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Provide the docket's number.	02-2034, 12-383

Leave a comment on the docket. *

In the last week there have been 4 power outages at my home, at least one during an extreme heat warning. I've lived in my home since 2018 and this has been a consistent issue. For me this has been inconvenient and sometimes pricy—I've lost full fridges of groceries and been hot. Once an appliance died because it kept getting shut on and off and I had to replace it. So this issue has not been inexpensive for me. But I think the consequences are potentially much more serious for a lot of people in my neighborhood and many of them are much less able to afford the costs of this than I am. With the weather this hot I also think power outages can become dangerous. I'm attaching a study I found that is very concerning. It says that power outages unrelated to payment happen more frequently in neighborhoods where people who are poor or people of color live. It's very disturbing to me that the neighborhoods least able to afford it are subsidizing power for the rest of this city.

Attach a File	brief__minnesota_household_energy_insecurity_disparities_final.pdf 1.22 MB · PDF

CENTER FOR SCIENCE, TECHNOLOGY, AND ENVIRONMENTAL POLICY

Racial and Economic Disparities in Electric Reliability and Service Quality in Xcel Energy's Minnesota Service Area

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Abstract

This paper asks whether disparities exist in access to shared infrastructure systems, focusing on the electric system, an essential service delivered by heavily regulated public utilities. We examine disparities in access to electricity service in the service area of Xcel Energy across three dimensions: utility disconnection, service reliability, and grid availability to host distributed energy resources. We quantify disparities across Census block groups by leveraging unique, high-resolution datasets of service quality and grid conditions that have only recently been made publicly available. We find significant and pervasive evidence of the disparities among different demographic groups across utility disconnection and service reliability. Across a battery of regression models, we find that living in poorer neighborhoods with a greater concentration of people of color is associated with a statistically and practically significant difference in the likelihood of disconnection from service due to non-payment and the experience of extended power outages. We also find evidence that hosting capacity for distributed generation is higher in disadvantaged communities and communities with high populations of people of color. These findings underscore the opportunity for policy initiatives to rectify deep-seated inequalities through affirmative investments and safety net programs that ensure all communities, regardless of their racial or economic composition, have equitable access to universal basic utility service and reliable, clean energy.

Keywords: racial equity; disconnection; distributional justice; grid hosting capacity; energy justice

1. Introduction

The impact of household energy insecurity on the physical, mental, and economic well-being of struggling families has been well documented (Harker Steele and Bergstrom, 2021; Hernández, 2016; Konisky et al., 2022; Memmott et al., 2021). In this paper, we look at multiple indicators that affect energy insecurity: involuntary disconnection from service, long-duration outages, and availability of the grid to interconnect consumer-owned energy resources. Utility disconnection can cause extreme economic distress (Baker et al., 2021; Flaherty et al., 2020). Utility disconnection can cascade into long-term financial hardship, homelessness, and even severe health-related issues (Flaherty et al., 2020). From 2019 to 2020, around 4.7 million U.S. households at or below 200 percent of the federal poverty line could not pay their energy bills, 4.8 million received a utility disconnection notice, and 2 million were disconnected from their electricity service (Memmott et al., 2021). Difficulty affording energy costs can create situations of "energy insecurity" that cause households into dilemmas, such as choosing between food and heat, especially during extreme weather events (Hernández, 2016).

Many low-income households and communities of color face significant, pervasive, and persistent conditions of energy insecurity due to their inability to afford energy bills and living in fear of being disconnected from their utility services (Graff and Carley, 2020; Hernández et al., 2014). To reduce their energy bills and to mitigate their utility-related issues, families use various coping strategies, such as keeping indoor temperatures at a unsafe or undesirable level, using gas stoves to heat living spaces, abstaining from air-conditioning, and delaying bill payments and arrearages (Carley et al., 2022; Cong et al., 2022; Hernández, 2016; Hernández et al., 2014). Turning down the heat and living in cold and damp housing—due to poor housing conditions or high energy prices—has been shown to have significant associations with decreased respiratory, mental, and sleep outcomes (Hernández and Siegel, 2019; Liddell and Guiney, 2015). However, the present-day household energy insecurity is not merely a function of affordability, housing condition, employment, home efficiency, poverty, or energy prices– but instead, deeply rooted in how cities and neighborhoods evolved over the century (Swope et al., 2022).

As the energy transition accelerates to meet climate goals and integrate distributed energy resources (DERs), such as rooftop solar and electric vehicles, scholars, policymakers, and advocates have identified opportunities to advance energy justice goals (Carley and Konisky, 2020; Chan and Klass, 2022; Elmallah et al., 2022; Welton and Eisen, 2019). Yet currently, adoption of DERs reflects existing inequalities across race and income, and addressing historic injustices in infrastructure investment will likely require careful implementation of justice-oriented infrastructure policy (Schott and Whyte, 2023).

In this paper, our research question is: *Is there evidence of neighborhood-level disparities across income and race in the electric service quality, involuntary disconnection, and access to the grid to interconnect distributed energy resources?*

We explore this question by looking at three outcome metrics in a large Midwestern utility using a unique compilation of datasets that report average service quality and distribution grid hosting capacity at a fine geographic scale. We link these datasets with demographic characteristics to quantify disparities across race, income, poverty rates, and population density in involuntary disconnections, long-duration electric outages, and hosting capacity on the local grid for DERs. We find robust, statistically significant associations between race, poverty, utility disconnection, and long-term service disruption in Minnesota. We also identify correlations that suggest neighborhoods with a higher proportion of people of color, lower income, and lower population density tend to have increased DER hosting capacity availability. However, this observation is not consistent across all models. The greater availability of DER hosting capacity in these more disadvantaged communities may reflect a lower adoption rate of DER among low-income populations in communities of color who live in densely populated areas, contributing to the expanding research in this area.

The results do not imply causality, as conventional quantitative methods that purport to estimate counterfactuals of race are often inconsistent with social-constructivist theories of racialization (Graetz et al., 2022). Instead, our analysis shows the critical associations between socioeconomic factors, including race, and key indicators related to advancing energy justice. It is important to distinguish that our findings do not necessarily imply deliberate racial bias on the part of energy system planners. Instead, the findings underscore how multiple systemic causes of economic hardship are reflected in yet another critical infrastructure system (Swope et al., 2022). The results point to a valuable opportunity to correct these inequalities through deliberate investments in the energy transition that affirmatively prioritize disadvantaged communities, low-income neighborhoods, and communities of color. By doing so, a more equitable energy system that provides reliable, high-quality utility services and equal opportunity to benefit from the energy transition for all people can be fostered, regardless of socioeconomic status or racial background. And further, grid planners have an opportunity to prioritize investments in communities that are at greatest risk for energy insecurity.

The paper is structured as follows: Section 2 describes the paper's data sources. Section 3 provides an overview of the methodology applied, Section 4 presents the results of the paper, and Section 5 concludes.

2. Data

Our study integrates three distinct data sources at the Census block group-level covering the service area of Xcel Energy, the largest electric utility in Minnesota: the U.S. Census American Community Survey's demographic and household estimates, the Council on Environmental Quality's Climate and Economic Justice Screening Tool (CEJST) map of disadvantaged communities, Xcel Energy's Minnesota Electric Service Quality Interactive Maps estimates of service quality and involuntary disconnections, and Xcel Energy's Hosting Capacity Analysis for Generation (Gen-HCA) estimates of distribution grid capacity to host DERs.

2.1. American Community Survey and Climate and Economic Justice Screening Tool

The unit of analysis for our study is a Census block group (CBG). A CBG is the "smallest geographic entity for which the decennial census tabulates and publishes sample data" and generally contains between 600-3,000 people (Bureau of the Census, 1994). The average CBG in our dataset has a population of approximately 1,250 people. We extract CBG-level average demographic and household characteristics from the 5-year American Community Survey (ACS) for variables such as building composition and age, race/ethnicity of the head of household, income and poverty level, education, unemployment rate, population density (a proxy for electric grid topology), and homeownership type.

We also integrate data from the Council on Environmental Quality's Climate and Economic Justice Screening Tool (CEJST). The CEJST map provides binary indicators of whether a census tract meets the definition of a "disadvantaged community" pursuant to Executive Order 14008, "Tackling the Climate Crisis at Home and Abroad." Federal agencies use the CEJST definition of disadvantaged communities to seek to deliver 40% of the overall benefits of certain investments in climate and clean energy to disadvantaged communities under the Justice40 Initiative. The CEJST identification of disadvantaged communities is based on indicators in eight categories: climate change, energy, health, housing, legacy pollution, transportation, water and wastewater, and workforce development.

2.2. Disconnection and Service Quality Data

Our study leverages unique publicly available data on involuntary disconnections and service interruptions from Xcel Energy's Minnesota Electric Service Quality Interactive Maps published from 2019-2022 and covering data from 2017-2022. Xcel Energy is the largest electric utility in Minnesota and serves 38 percent of residential customers in some of the most densely populated areas of the state, including the Minneapolis-St. Paul metropolitan area (see Figure 1).

The dataset reports CBG-level averages of utility disconnection and service quality across Xcel Energy's service area. Utility disconnection is reported as ratio of the number of disconnected premises to the total number of premises in a CBG.

Service quality is reported in two metrics, CEMI-6 and CELI-12. CEMI-6 is the percent of customers in a CBG that experience 6 or more sustained outages per year. CELI-12 is the percent of customers in a CBG that experience an outage with a duration of 12 hours or more per year. For each year from 2019-2022, disconnection, CEMI-6, and CELI-12 rates are reported as three-year averages: 2017-2019 for the 2019 map, 2018-2020 for the 2020 map, and so on. Table 1 shows average yearly rates of disconnection, CELI-12, and CEMI-6 across CBGs.

Table 1. Disconnection and Service Quality Statistics for Xcel Energy's service areas from 2017-2022. All the numbers are per 1,000 households and standard deviations are included inside the brackets.

Years	Average disconnection rate (per 1,000 households)	CELI-12: Average number of households experiencing an outage longer than 12 hours (per 1,000 households)	CEMI-6: Average number of households experiencing 6 or more outages per year (per 1,000 households)
2017-2019	11.9 (14.2)	6.36 (28.7)	23.6 (57.7)
2018-2020	4.06 (6.06)	24.4 (55.7)	7.56 (30.3)
2019-2021	4.27 (6.16)	24.4 (55.3)	6.89 (28.0)
2020-2022	6.62 (10.6)	33.0 (70.4)	8.12 (31.0)
Overall	6.82 (10.51)	23.0 (57.19)	11.38 (38.97)

2.3. DER Hosting Capacity

We extract a CBG's DER hosting capacity from the publicly available 2023 Hosting Capacity Analysis for Generation (Gen-HCA) maps published by Xcel Energy. The Gen-HCA maps are used as a first-pass tool for developers to assist in site-selection processes for new DER generation, such as distributed solar, wind, and batteries. The Gen-HCA map is displayed as a heat map for a distribution feeder-line in most of Xcel Energy's service area in Minnesota. Hosting data was accessed in late 2023, representing a snapshot of current hosting capacity. Xcel Energy updates its hosting capacity analysis at each feeder at least once annually. Table 2 summarizes service area-wide descriptive statistics used in the regression.

Table 2. Descriptive Statistics of the variables used in the analysis.

Variable	Mean	S.D.	Min	Max
POC (0-100%)	25.09	23.04	0.00	99.54
Poverty (0-100%)	21.32	17.36	0.00	95.30
Median HH Income ($)	81,145	39,461	0	250,001
Population Density (1,000 households per sq. mile)	4.94	6.46	0.00	148.83
Unemployment Rate (0-100%)	4.08	4.53	0.00	56.72
Renters (0-100%)	30.16	25.60	0.00	100.00
Built after 90s (0-100%)	22.84	22.87	0.00	100.00
Disconnections (per 1,000 homes)	6.82	10.51	0.00	121.40
CELI-12: Average number of households experiencing an outage longer than 12 hours (per 1,000 households)	23.00	57.19	0.00	681.90
CEMI-6: Average number of households experiencing 6 or more outages per year (per 1,000 households)	11.38	38.97	0.00	525.50
Average Maximum Hosting Capacity Per Household (kW/household)	1.78	1.61	0.00	14.83
Maximum Area Hosting Capacity (kW)	801.37	605.52	0.00	4370.1

Unlike hosting capacity maps for used in previous research in states like California (Brockway et al., 2021), Gen-HCA maps intentionally omit specific details of distribution feeder lines due to security concerns, instead providing generalized representations as "blurred" spatial heat polygons. These polygons reflect only a snapshot of data and do not disclose the precise locations of the distribution lines. Based on the maximum area method, we execute a spatial overlay, aligning the 2010 Census Block Group (CBG) boundaries with the Gen-HCA maps. This process assigns unique CBG identifiers to each polygon, effectively integrating the two data sets.

Xcel's Gen-HCA polygons incorporate a variable denoting diverse hosting capacities along the distribution line; however, many polygons within the dataset have multiple hosting capacities. The Xcel Gen-HCA map uses the maximum value of each polygon to classify the available hosting capacity range (> 1 MW, 751-1 MW, 501-750 MW, 251-500 MW, 1-250 MW, 0 MW). To extrapolate the polygon data to a CBG level, we utilize the highest hosting capacity value from the Gen-HCA polygons, averaging these figures to derive a single hosting capacity metric for each CBG– this is the Maximum

Area Hosting Capacity (kW). Dividing this number by the total number of housing units in the CBG gives the Average Maximum Hosting Capacity per household (kW per household). This approach is conceptually consistent with the visual representation of the Gen-HCA map in the web interface. When polygons intersect with multiple CBGs, we attribute the polygon to the CBG covering the largest segment of the polygon, ensuring a representative allocation. To calculate per household hosting capacity i.e. Average Maximum Hosting Capacity per household (kW per household). for each CBG, we divide the calculated CBG hosting capacity by the total housing units in the CBG (excluding the two CBGs with fewer than 10 reported housing units). To remove outliers, we limit the average maximum hosting capacity per household value to 15 kW.

We note that our approach to averaging hosting capacity within a CBG could obscure more micro-level dynamics in hosting capacity within a CBG. Hosting capacity is a complex function of grid topology and depends on highly context-specific, often trade-secret characteristics of the grid. Nevertheless, our approach is still able to provide a high-level estimate of hosting capacity that approximates what could be considered a "screening" type of hosting capacity assessment. Detailed and accurate hosting capacity data could help in refining energy justice assessments by highlighting the disparities in access to DERs. The granular data would enable utilities to pinpoint underserved areas for targeted grid improvements, or even pinpoint areas with a high availability of hosting capacity to integrate DERs. Such data-driven strategies can inform nuanced energy policies that address unique community barriers to DER adoption, facilitating a more inclusive and justice-focused energy transition.

2.4. Descriptive Analysis

In this section, we present a descriptive analysis of disparities across our key outcome variables. Figure 1 shows maps that present spatial representation of key variables in our dataset, showing the resolution of our CBG-level data for the two largest counties in Xcel Energy's service area, Hennepin and Ramsey counties.

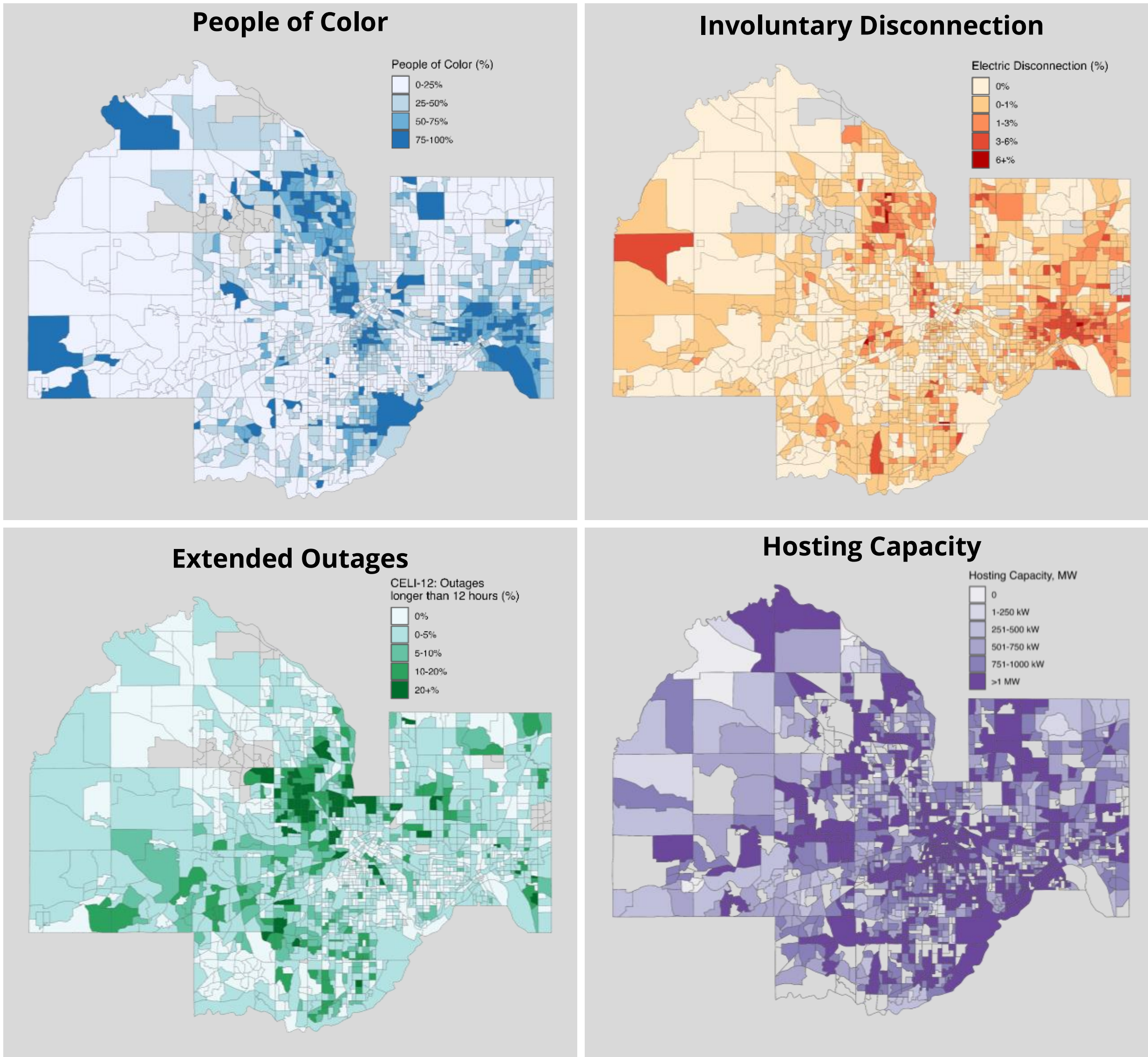

Figure 1. Illustration of data resolution. Maps display relative magnitude of key variables in the dataset at the Census block group-level for Hennepin and Ramsey counties (encompassing Minneapolis and St Paul and the majority of customers in Xcel Energy's service area). Top left: people of color as percent of population. Top right: involuntary disconnections as a percent of customers. Bottom left: extended outages over 12 hours per year as a percent of customers. Bottom right: hosting capacity of the distribution grid as percent of population.

2.4.1. Descriptive Analysis of Disconnections

The first line of inquiry is to explore the relationships between a CBG's percentage of people of color and the number of customers disconnected due to non-payment every year. Figure 2 shows scatterplots for the proportion of households disconnected due to non-payment across three-year periods with moving averages by a CBG's percent people of color. The figure shows upward trends across all three-year periods with communities with a higher percentage of people of color experiencing higher rates of electric disconnection. We display disparities in disconnection rates in CEJST-designated disadvantaged communities compared to other communities in Figure 3. And we affirm the relationship between disconnections and race shown in Figure 2 again in Figure 4, emphasizing the higher disconnection rate in the CBGs in the top 10% of population of people of color.

Our data covers a period during which Minnesota implemented a moratorium on utility disconnections that applied to Xcel Energy during the COVID-19 pandemic, which was in place from the start of the pandemic in early 2020 through August 2021 (Baker et al., 2021). The impact of the disconnection moratorium can be seen in the lower average disconnection rates in the periods with greater overlap with the moratorium. Yet we still see visually apparent upward trends between a CBG's population of color and disconnection rates.

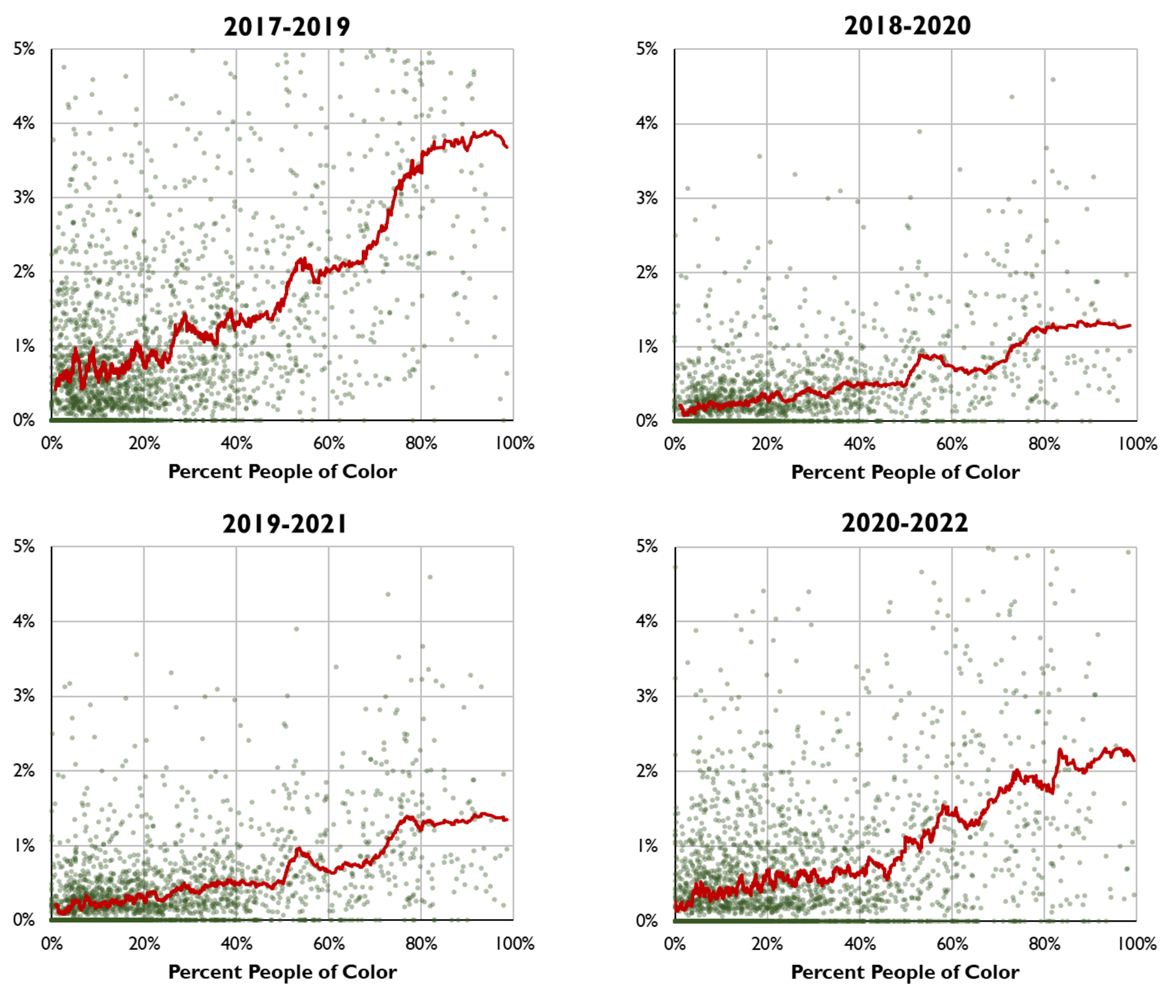

Figure 2. The relationship between CBG average disconnection rates compared to its percent people of color, 2019-2022. The moving average line shows a clear positive relationship for all years.

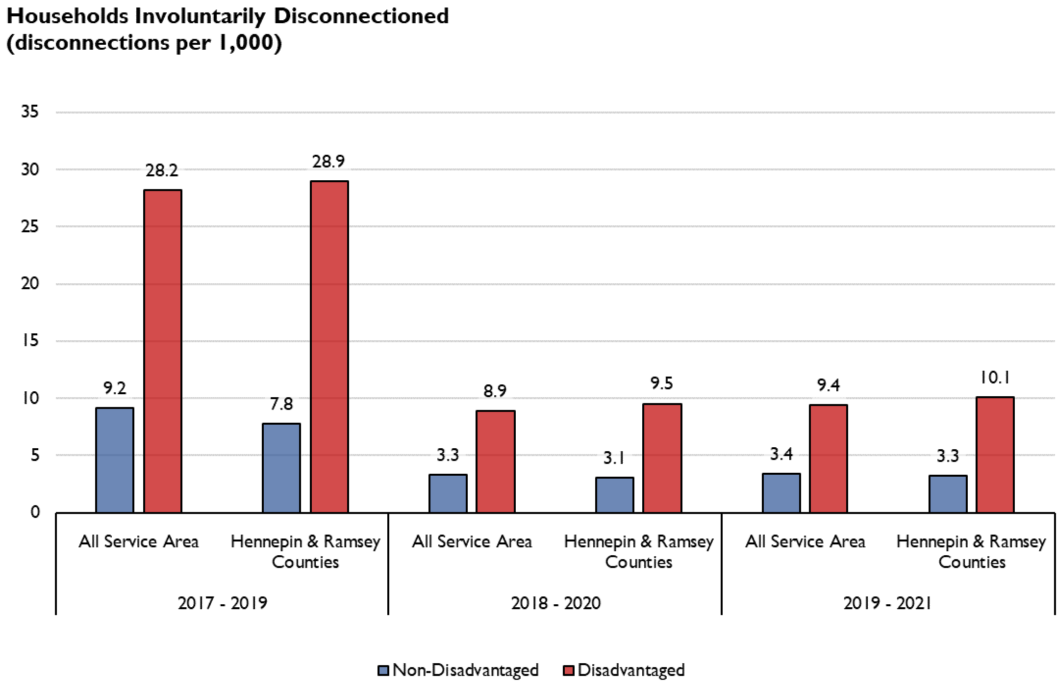

Figure 3. Disconnected households, comparing non-disadvantaged versus disadvantaged CBGs in Xcel Energy's service area and in Hennepin and Ramsey Counties from 2017-2021.

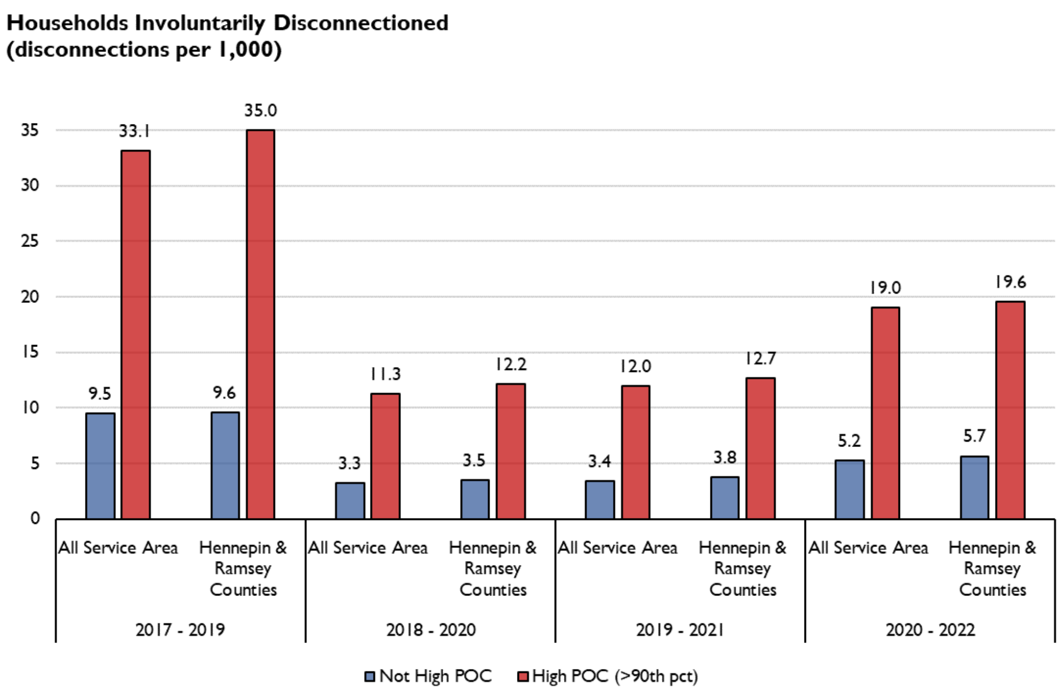

Figure 4. Disconnected households, comparing CBGs with high percentage of people of color (POC) with others in Xcel Energy's Service Area and in Hennepin and Ramsey Counties from 2017-2022.

One possible explanation for the positive association between a CBG's percent people of color and disconnection rate is confounding by income. To address this possibility, Figure 5 shows disconnection rates within bands of CBG median household income and bands of percent people of color. The figure shows that the upward association between disconnection rates and percent people of color holds even within CBG's with low income. Potential confounding is addressed more holistically in the regression analysis presented in Section 4.1.

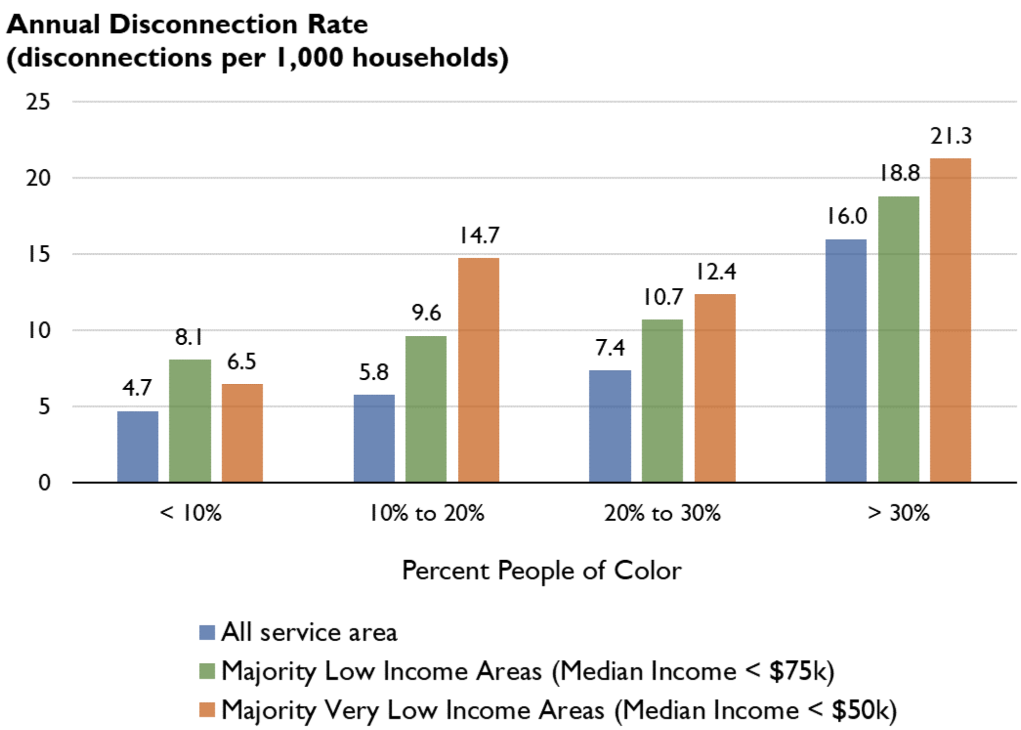

Figure 5. Rate of disconnection by an area's percent people of color overall and below different income levels, 2017-2022. Data for this figure combines data shown in Figure 2 for the period 2017-2019 and 2020-2022 to avoid double counting any years. Note that the time period in this figure covers a moratorium on disconnections during the COVID-19 pandemic, and therefore disparities largely reflect disparities in disconnections from 2017-2019 and in 2022.

2.4.2. Descriptive Analysis of Service Quality

Figure 6 reveals a concerning trend in power outage disparities between non-disadvantaged and disadvantaged communities across Xcel Energy's service area and specifically within Hennepin & Ramsey Counties over consecutive years from 2017 to 2021. We classify CBGs on their disadvantaged community status based on the White House's Climate and Economic Justice Screening Tool (CJEST). Despite fluctuations, there is a discernible pattern where disadvantaged CBGs consistently endure a greater frequency of power outages exceeding 12 hours (CELI-12). For 2018-2020 and 2019-2021, disadvantaged CBGs had a higher incidence of more extended power outages across all service areas and also within Hennepin & Ramsey Counties. This finding suggests potential systemic vulnerabilities or unequal distribution of resources affecting power stability. We do not analyze 2020-2022 because the Xcel service quality maps are based on census 2020 boundaries whereas the CJEST classifications are based on 2010 census boundaries.

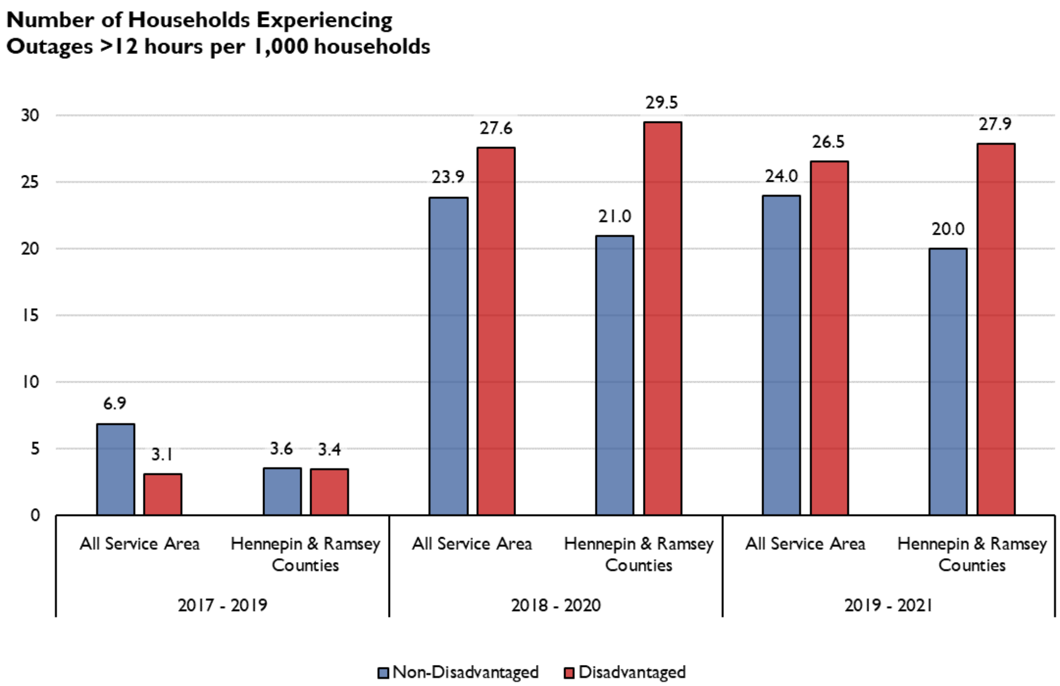

Figure 6. Households experiencing outages longer than 12 hours (CELI-12), comparing non-disadvantaged versus disadvantaged CBGs in Xcel Energy's service area and in Hennepin and Ramsey Counties from 2017-2021.

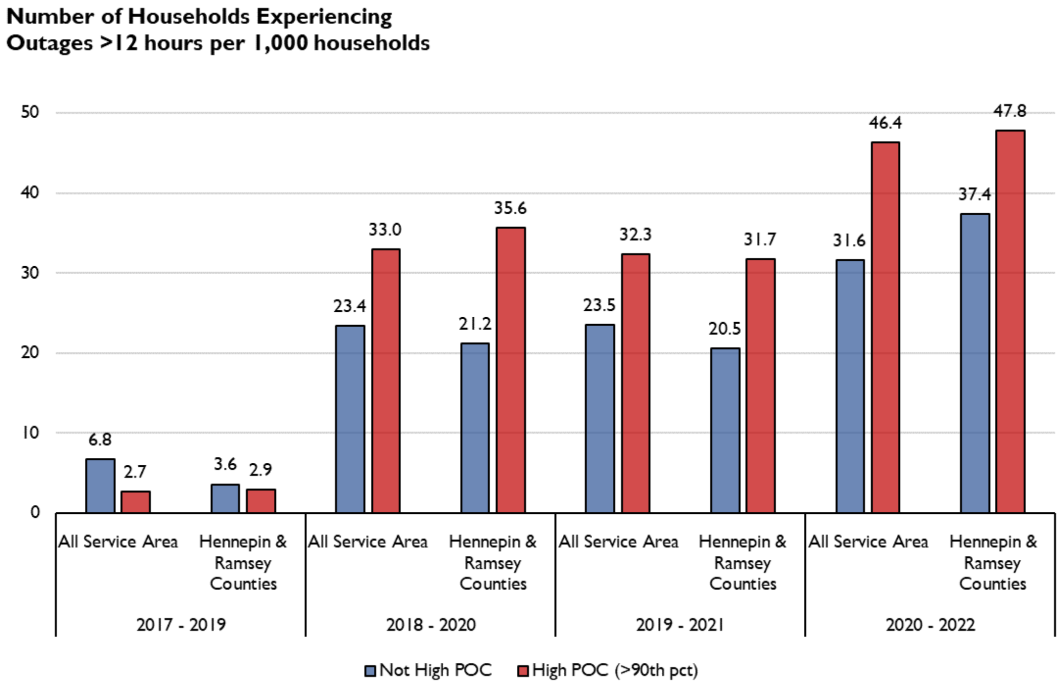

Figure 7. Households experiencing outages longer than 12 hours (CELI-12), comparing CBGs with high percentage of people of color (POC) with other CBGs in Xcel Energy's Service Area and in Hennepin and Ramsey Counties from 2017-2022.

Figure 7 provides a visual analysis of the stark differences in long-duration outages (CELI-12) for CBGs that have a high percentage of people of color (above 90th percentile) and those that do not, by comparing the metrics in Hennepin & Ramsey counties and all of Xcel's service area. The figure shows that, except for 2017-2019, high POC CBGs experienced significantly longer power outages. For instance, in the 2020-2022 period, Hennepin & Ramsey Counties reported nearly 48 outages per 1,000 high POC households, significantly more than the just over 37 outages per 1,000 non-high POC households. This pattern indicates not only a reliability issue within the power infrastructure but also underscores a social equity concern, as the communities with higher percentages of POC are disproportionately affected by power service disruptions.

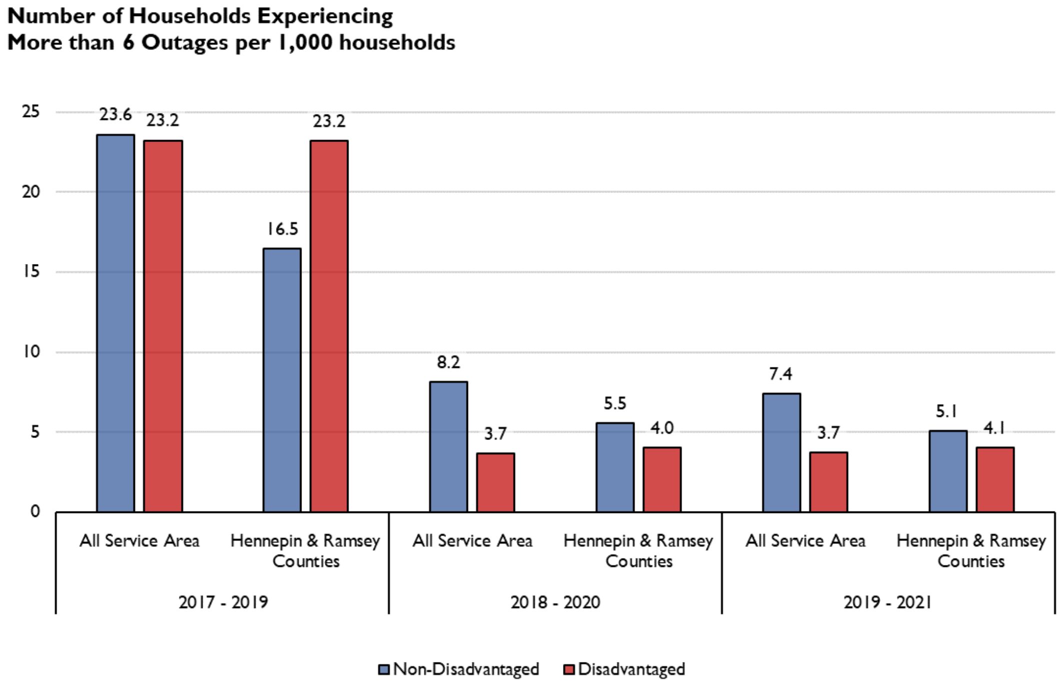

Figure 8. Households experiencing six or more sustained outages per year (CEMI-6), comparing non-disadvantaged versus disadvantaged CBGs in Xcel Energy's service area and in Hennepin and Ramsey Counties from 2017-2021.

Figure 8 shows the number of households per 1,000 experiencing 6 or more sustained outages per year (CEMI-6). Except for outages in Hennepin & Ramsey Counties in 2017-2019, disadvantaged communities in all of Xcel's Service Area and Hennepin & Ramsey Counties had lower incidences of frequent power outages. For disadvantaged communities in Hennepin & Ramsey Counties, the number of households experiencing more than 6 or more sustained outages also reduce significantly– from 23.7 in 1,000 households in 2017-2019 to about 3.7-4.1 per 1,000 households in 2018-2021.

Similarly, Figure 9 shows the number of households per 1,000 experiencing 6 or more sustained outages per year for CBGs classified into either high POC (more than 90th percentile) or not high POC. Like the trend shown in Figure 8, the number of households experiencing more sustained outages is higher for high POC CBGs only in 2017-2019, for all customers. The number of sustained outages experienced by homes in high POC CBGs within Hennepin & Ramsey Counties range from 3.7-6.3 per 1,000 households from 2018-2022. Likewise, 7.1-8.4 per 1,000 households homes (that do not get categorized as high POC) experience frequent outages.

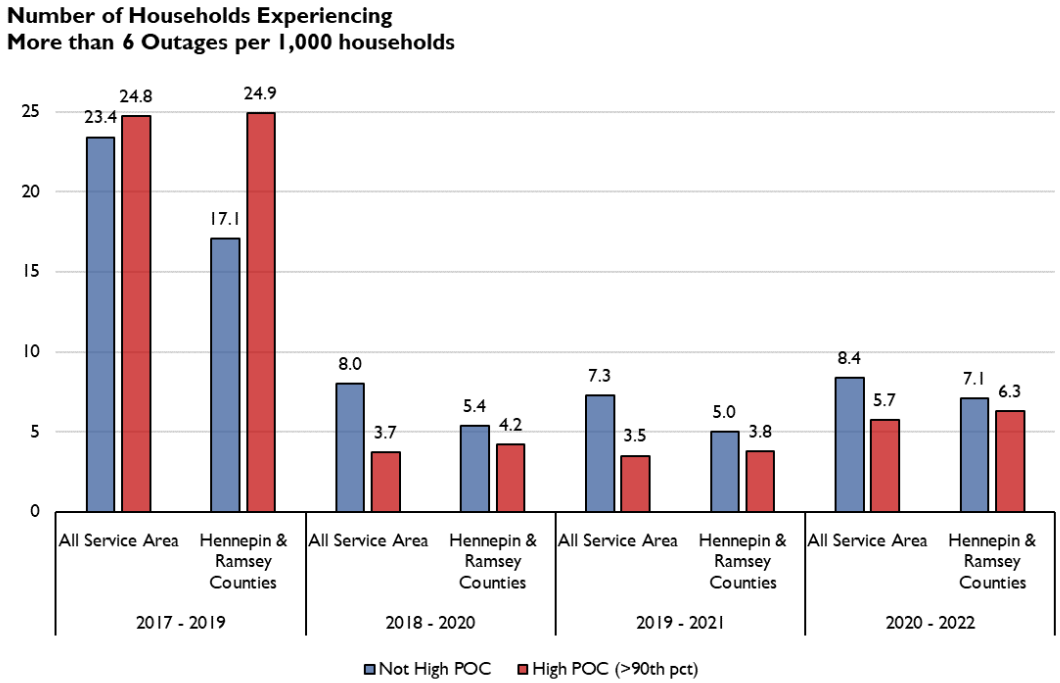

Figure 9. Households experiencing six or more sustained outages per year (CEMI-6), comparing CBGs with high percentage of people of color (POC) with other CBGs in Xcel Energy's Service Area and in Hennepin and Ramsey Counties from 2017-2022.

2.4.3. Descriptive Analysis of Hosting Capacity

Figure 10 compares hosting capacity metrics across CEJST-designated disadvantaged communities to other communities. The results show that hosting capacity is significantly higher in disadvantaged communities than other communities based both on the average area maximum hosting capacity and the average maximum hosting capacity per household.

Similarly, Figure 11 shows that hosting capacity is also higher on an area-average and per-household basis in communities in the top 10 percent of population of people of color.

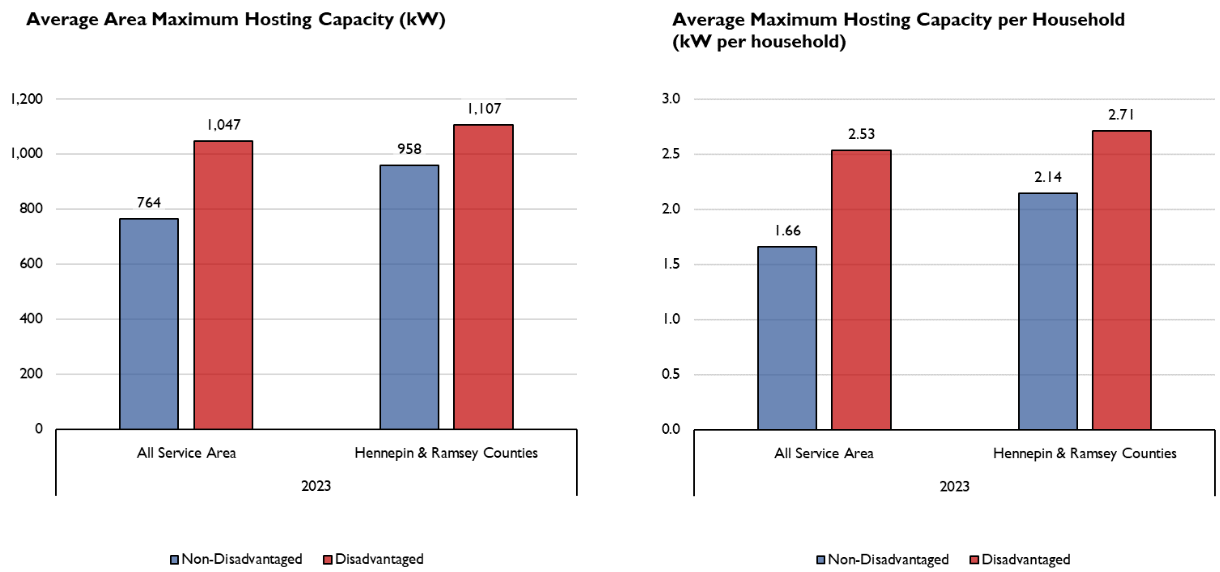

Figure 10. Average area maximum hosting capacity (left) and per household hosting capacity (right) comparing non-disadvantaged versus disadvantaged CBGs in Xcel Energy's service area and in Hennepin & Ramsey Counties from 2017-2021. Hosting capacity estimates shown for 2023.

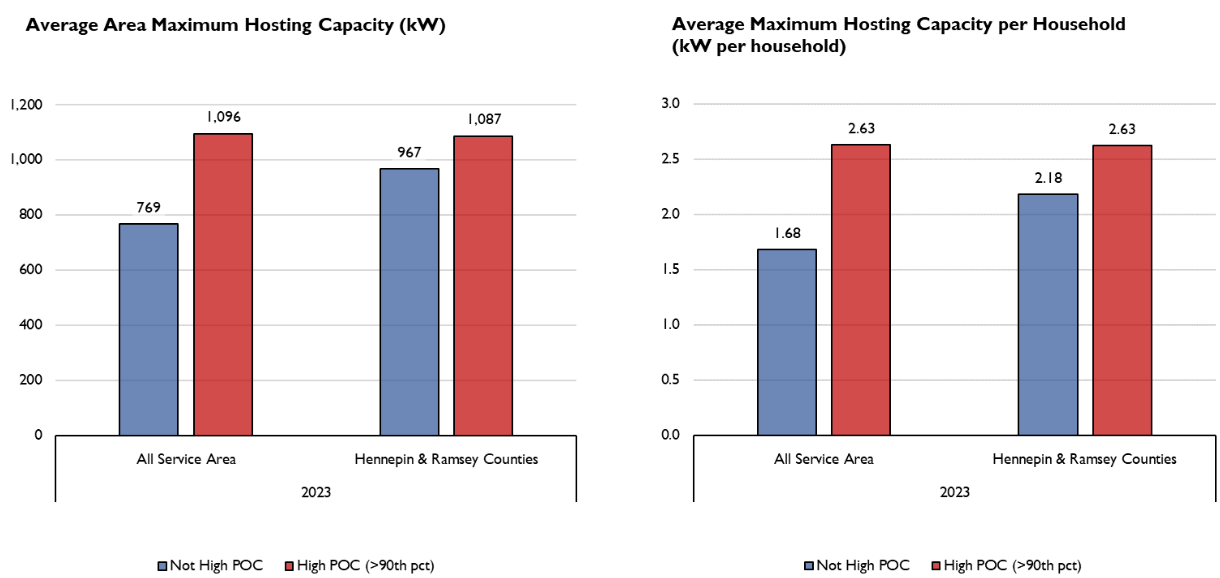

Figure 11. Average area maximum hosting capacity (left) and per household hosting capacity (right) comparing CBGs with high percentage of people of color (POC) with other CBGs in Xcel Energy's Service Area and in Hennepin and Ramsey Counties. Hosting capacity estimates shown for 2023.

2.4.4. Difference-in-Means Hypothesis Tests

In this section, we present results of difference-in-means hypothesis tests for each of the key outcome variables (long-term outages, multiple outages, involuntary disconnections, and hosting capacity) across each of the years of data. In Table 3, we conduct difference-in-means hypothesis tests comparing CEJST-designated disadvantaged communities to other communities. In Table 4, we conduct difference-in-means hypothesis tests comparing CBGs in the top 10% of population of people of color to other CBGs.

Table 3. Difference-in-means hypothesis tests comparing CEJST-designated disadvantaged communities to other communities across the rate of long-term outages, multiple outages, involuntary disconnections, and measures of hosting capacity.

		Non-Disadvantaged Communities (Non-DAC)	Disadvantaged Communities (DAC)	Difference (Non-DAC - DAC)	p-value	Statistically Significant?
Long-Term Outages: Customers Experiencing an Outage > 12 hours in a Year, per 1,000 households (CELI-12 x 1,000)						
2017-2019	All Service Area	6.90	3.12	3.77	0.0472	Yes
	Hennepin & Ramsey Counties	3.56	3.44	0.12	0.9037	No
2018-2020	All Service Area	23.89	27.60	-3.71	0.3803	No
	Hennepin & Ramsey Counties	20.98	29.51	-8.53	0.0414	Yes
2019-2021	All Service Area	24.01	26.54	-2.53	0.4905	No
	Hennepin & Ramsey Counties	20.02	27.91	-7.89	0.0247	Yes
Multiple Outages: Customers Experiencing > 6 Outages in a Year, per 1,000 households (CEMI-6 x 1,000)						
2017-2019	All Service Area	23.61	23.24	0.37	0.9231	No
	Hennepin & Ramsey Counties	16.48	23.23	-6.75	0.0312	Yes
2018-2020	All Service Area	8.16	3.69	4.47	0.0518	No
	Hennepin & Ramsey Counties	5.54	4.04	1.50	0.3946	No
2019-2021	All Service Area	7.41	3.74	3.67	0.0479	Yes
	Hennepin & Ramsey Counties	5.08	4.05	1.03	0.4767	No
Involuntary Disconnections, per 1,000 households						
2017-2019	All Service Area	9.17	28.19	-19.02	0.0000	Yes
	Hennepin & Ramsey Counties	7.76	28.95	-21.18	0.0000	Yes
2018-2020	All Service Area	3.30	8.92	-5.61	0.0000	Yes
	Hennepin & Ramsey Counties	3.08	9.54	-6.46	0.0000	Yes
2019-2021	All Service Area	3.42	9.43	-6.01	0.0000	Yes
	Hennepin & Ramsey Counties	3.25	10.07	-6.82	0.0000	Yes
Hosting Capacity (Maximum Area Hosting Capacity, kW)						
2023	All Service Area	763.90	1047.45	-283.55	0.0000	Yes
	Hennepin & Ramsey Counties	957.89	1106.81	-148.92	0.0000	Yes
Hosting Capacity per Households (Maximum Area Hosting Capacity per Household, kW/household)						
2023	All Service Area	1.66	2.53	-0.87	0.0000	Yes
	Hennepin & Ramsey Counties	2.14	2.71	-0.57	0.0000	Yes

Table 4. Difference-in-means hypothesis tests comparing communities with in the top 10% of populations of people of color to other communities across the rate of long-term outages, multiple outages, involuntary disconnections, and measures of hosting capacity.

		Not High People of Color Population (Bottom 90%)	High People of Color Population (Top 10%)	Difference (Not High POC - High POC)	p-value	Statistically Significant?
Long-Term Outages: Customers Experiencing an Outage > 12 hours in a Year, per 1,000 households (CELI-12 x 1,000)						
2017-2019	All Service Area	6.77	2.69	4.08	0.0655	No
	Hennepin & Ramsey Counties	3.61	2.90	0.71	0.5820	No
2018-2020	All Service Area	23.43	32.98	-9.55	0.0469	Yes
	Hennepin & Ramsey Counties	21.20	35.62	-14.43	0.0089	Yes
2019-2021	All Service Area	23.48	32.33	-8.85	0.0375	Yes
	Hennepin & Ramsey Counties	20.53	31.71	-11.18	0.0183	Yes
2020-2022	All Service Area	31.56	46.37	-14.81	0.0012	Yes
	Hennepin & Ramsey Counties	37.41	47.77	-10.36	0.0941	No
Multiple Outages: Customers Experiencing > 6 Outages in a Year, per 1,000 households (CEMI-6 x 1,000)						
2017-2019	All Service Area	23.42	24.77	-1.34	0.7635	No
	Hennepin & Ramsey Counties	17.09	24.92	-7.83	0.0641	No
2018-2020	All Service Area	7.99	3.69	4.29	0.1006	No
	Hennepin & Ramsey Counties	5.37	4.20	1.16	0.6172	No
2019-2021	All Service Area	7.27	3.50	3.76	0.0804	No
	Hennepin & Ramsey Counties	4.99	3.81	1.18	0.5449	No
2020-2022	All Service Area	8.39	5.74	2.65	0.1887	No
	Hennepin & Ramsey Counties	7.10	6.29	0.81	0.7087	No
Involuntary Disconnections, per 1,000 households						
2017-2019	All Service Area	9.52	33.15	-23.63	0.0000	Yes
	Hennepin & Ramsey Counties	9.58	35.03	-25.45	0.0000	Yes
2018-2020	All Service Area	3.25	11.29	-8.03	0.0000	Yes
	Hennepin & Ramsey Counties	3.47	12.15	-8.68	0.0000	Yes
2019-2021	All Service Area	3.42	11.98	-8.57	0.0000	Yes
	Hennepin & Ramsey Counties	3.76	12.68	-8.91	0.0000	Yes
2020-2022	All Service Area	5.25	19.01	-13.76	0.0000	Yes
	Hennepin & Ramsey Counties	5.67	19.56	-13.89	0.0000	Yes
Hosting Capacity (Maximum Area Hosting Capacity, kW)						
2023	All Service Area	768.82	1095.63	-326.81	0.0000	Yes
	Hennepin & Ramsey Counties	966.99	1087.00	-120.01	0.0027	Yes
Hosting Capacity per Households (Maximum Area Hosting Capacity per Household, kW/household)						
2023	All Service Area	1.68	2.63	-0.95	0.0000	Yes
	Hennepin & Ramsey Counties	2.18	2.63	-0.45	0.0002	Yes

3. Methods

In the three major analyses we conduct for disconnection rates, service quality, and DER hosting capacity analysis, we compute the conditional and unconditional annual rates (disconnections, CELI-12, and DER hosting capacity) using Ordinary Least Squares (OLS) regression models by regressing these rates on an indicator of the percent of households that identify as people of color, poverty rates, and median household income at the CBG level. We also use year and county fixed effects and an additional set of CBG-level controls. In equation (1), we show the basic model for our regression models.

$$y_{it} = \alpha_c + \lambda_t + \delta POC_{it} + \beta X_{it} + \varepsilon_{it} \quad (1)$$

where, y_{it} is the annual block group (i) dependent variable: disconnected homes (per 1,000 homes), CELI-12 (per 1,000 homes), and hosting capacity (kW per household), **δ** represent the variables of interest- representing the impact of POC on the dependent variable, α_c are county-level fixed effects, λ_t are year fixed effects, and X_{it} includes block group characteristics: median household income, poverty rate, unemployment rate, population density, renters, multifamily housing, newly built buildings, and households with no access to the internet.

The way that Xcel Energy reports the disconnection and CELI-12 data (by average disconnection rates over 3 years) biases the actual rates due to multiple overlaps between different periods. For example, the 2020 rates (the average of 2018, 2019, and 2020) and the 2021 rates (the average of 2019, 2020, 2021) biases the actual rates which can lead to underestimation of the variability in the dataset and overstate the significance of the findings. To account for this possible violation, we create a panel using rates from two reporting periods: 2019 and 2022 to eliminate any overlapping years.

4. Regression Results

In this section we present the results of our analysis of disconnection rates (Section 4.1), rates of extended outages (Section 4.2), and hosting capacity (Section 4.3) against demographic indicators. For each outcome variable, we implement nearly identical regression model specifications.

4.1. Electric Service Disconnection

Table 5 presents the outcomes of a fixed effects model employed to examine the correlation between utility disconnection rates and various variables, with a focus on the percentage of people of color (POC) within a CBG. Model (1) only regresses the POC percent value with disconnection rates. The result of Model (1) shows that increasing a CBG's POC population by 10 percentage points is associated with an increase of 2.93 disconnections per 1,000 households, controlling for year and county-fixed effects. This is a practically significant finding when compared to the average disconnection rate of 6.82 disconnections per 1,000 households shown in Table 1. The estimate for POC across all models is statistically significant at the 0.01 level when controlled for the economic and structural characteristics of the block group (separately and together.

In Model (5), we control for the CBG's median household income ($100,000), poverty (%), population density (1,000 homes per sq. miles), unemployment rate (%), renters (%), and the proportion of homes built after 1990 (%). The linear regression model suggests significant correlations between a CBG's POC and the rate of electric utility disconnection. Model (5) reports that after controlling for a number of variables, a 10 percentage point increase in the POC share of the population is associated with the number of disconnected homes per 1,000 increasing by 2.24.

Table 5. OLS Regression Model of Electric Utility Disconnections for the panel of 2017-2019 average and 2020-2022 average disconnections

Dependent Variable:	Disconnected homes (per 1,000 households)				
Model:	(1)	(2)	(3)	(4)	(5)
POC (0-100%)	0.2927*** (0.0116)	0.2271*** (0.0132)	0.2645*** (0.0118)	0.2940*** (0.0118)	0.2236*** (0.0133)
Poverty (0-100%)		0.1201*** (0.0171)			0.0777*** (0.0210)
Med. HH Inc. ($100,000)			-3.492*** (0.3699)		-1.296** (0.5153)
Population Density (1,000 households per sq. mile)				-0.0147 (0.0307)	-0.0925*** (0.0321)
Unemp. Rate (0-100%)					0.1633*** (0.0528)
Renters (0-100%)					0.0184 (0.0112)
Built after 90s (0-100%)					-0.0379*** (0.0066)
Year FE	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓
Observations	4,511	4,511	4,511	4,511	4,451
R^2	0.3638	0.3776	0.3737	0.3639	0.3852

Significance Codes: *** p < 0.01, ** p < 0.05, * p < 0.1

4.2. Service Reliability

In the following analysis, the focus shifts to long-duration outages as captured by the CELI-12 metric, which likely has a more pronounced impact on under-resourced communities compared to multiple short-duration outages, as gauged by the CEMI-6 metric.

Table 6. Regression Model of Long Duration Service Disruption in Minnesota for the panel of 2017-2019 average and 2020-2022 average service disruptions.

Dependent Variable:	CELI-12: Homes Experiencing Outages >12 hrs (per 1,000 households)				
Model:	(1)	(2)	(3)	(4)	(5)
POC (%)	0.0652 (0.0441)	0.1992*** (0.0563)	0.1009** (0.0452)	0.1089** (0.0042)	0.2078*** (0.0561)
Poverty (%)		-0.2455*** (0.0630)			-0.0770 (0.0790)
Med. HH Inc. ($100,000)			4.424** (1.814)		-7.307** (2.876)
Population Density (1,000 households per sq. mile)				-0.4941*** (0.1001)	-0.2258** (0.0989)
Unemp. Rate (%)					0.0177 (0.2021)
Renters (%)					-0.3180*** (0.042)
Built after 90s (%)					-0.3027*** (0.0275)
Year FE	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓
Observations	4,511	4,511	4,511	4,511	4,451
R^2	0.1187	0.1213	0.1194	0.1211	0.1493

Significance Codes: *** p < 0.01, ** p < 0.05, * p < 0.1

The outcomes of the regressions are shown in Table 6. Model (1) estimates the association between a CBG's percent POC and CELI-12 rates, accounting for year and county fixed effects. Models (2-5) estimate multivariate regressions with multiple controls. For Models (2-5), the percent POC in a CBG is statistically significant, indicating the robustness of the estimated value. Model (5) estimates a coefficient of 0.2078 for POC. The interpretation of the estimate is that, after controlling for different neighborhood characteristics, a 10 percentage point rise in the POC population is associated with 2.078 additional homes experiencing long-duration outages, controlling for multiple socioeconomic factors. The estimates in Model (2-5) are statistically significant at the 0.01 level.

4.3. DER Hosting Capacity

Table 7 shows the effect of a CBG's demographics on the average maximum hosting capacity per household. Hosting capacity is measured in kilowatts (kW) per household. Model (1) estimates the impact of a CBG's POC concentration on the grid's available hosting capacity. The model's estimate shows that a 10 percentage point increase in the POC population increases the per household hosting capacity by 0.107 kW. However, this estimate is only robust when controlling with control (Model 1), and when controlling for Median Household Income (Model 3) and Population Density (Model 4), at the 0.001 level.

Table 7. Regression model of per household hosting capacity in 2023.

Dependent Variable:	Average Maximum Hosting Capacity per Household (kW per household)				
Model:	(1)	(2)	(3)	(4)	(5)
POC (%)	0.0107*** (0.0018)	0.0036 (0.0025)	0.0085*** (0.0021)	0.0112*** (0.0019)	0.0036 (0.0026)
Poverty (%)		0.0141*** (0.0039)			0.0111** (0.0047)
Med. HH Inc. ($100,000)			-0.1769* (0.1007)		0.1836 (0.1254)
Population Density (1,000 households per sq. mile)				-0.0059 (0.0046)	-0.0173*** (0.006)
Unemp. Rate (%)					0.0264*** (0.0088)
Renters (%)					0.0038 (0.0024)
Built after 90s (%)					-0.0041** (0.0016)
County FE	✓	✓	✓	✓	✓
Observations	2,028	2,028	2,028	2,028	1,985
R^2	0.213	0.225	0.213	0.213	0.232

Significance Codes: *** p < 0.01, ** p < 0.05, * p < 0.1

Model (3) includes the POC and median household income, excluding the poverty percentage. The coefficient for the median household income (-0.1769) is statistically significant at the 0.1 level, indicating that neighborhoods with higher median income are associated with a lower available hosting capacity.

From Model (5), the per household hosting capacity is not associated with the POC, as indicated by the estimate that is not statistically significant. However, Model (5) shows that the per household hosting capacity decreases in denser neighborhoods. The relationship shows that, controlling for various neighborhood characteristics, a 10 percentage point increase in the population density (1,000 households per sq. mile) of a neighborhood decreases the per household hosting capacity by 0.173 kW.

5. Conclusion

The findings of this paper reveal strong associations between socioeconomic variables, including race and income, with utility disconnections and reliability metrics. Although the findings do not make causal claims, we believe that these statistically significant associations demand attention from energy system planners and policymakers. While we do not believe that our findings necessarily imply deliberate racial bias on the energy system planners' part, this does not negate the potential for utilities and policymakers to take proactive steps toward fostering equity in the electric system through the principles of energy justice. Some measures to address these issues include protecting low-income customers from disconnections, investing in marginalized communities to improve utility service quality, and equitably expanding distributed energy resources capacity.

This paper highlights the urgent need for policy interventions to rectify these deep-seated disparities, ensuring access to reliable, high-quality utility services for all people, irrespective of their socioeconomic or racial backgrounds. Moving forward, the goal should not merely be to avoid deliberate injustices but to create systems that ensure fairness and equity, particularly as the energy system is poised to see once-in-a-generation infusions of capital to decarbonize the economy. While this research focused on Minnesota, the findings and proposed interventions have broader implications, offering valuable insights for other states grappling with similar disparities. We hope this study stimulates and encourages further research and dialogue toward policy changes prioritizing energy equity and justice.

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