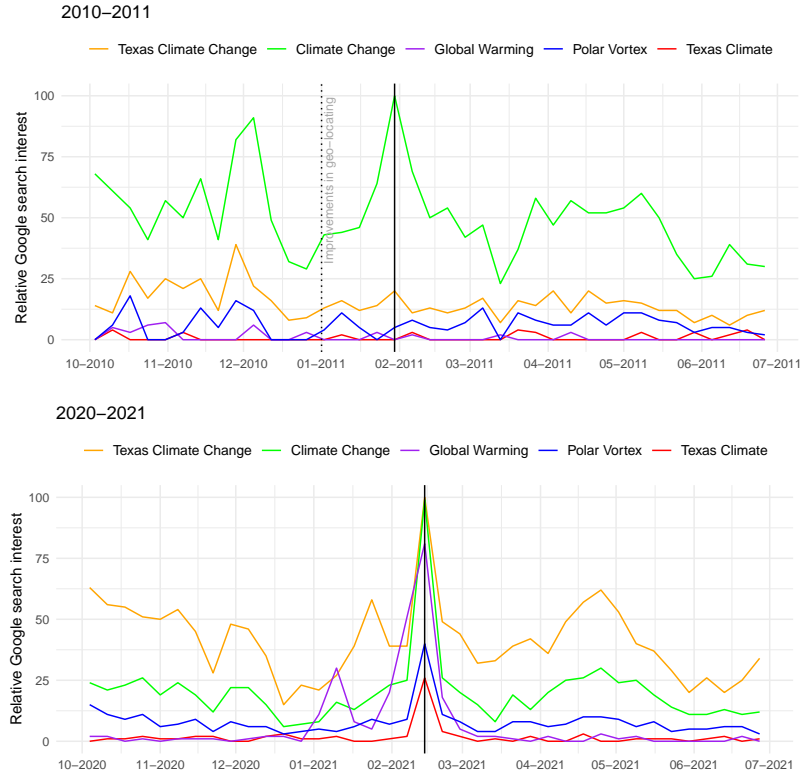
The climate change narrative. Concerning the adaptive nature of investments, a descriptive analysis of Google search data suggests, that the 2021 response may indeed have been also a climate change adaptation-related behavior. While both during the similar event in 2011 and in 2021, searches for blackout-related keywords saw a spike, the search patterns for the reasons and climate context of the cold spell look very different between the two events (Figure 10). It seems that the 2011 event left Texans mainly puzzled about how an unusual snowstorm occurs in times of global warming (upper panel), as other climate change-related keywords saw virtually no response. Notably, also no striking response in terms of generator permits was recorded (Figure 11). In contrast, following the 2021 event (lower panel of Figure 10), Texans seemed to understand the weather event as a polar vortex breakout and its possible relationship with climate change (and thus risk of recurrence) after being hit the second time in 10 years. Note how, after the 2021 event, searches now also spike for the more sophisticated weather phenomena and more differentiated climate-related keywords. This suggests that the very clear response after the 2021 event that I find econometrically and that is also visible from the time series in Figure 11, may also be an adaptive resilience response to the impacts of climate change-related extreme weather. This intuition is in line with survey results in Jones et al. (2024), who find that 69 % of Texans expect that due to climate change, Texas will more negatively impacted by extreme weather events than 30 years ago.

My results also complement suggestions and findings of recent literature on similar response dynamics.

Suitability as grid substitutes. To recap, the two interventions in this study, generators and PV with storage, each embody distinct advantages and disadvantages.¹⁹ Generators have lower upfront cost and can run as long as fuel is available (e.g. through emergency tanks). It is possible to pre-stock fuel in larger amounts, however, once it runs out, households are exposed to possible fuel shortages and price spikes during prolonged disaster events. Running a generator always causes marginal (fuel) cost, such that they are an inferior substitute when cheaper grid electricity is available. In contrast, PV installations with storage have higher upfront cost and bureaucratic hurdles (e.g. tax incentives, feed-in remuneration). The duration of emergency supply via the battery depends on its initial charging level and the size of the battery. When sun is absent (likely the case during

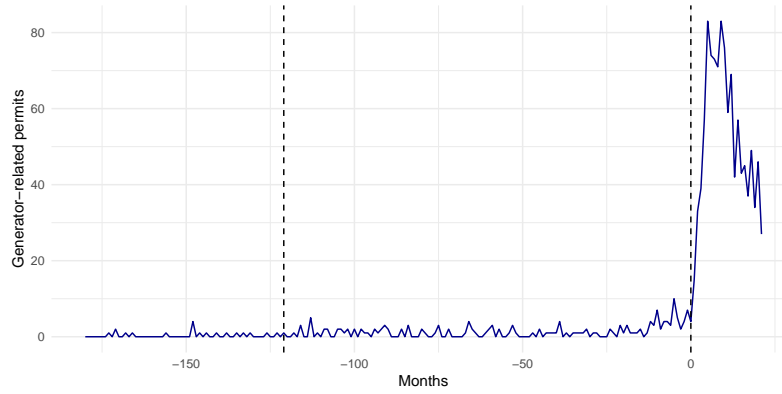
¹⁹See also the complementary comparison in Table A.1.

Figure 10: Google trends showing relative search interest in Texas for multiple keywords



Google (2023) Search interests are aggregated at the weekly level. Most popular search interest among a keyword comparison of a given time period is normalized to 100. The black vertical line in each plot marks the freeze event week.

Figure 11: Generator-related permits, time series



Dashed lines mark the 2011 and 2021 freeze events. Cumulative number for the city of Austin.

a winter storm), no re-charge is possible. But once installed, they can be used year-round and generate electricity bill savings. Now, I find a stronger treatment effect for generators than for PV

with storage. Abstracting from local policy incentives for PV (with or without storage), Texas is a state with excellent sun conditions for rooftop solar PV.

Given that I still find generators a much more widely chosen intervention measure – despite the aforementioned disadvantages – it is likely that studies considering only PV with storage as grid substitutes, substantially underestimate both the value of lost load (Brown and Muehlenbachs, 2024)²⁰ and the welfare implications of grid independency investments (Brehm et al., 2024, who also leave social damages from carbon and air pollutant emissions from generators unconsidered). All of these considerations are even reinforced when considering that I only observe stand-by generators and not portable generators. Despite portable generators being only an imperfect substitute for grid electricity due to lower power, they represent a much lower-barrier investment both in terms of financial and bureaucratic barriers. Ongoing work by Harris (2023) on portable generators suggests that they likely saw a rise in sales, too. Brehm et al. (2024) point out that private investments into grid substitutes decrease the level of efficient public investments into grid reliability. In this context, it is important to consider that if many households invest into generators because PV with storage is less accessible to them (financially, bureaucratically or otherwise), this leaves them exposed to fuel shortages, fuel price spikes, and air pollution from generator emissions (Lin and Kassem, 2025). This should be taken into account in the decision on optimal public grid reliability investments and evaluation of disaster damage exposure.

Distributional implications. My results of lower adaptive capacity even for generators in high-minority, low-income, and low-education neighborhoods, reinforce the adverse distributional implications of lower levels of public investments in outage prevention and resilience. If these investments are either kept at a low level (as in the Texan case), or decreased as a reaction to private investment responses as Brehm et al. (2024) present as the optimal strategy, I show that this leads to significant over-exposure to outage costs for high-minority, low-income, and low-educated population. Taking these disparities into account, the result of Brehm et al. (2024) is no longer optimal from a distributional perspective. My finding of socio-economic disparities in the adaptive capacity and promptness of response also has relevant implications for the design of support policies. First, I obtain the same average timing of response peaks as Brehm et al. (2024), despite using different data, a different geographical location, and a different type of extreme event causing the outages. This suggests, that the timing of responses is consistent across different settings.

²⁰The authors acknowledge this by presenting their VOLL estimate as a lower-bound estimate for this precise reason. My study results strongly support this rationale.

However, I find that behind these aggregate effects, more weakly reacting neighborhoods also react more slowly than average. This should be addressed in post-disaster aid policies. They are often tied to a specific time window after the event, which should be long enough to also accommodate delayed responses of disadvantaged households. Policies could also be designed to specifically facilitate more prompt responses for disadvantaged households, e.g. lowering financing barriers and providing support in facing procedural barriers. In addition to that, even if I do not find significant evidence for disparities regarding dwelling characteristics, policymakers should address the fact that some households do not have any adaptive capacity due to their housing situation. For instance, landlords may not allow permanent modifications such as generator or PV-battery installations, and multi-unit housing restricts individual installation decisions.

My work comes with some limitations. Firstly, the data sample size is relatively small and restricted to ZIP codes in Austin. This is due to the fact that Austin exhibited both good data quality and a historical time span of the city archive data on permits, as well as good data quality and granularity of the outage data. This combination was not given for other major cities. Secondly, I can only exploit one single, large-scale outage event caused by cold-stress. Such events are rare and my outage data was constrained to February 2021. With a larger permit and outage data sample and longer time span of outage data, e.g. more refined econometric estimations would be possible without losing statistical power, and effects of staggered and repeated treatment could be analyzed.

7. Conclusion

Climate change is associated with an increase of extreme weather events (IPCC Synthesis Report, 2023). While heat stress and drought-related weather anomalies receive much attention, cold-stress events, whose frequency is also associated with climate change (Cohen et al., 2018), are also causing recurring service disruptions of critical infrastructure (Do et al., 2023). A lack of public investments into adaptive resiliency measures can leave households exposed and may induce private responses. I analyze household investment responses in Austin after experiencing prolonged outages during an extreme cold-stress event in Texas in 2021. In particular, I collect and analyze novel data on permit applications for electricity home generators and rooftop-solar-PV installations with storage. Using event study methods with time-varying treatment effects and a continuous treatment dosage, I find that at the response peak, an increase of 10 percentage points in grid electricity service disruption during the treatment event, led to 16.4 (8) additional

quarterly permit applications for generators (solar-PV-battery systems) per 10,000 households. For comparison, the very stable baseline level of generator permit applications in Austin was at a median of around 3.5 quarterly permits per 10,000 households in the preceding 10 years, while mean treatment dosage was recorded at 22.45 %. Accounting for salience spillovers shows significant treatment spillovers both based on geographic proximity and social connectedness of neighborhoods.

These response results are particularly interesting from a climate change adaptation and distributional angle. Based on Google search data, during a similar prior event in 2011, the public did not make a systematic association of the cold wave with climate change and historical time series data shows that clear responses in investments into generators were absent. In the 2021 event instead, Google search data reveals a systematic association with climate change, coinciding with my finding of significant investment responses after this event. Time-varying effects show that the response builds up after the treatment event, peaks in the second quarter after treatment, and then begins to fade out. A subsequent heterogeneity analysis via sample splits based on socio-economic characteristics shows that ZIP codes with lower median income, higher minority shares, lower share of university education, and lower share of retirement-age population exhibit not only a weaker but also consistently slower response to treatment (peaking in quarter 3 instead of 2). This muted magnitude and delay of response could both be a consequence of e.g. financial constraints, hurdles to completing bureaucratic procedures, or systemic under-privileges. These systematic differences illustrate the disparity of households' adaptive capacity both in terms of magnitude and promptness – leaving underprivileged households more vulnerable and less prepared for recurring extreme weather events, as well as overly disadvantaged by low levels of public investments in outage prevention and resilience.

In summary, my findings show that cold-stress events can induce adaptive resilience responses in households through the channel of major electricity disruptions, that both fossil and renewable resilience interventions are sought out, but the former dominate, and that socio-economic disparities exist in household responses. This provides an opportunity for policymakers to incentivize renewable intervention options, given that a household chooses to invest. Policymakers should at the same time consider that households have heterogeneous adaptive capacity based on socio-economic characteristics. Policies should be designed to prevent households with less adaptive capacity from systematic vulnerability during recurring extreme weather events, as long as public, exposure-decreasing resiliency investments are missing.

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Appendix A. Supplementary background information

Figure A.1: Hourly outage intensity by ZIP code from Feb 15 to Feb 18

Based on data from Bluefire Studios LLC (2023).

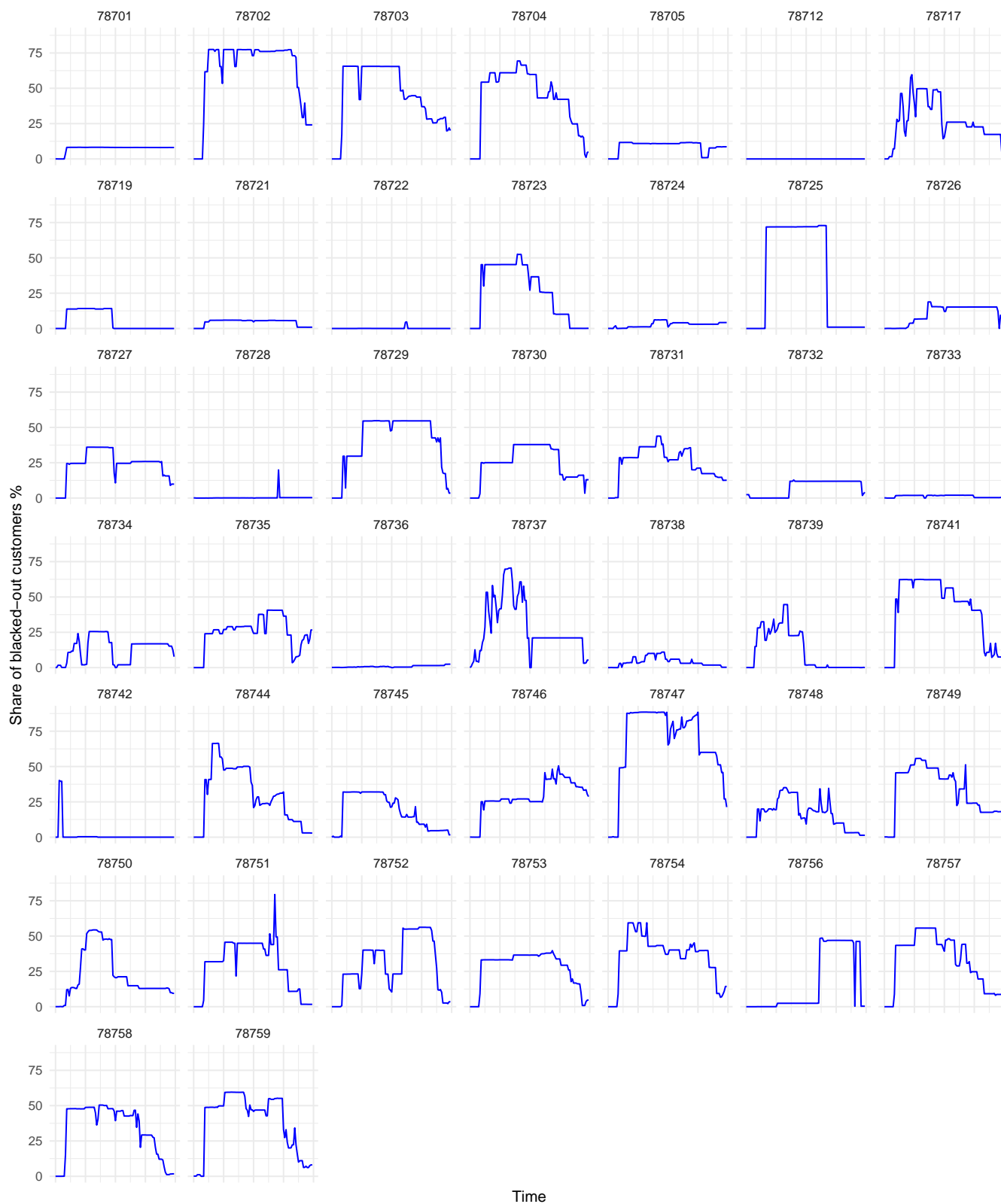


Table A.1: Comparison of potential grid substitutes

	Portable generator	Stand-by generator	Battery for rooftop solar PV
Installation permit required	No	Yes	Yes
Weatherization	No	Yes	Yes
Transfer switch	Optional, manual	Integrated, automatic	Integrated
Professional installation	Optional	Required	Required
Usual power/ energy output	<8-10 kW	8-24+ kW	10-20 kWh (stackable)
Multi-day emergency coverage	Selected appliances*	Entire home*	Up to entire home**
Usual price range	<1,500 USD	2,000-15,000+ USD	15,000+ USD

Generators are usually available to buy at (online) retailers and specialized electricity equipment resellers.

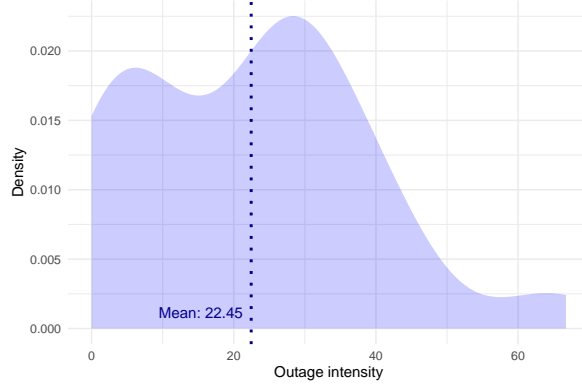
* Based on 7-12 kW power for emergency use of essential appliances (e.g. from <https://www.hinen.com>, <https://www.electricgeneratorsdirect.com>, <https://dial1plumbing.com>)

** Stacked set-up can power a home for multiple days based on average daily electricity consumption of 39 kWh of a Texan household (EIA, 2025). Daily consumption during emergency use can be lower.

Prices are before incentives and tax credits. Information, product characteristics, and price ranges are available from generator production companies, solar PV installation companies, and energy marketplace and information platforms. E.g. <https://www.duromaxpower.com>, <https://www.generac.com>, <https://www.sunenergyguide.com>, <https://www.canarymedia.com>, <https://www.energysage.com>

Appendix B. Supplementary empirical information

Figure B.2: Density plot of outage intensity across the ZIP code sample



The treatment variable

I calculate the treatment intensity OUT as percentage share of blacked-out customer \times hours, i.e. as the sum of affected customers²¹ over over all hours relative to the sum of tracked customers over all hours²²:

$$OUT_i = \frac{\sum_h CUST_{i,h}}{\sum_h TRACKED_{i,h}} * 100 \quad (\text{B.1})$$

where $CUST$ is the number of customers blacked-out per each hour h of the event period in each ZIP code area i and $TRACKED$ is the number of customers tracked per hour and ZIP code. This allows to capture different outage patterns like widespread short outages as well as long lasting concentrated outages. Let for instance the event period be a 24-hour day affecting two ZIP codes A and B, with each 100 customers. For simplicity let us assume that in each hour all of the 100 customers are tracked in both A and B. Let A experience a short but widespread blackout, where over the course of the 24-hour event period 25 customers in total are affected in hour 9, and 23 customers in total were affected in hour 10. In all other hours the number of affected customers is 0. For ZIP code area A OUT_A would therefore record $\frac{(25+23)}{100 \times 24} \times 100 = 2\%$ blacked-out customer \times hours. Meanwhile, let ZIP code area B experience 2 affected customers for all 24 event hours. OUT_B would therefore also record 2% blacked-out customer-hours.

²¹Remember that this is ZIP code time series data, not household panel data, meaning that I do not know which exact customers are affected from one hour to the next.

²²Note that the number of tracked customers varies over time.

Table B.2: Regressing PV with storage-related permits on PV-related permits without storage

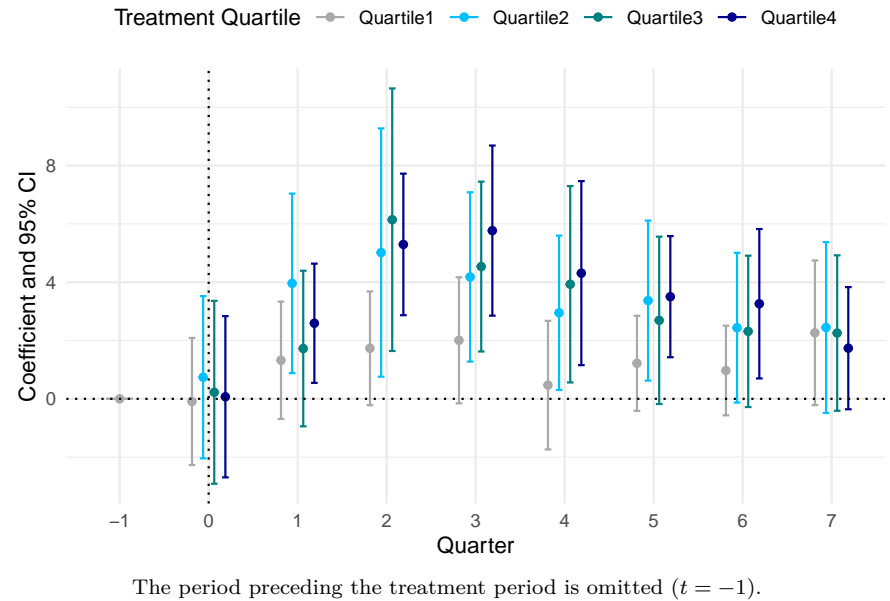
	<i>Dependent variable:</i>
	PVStor
PVnoStor	0.006*** (0.002)
clust-rob. SE	ZIP
Observations	688
R ²	0.015
Adjusted R ²	0.013
Residual Std. Error	0.525 (df = 686)
F Statistic	10.334*** (df = 1; 686)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

Appendix C. Supplementary results – generators

Table C.3: Treatment effect coefficients for generator-related permits with tertile treatment

	<i>Dependent variable:</i>
	Gen_per10kHH By tertile/FE
Tertile1:T0	−0.065 (0.847)
Tertile2:T0	0.759 (1.463)
Tertile3:T0	0.052 (1.066)
Tertile1:T1	1.706* (0.902)
Tertile2:T1	3.642** (1.419)
Tertile3:T1	1.961** (0.797)
Tertile1:T2	1.794** (0.742)
Tertile2:T2	7.470*** (2.250)
Tertile3:T2	4.576*** (0.976)
Tertile1:T3	1.882** (0.805)
Tertile2:T3	5.632*** (1.463)
Tertile3:T3	4.950*** (1.106)
Tertile1:T4	0.783 (0.825)
Tertile2:T4	4.207*** (1.545)
Tertile3:T4	3.863*** (1.190)
Tertile1:T5	1.330* (0.660)
Tertile2:T5	4.176*** (1.408)
Tertile3:T5	2.689*** (0.815)
Tertile1:T6	0.912 (0.605)
Tertile2:T6	3.287** (1.285)
Tertile3:T6	2.607** (0.980)
Tertile1:T7	1.944** (0.925)
Tertile2:T7	3.093** (1.424)
Tertile3:T7	1.531* (0.813)
FE	ZIP
clust-rob. SE	ZIP
Observations	387
R ²	0.717
Adjusted R ²	0.658
Residual Std. Error	2.800 (df = 320)
F Statistic	12.275*** (df = 66; 320)
<i>Note:</i> Based on t-distribution: * p<0.1; ** p<0.05; *** p<0.01	

Figure C.3: Treatment effect coefficients for generator-related permits with quartile treatment



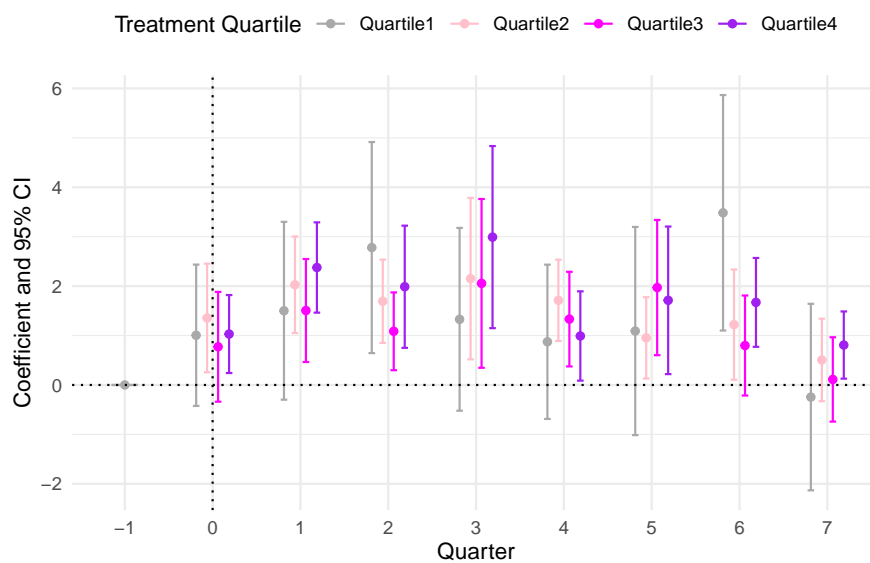
Appendix D. Supplementary results – PV with storage

Table D.4: Treatment effect coefficients for PV with storage-related permits with continuous treatment

	Dependent variable:
	PVStor_per10kHH
	Continuous/FE
PVnoStor_per10kHH	0.005 (0.012)
Out:T0	0.033*** (0.008)
Out:T1	0.063*** (0.008)
Out:T2	0.051*** (0.009)
Out:T3	0.080*** (0.016)
Out:T4	0.039*** (0.008)
Out:T5	0.045*** (0.013)
Out:T6	0.041*** (0.008)
Out:T7	0.018** (0.007)
FE	ZIP
clust-rob. SE	ZIP
Observations	387
R ²	0.416
Adjusted R ²	0.327
Residual Std. Error	1.712 (df = 335)
F Statistic	4.683*** (df = 51; 335)

Note: Based on t-distribution: *p<0.1; **p<0.05; ***p<0.01

Figure D.4: Treatment effect coefficients for PV with storage-related permits with quartile treatment



The period preceding the treatment period is omitted ($t = -1$).

Table D.5: Treatment effect coefficients for PV with storage-related permits with tertile treatment

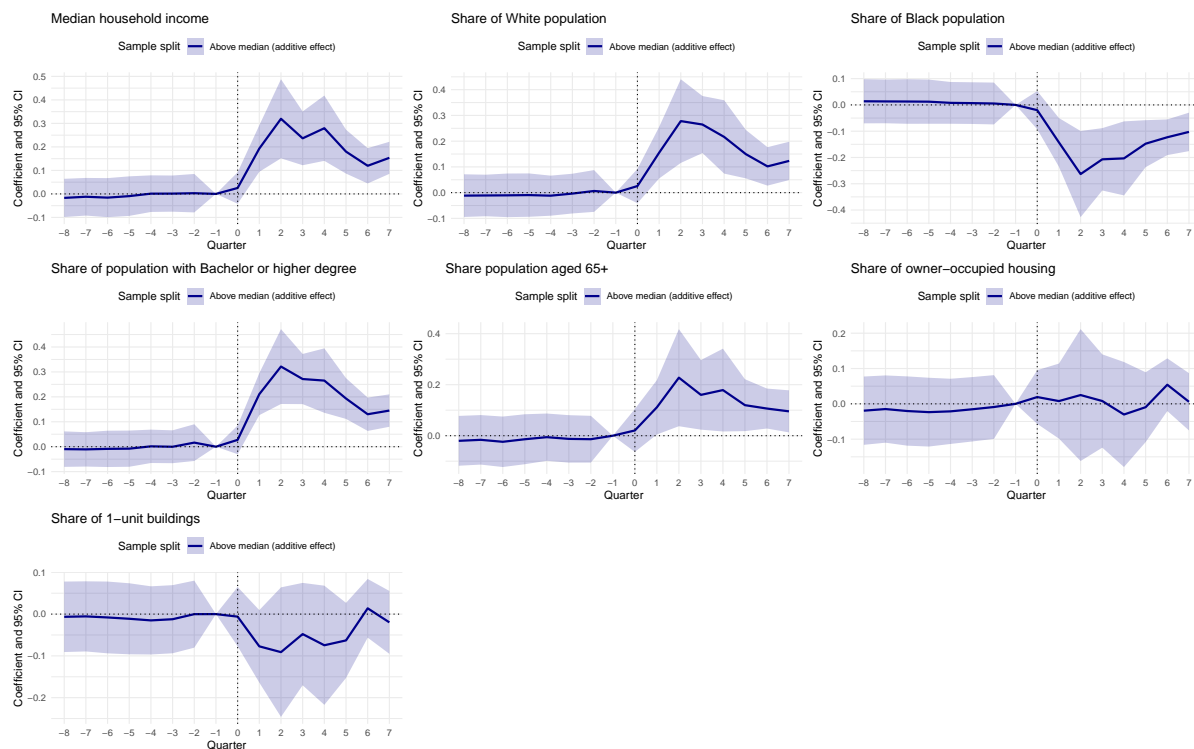
	Dependent variable:
	PVStor_per10kHH By tertile/FE
PVnoStor_per10kHH	-0.001 (0.013)
Tertile1:T0	1.101* (0.559)
Tertile2:T0	0.973** (0.482)
Tertile3:T0	1.094*** (0.392)
Tertile1:T1	1.393** (0.674)
Tertile2:T1	2.155*** (0.444)
Tertile3:T1	2.054*** (0.386)
Tertile1:T2	2.426*** (0.796)
Tertile2:T2	1.417*** (0.312)
Tertile3:T2	1.777*** (0.490)
Tertile1:T3	1.720* (0.883)
Tertile2:T3	2.259*** (0.629)
Tertile3:T3	2.456*** (0.742)
Tertile1:T4	1.065* (0.616)
Tertile2:T4	1.652*** (0.375)
Tertile3:T4	1.036*** (0.375)
Tertile1:T5	0.869 (0.777)
Tertile2:T5	1.511*** (0.374)
Tertile3:T5	1.894*** (0.692)
Tertile1:T6	2.472** (0.981)
Tertile2:T6	1.237*** (0.387)
Tertile3:T6	1.547*** (0.417)
Tertile1:T7	0.044 (0.717)
Tertile2:T7	0.061 (0.322)
Tertile3:T7	0.814** (0.313)
FE	ZIP
clust-rob. SE	ZIP
Observations	387
R ²	0.462
Adjusted R ²	0.349
Residual Std. Error	1.684 (df = 319)
F Statistic	4.085*** (df = 67; 319)
Note: Based on t-distribution: *p<0.1; **p<0.05; ***p<0.01	

Appendix E. Supplementary results from heterogeneity analysis

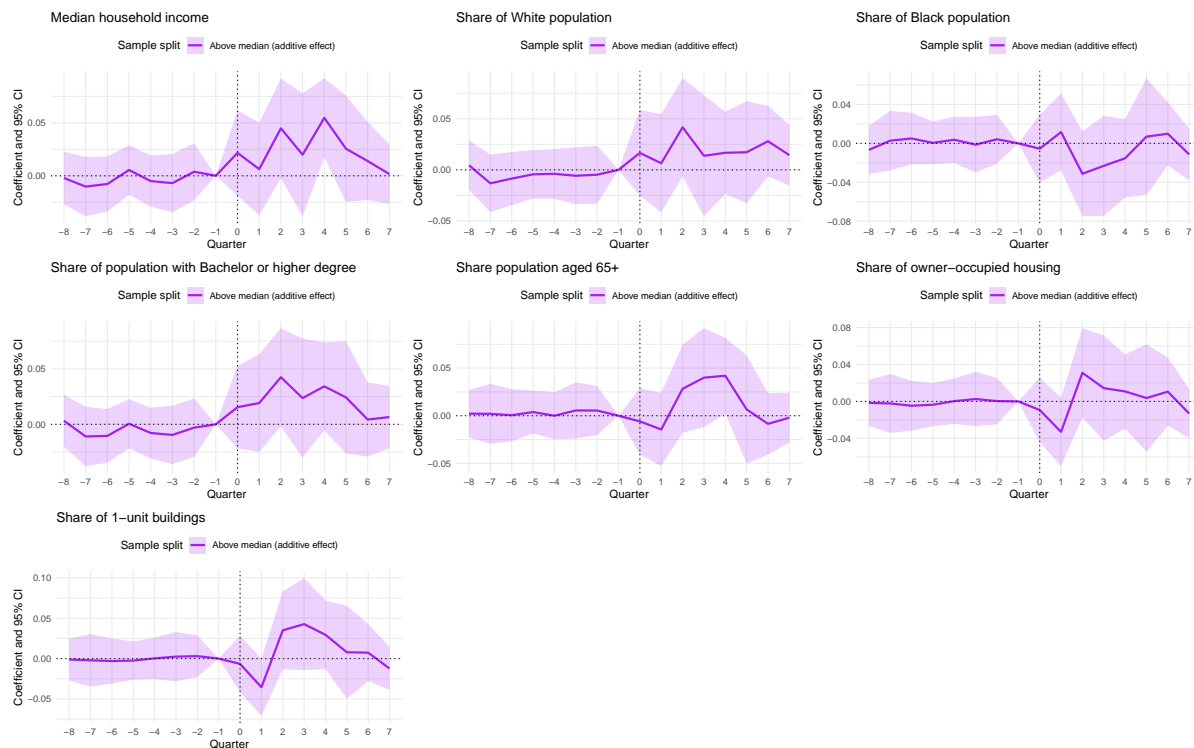
Figure E.5: Heterogeneous treatment effects by socio-economic characteristics (interaction effects)

Notes: The period preceding the treatment period is omitted ($t = -1$). *Above median (additive effect)* is the interaction effect.

(a) Generator-related permits



(b) PV with storage-related permits



Appendix F. Supplementary results from spillover analysis

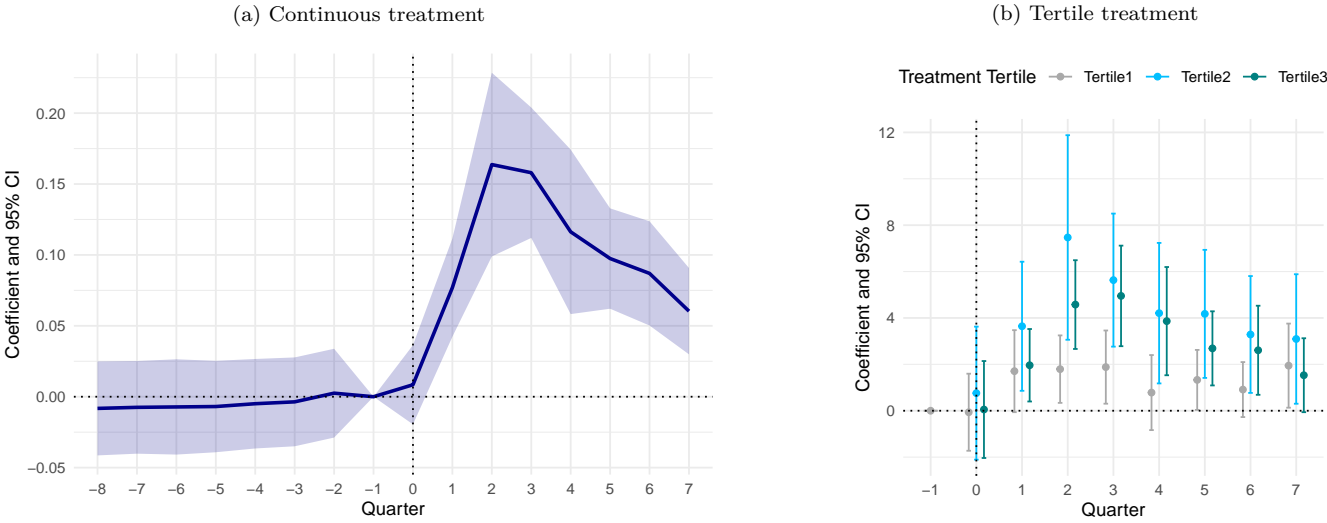
Table F.6: Treatment and spillover effect coefficients for generator-related permits with continuous treatment

	<i>Dependent variable:</i>	
	Gen_per10kHH	
	Continuous/OLS	Continuous/OLS
	(1)	(2)
Out:T0	0.017 (0.015)	0.032** (0.015)
Out:T1	0.043** (0.018)	0.036** (0.018)
Out:T2	0.130*** (0.031)	0.123*** (0.030)
Out:T3	0.124*** (0.025)	0.117*** (0.025)
Out:T4	0.083*** (0.031)	0.075** (0.030)
Out:T5	0.064*** (0.019)	0.056*** (0.019)
Out:T6	0.053** (0.024)	0.046* (0.024)
Out:T7	0.027* (0.016)	0.019 (0.016)
Spill_dist_scaled:Post	0.033*** (0.011)	
Spill_SCI_scaled:Post		0.024*** (0.005)
FE	-	-
clust-rob. SE	ZIP	ZIP
Spillovers	Distance	SCI
Observations	387	387
R ²	0.425	0.443
Adjusted R ²	0.402	0.420
Residual Std. Error (df = 371)	3.707	3.648
F Statistic (df = 15; 371)	18.270***	19.650***
<i>Note:</i> Based on t-distribution		
* p<0.1; ** p<0.05; *** p<0.01		

Appendix G. Supplementary results without adjusted p-values

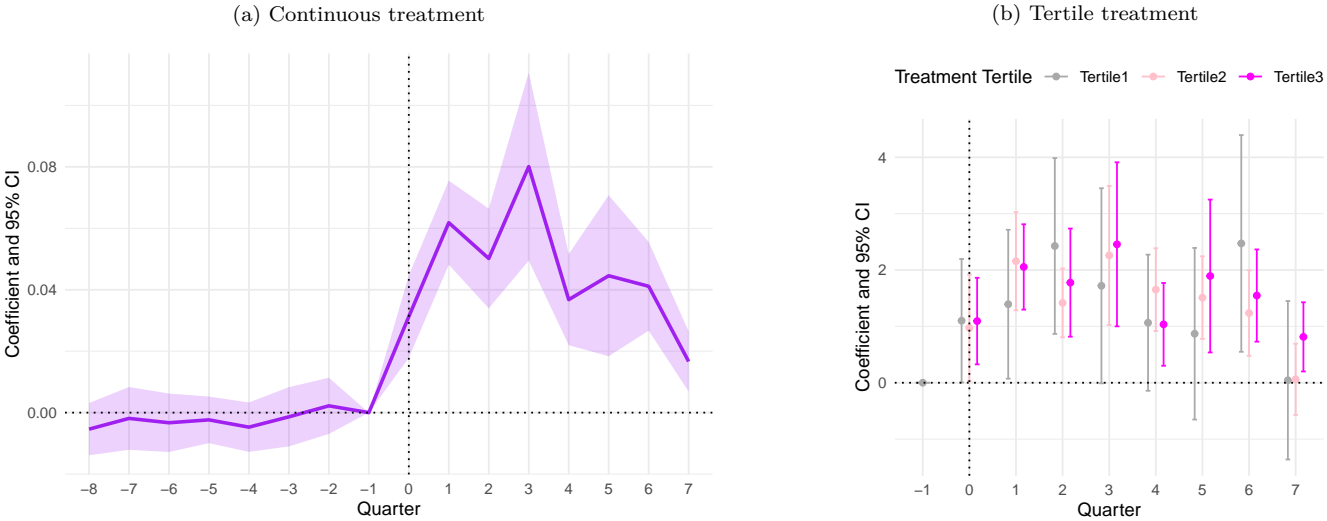
The following results replicate estimations while conventionally testing significance thresholds against a normal distribution (i.e. instead of against a t-distribution to account for small numbers of clusters).

Figure G.6: Treatment effect coefficients for generator-related permits (conventional p-values)



The period preceding the treatment period is omitted ($t = -1$).

Figure G.7: Treatment effect coefficients for PV with storage-related permits (conventional p-values)

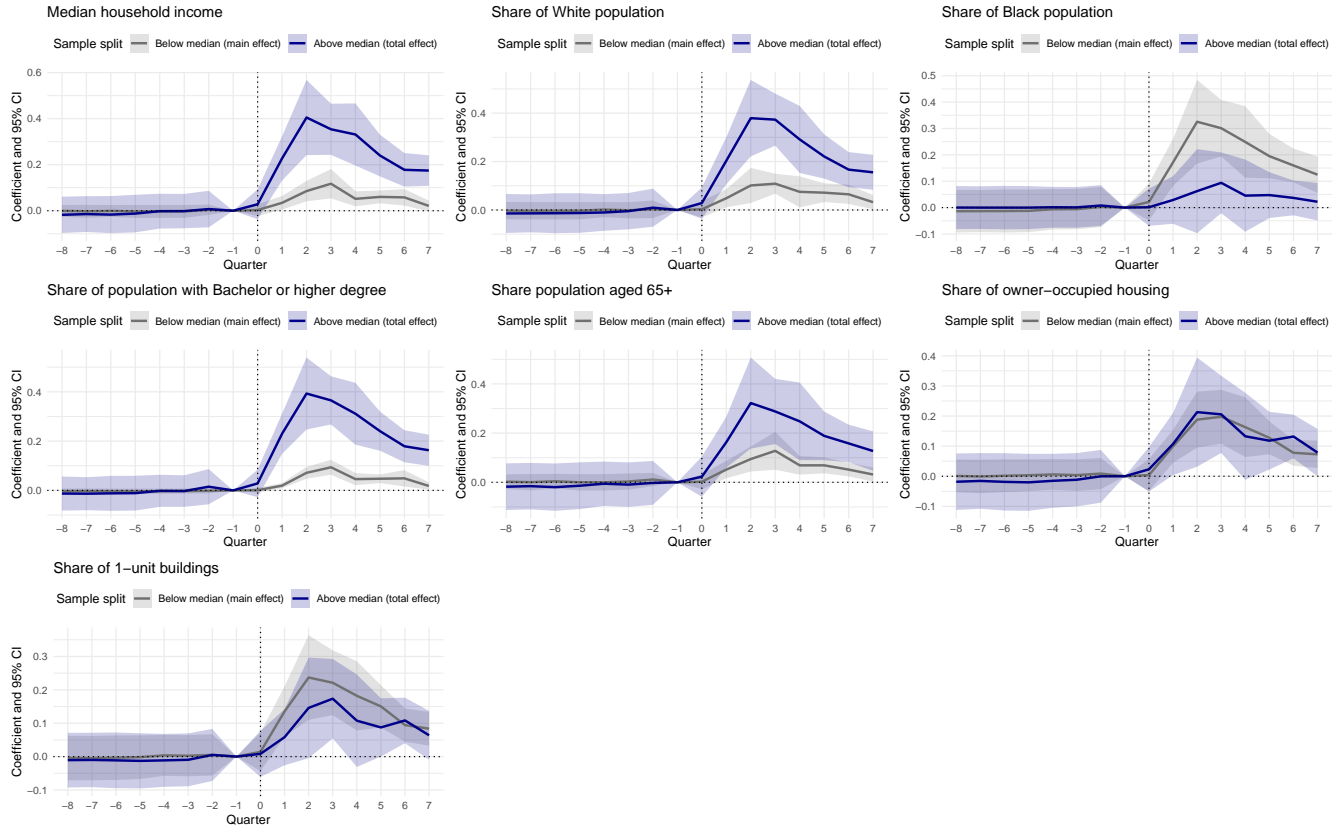


The period preceding the treatment period is omitted ($t = -1$).

Figure G.8: Heterogeneous treatment effects by socio-economic characteristics (conventional p-values)

The period preceding the treatment period is omitted ($t = -1$).
Above median (total effect) is plotted as the sum of the main effect point estimate and the interaction effect.

(a) Generator-related permits



(b) PV with storage-related permits

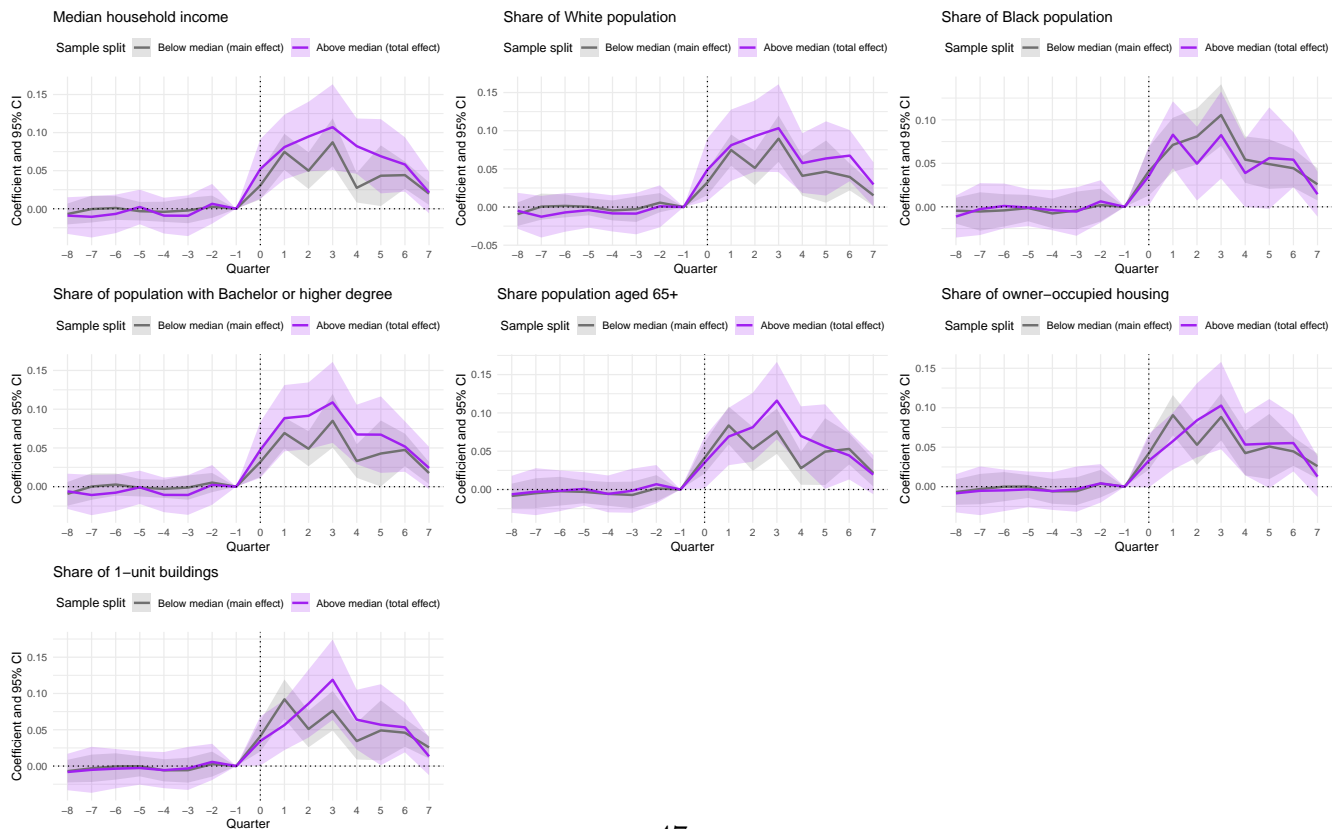
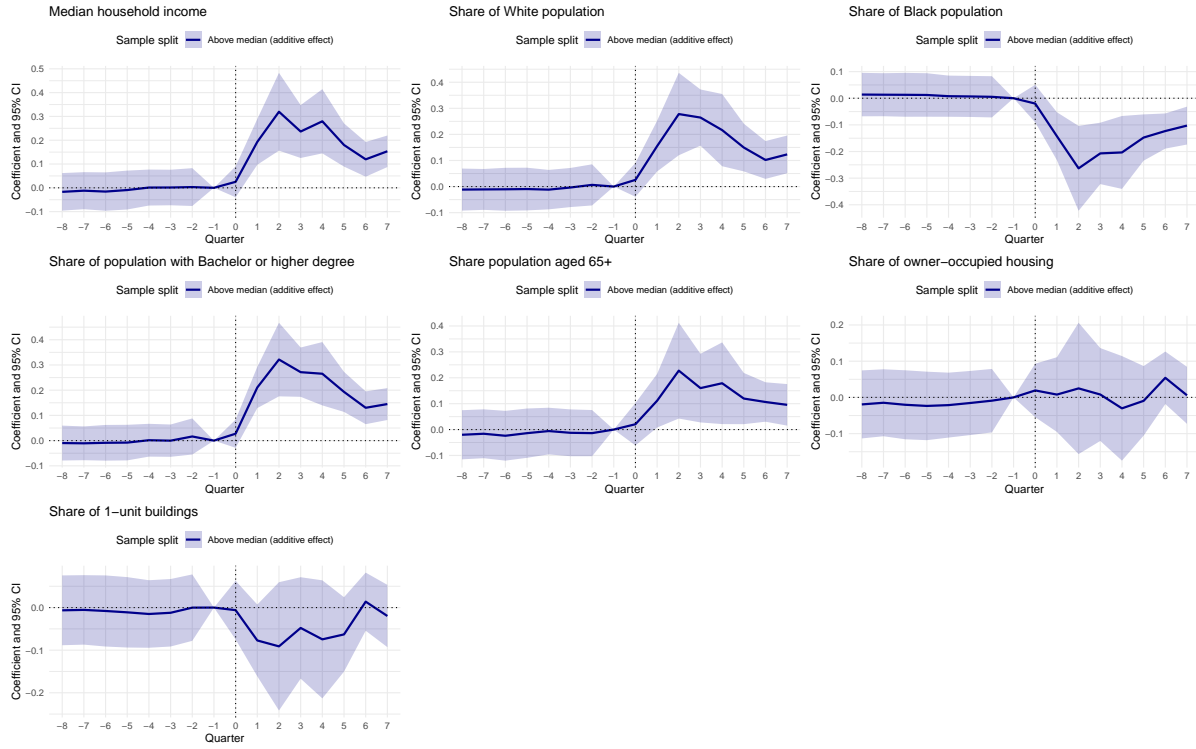


Figure G.9: Heterogeneous treatment effects by socio-economic characteristics (interaction effects) (conventional p-values)

Notes: The period preceding the treatment period is omitted ($t = -1$).
Above median (additive effect) is the interaction effect.

(a) Generator-related permits



(b) PV with storage-related permits

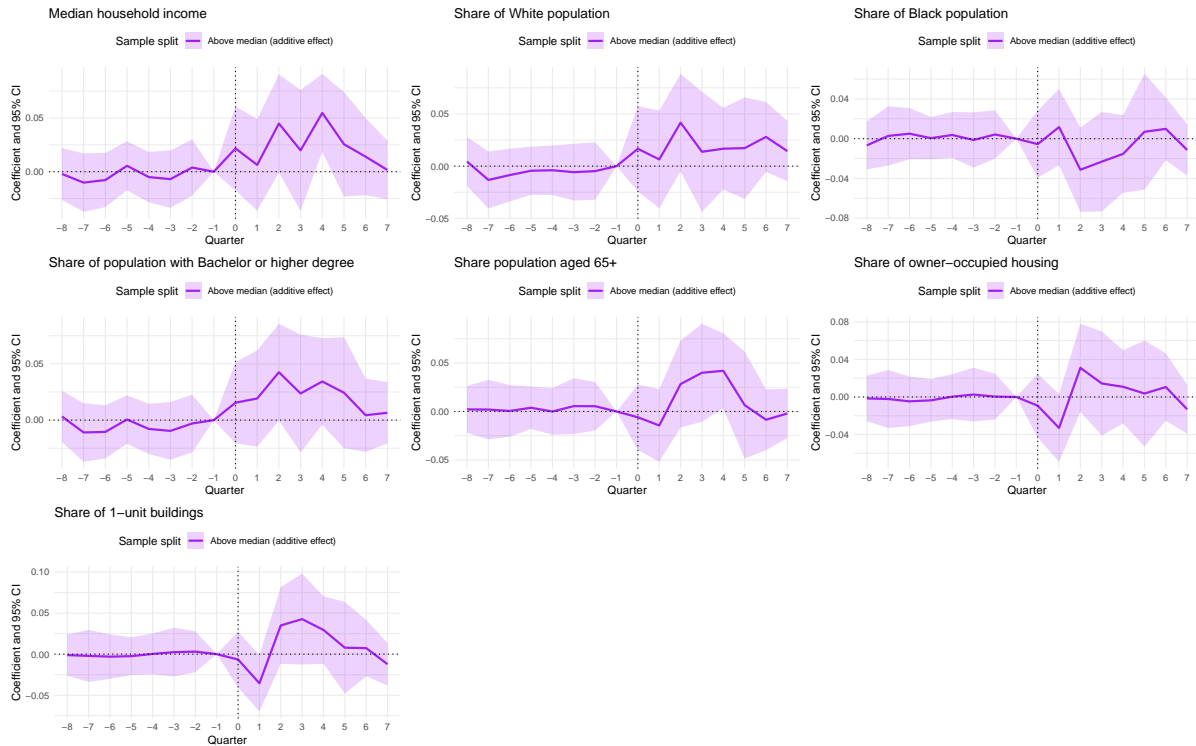


Table G.7: Treatment and spillover effect coefficients for generator-related permits with continuous treatment (conventional p-values)

	<i>Dependent variable:</i>	
	Gen_per10kHH	
	Continuous/OLS	Continuous/OLS
	(1)	(2)
Out:T0	0.017 (0.015)	0.032** (0.015)
Out:T1	0.043** (0.018)	0.036** (0.018)
Out:T2	0.130*** (0.031)	0.123*** (0.030)
Out:T3	0.124*** (0.025)	0.117*** (0.025)
Out:T4	0.083*** (0.031)	0.075** (0.030)
Out:T5	0.064*** (0.019)	0.056*** (0.019)
Out:T6	0.053** (0.024)	0.046* (0.024)
Out:T7	0.027* (0.016)	0.019 (0.016)
Spill_dist_scaled:Post	0.033*** (0.011)	
Spill_SCI_scaled:Post		0.024*** (0.005)
FE	-	-
clust-rob. SE	ZIP	ZIP
Spillovers	Distance	SCI
Observations	387	387
R ²	0.425	0.443
Adjusted R ²	0.402	0.420
Residual Std. Error (df = 371)	3.707	3.648
F Statistic (df = 15; 371)	18.270***	19.650***
<i>Note:</i>		
* p<0.1; ** p<0.05; *** p<0.01		