The Inequitable Impact of Equal Rationing: The Case of Load Shedding in South Africa *

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Abstract

This paper examines how the unreliability of the electrical grid affects economic inequality by analyzing the effects of South Africa's system of rotating power outage implemented between 2019 and 2024. I use a novel methodology that matches daily satellite luminosity data with outages schedules to estimate the geographical extent of power outages. I find that areas with the highest concentration of low-income households experience an additional 28% decrease in nighttime luminosity during power outages compared to the wealthiest areas. This differential exists despite equal exposure to outages across the income distribution. Consistent with richer households adapting to power outages by installing fuel-operated generators, I show that the differential impact is reduced when oil prices increase.

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1 Introduction

Connection to the electrical grid is widely recognized as a fundamental step toward economic development (UN Sustainable Development Goal number 7). As developing countries grow from low- to middle-income, they face increasing difficulty in meeting the rising demand for electricity, as faulty power supply systems are insufficient to sustain rapid growth. Power outages are ubiquitous in urban contexts in developing countries (Gertler et al., 2017): in India 76% of households face unanticipated power outages (Agrawal et al., 2020), while firms in Nigeria report experiencing on average 32.8 power outages per month (The World Bank, 2014). The effects are disruptive to both the economic activity of firms as well as the everyday lives of households.

When power outages become frequent, investing in backup power sources becomes highly valuable. However, the costs of these systems (i.e. generators, battery systems with inversters, solar panels) are prohibitive for most households in low- and middle-income countries. This creates two opposing effects on economic inequality. On one hand, high-income households may suffer greater economic losses during outages since their economic activity relies more heavily on electricity. On the other hand, they can afford to adapt by installing backup systems, insulating themselves from continued disruptions while low-income households remain fully exposed. Credit constraints prevent poor households from making similar investments, potentially leaving them to bear the entire burden of unreliable power supply. The net effect of widespread power outages on economic inequality is therefore theoretically ambiguous and ultimately an empirical question. Despite the widespread prevalence of this phenomenon and the size of the population affected, there is limited research on the consequences of power outages and electricity reliability on household outcomes, particularly on the differential impact across socioeconomic strata of the population and its implications for inequality.

This paper addresses this gap by studying the effects of the energy crisis in South Africa, currently the most unequal country in the world (World Bank, 2023). In recent years, South Africa has been unable to meet the increasing demand for electricity, which grew extremely rapidly after the end of Apartheid, when almost the entirety of the Black population was connected to the electrical grid. Power plant maintenance was disregarded in favor of constructing additional connections to the grid. As a result, starting in 2019 a faulty and aging system of coal-fired power plants began to dramatically fail, forcing South Africa to implement "load shedding" almost daily. Load shedding is the intentional disconnection of part of the electrical grid in order to artificially reduce electricity demand and prevent the collapse of the electrical system when supply is insufficient. This translates into a system of recurring power outages that rotate over time across different geographical areas.

In 2023, the South African population experienced almost 5 hours of power outages per day, with dramatic consequences across all sectors of society. Households lost electricity for lighting, cooking and basic appliances, local businesses and restaurants were forced to shut down due to lack of refrigeration, and large firms' inability to maintain food production made food prices spike. As the persistence of the crisis became clear, a stark divide emerged in adaptive capacity. Wealthy households and businesses began installing generators, inverters, and solar panels to complement or substitute for unreliable public provision. However, these systems require substantial upfront investments unaffordable to the majority of the population. A small residential solar system costs between R70,000 and R150,000, equivalent to 1.11-2.38 times the median annual income in 2023. This investment barrier effectively excludes the poorest segments of the population from adaptive solutions, potentially exacerbating inequality as only the wealthy can shield themselves from the consequences of power outages. This context makes South Africa an ideal setting to study how power outages affect economic inequality.

The main empirical challenges in addressing my research question lie in data limitations and causal identification. First, it is difficult to establish the geographical extent of power outages, and usually maps of the electrical grid are unavailable. I address this challenge by developing an algorithm to match load shedding schedules with daily nightlight satellite captures, in order to estimate when each area is affected by power outages. In addition, when power outages last around two hours and affect a small portion of the country at a time, it is difficult to find measures of economic activity at such high frequency and fine-grained geographical detail. In this paper, I overcome this data limitation issue by proposing the use of high-frequency satellite images to measure both the area of impact and the consequences of power outages. Second, outages are hardly random and are usually correlated with many infrastructural, geographical, and economic characteristics of the affected areas, making it hard to causally identify the distributional consequences of power outages. I address this issue by combining high-frequency and geographically precise outcome data with the quasi-random nature of load shedding activation, which is independent from specific local characteristics.

The results of the analysis show strong support for the hypothesis of unequal effects between high- and low-income areas of the country. I show that load shedding is applied evenly, and that the monthly number of hours of power outages that neighborhoods experience are independent of income, and the same is true for their distribution over different times of the day or days of the week. Nevertheless, households residing in neighborhoods with 50% share of low-income population experience an additional 27% decrease in luminosity during a power outage in addition to 35% decrease experienced by the richest neighborhoods. To understand the magnitude of the impact, this difference corresponds to around 1.75 times the difference between luminosity in winter versus other seasons, or a decrease of 49% in energy consumption. By using fluctuations in the buying price of diesel, which is the main fuel for the generators available in South Africa, I show that the additional decrease of luminosity in poor areas is mitigated in times of high fuel prices, providing additional support for the hypothesis that high-income areas are more likely to supplement public provision of electricity with private adaptation mechanisms. I show that results are robust to different methods of estimating power outage occurrence, different sample restrictions, and falsification tests.

It is striking how large the effects are in a context like South Africa, which intentionally created a schedule so that outages could be planned for and are equally dispersed across the whole population. While the magnitude must be cautiously interpreted as coming from this specific and controlled setting, the insight that load shedding and unreliability of the power sector can exacerbate inequality is generalizable. The principle according to which poor people suffer more from resource scarcity is definitely generalizable to different forms of rationing (electricity, fuel, water, etc.) commonly practiced in rapidly growing economies.

My findings contribute to several strands of literature. First, the literature on the effects of blackouts and reliability of the electrical grid in developing countries. A few papers focus on the effects of outages and unreliability of power on firm outcomes and productivity, finding detrimental effects for both firms (Allcott et al., 2016; Cole et al., 2018) and employment (Bhorat and Köhler, 2025). Effects on household and individual outcomes are more scarce, as identifying causal effects is difficult (Meeks and Mahadevan, 2025; Gertler et al., 2017). Burlando (2014) finds a reduction in birth weight and an increase in teenage pregnancy as a result of power outages in Tanzania. Budlender (2024), looking at load shedding, finds a decrease in mortality for areas that are able to mitigate the hours of blackouts. To the best of my knowledge, mine is the first paper focusing on the distributional effects of power unreliability, an issue of growing importance given the focus on rapid electrification as well as increasing inequality all over the world. In this regard, my findings also contribute to the debate on energy provision in developing countries and the effectiveness of connection to the electrical grid. Lee et al. (2020a) discusses various studies showing positive effects of electrification on economic development (Dinkelman, 2011; Lipscomb et al., 2013), but at the same time underlines how more recent studies exploiting experimental or quasi-experimental designs find more limited economic impacts (Burlig and Preonas, 2024; Lee et al., 2020b) and how this might be related to various factors, including reliability of electricity access. I show that unreliability of the grid can have strong negative economic impacts, and thus definitely reduce the gains from electrification.

Moreover, I contribute to the vast literature on inequality. This literature covering both high- and low-income countries, proposed various explanations for the persistence of economic inequality: structural changes in society as economies transition from agriculture to manufacturing and services, which can create wage gaps between sectors (Kuznets, 1955); increasing returns to human capital investment driven by skill-biased technological change that favors educated workers (Acemoglu, 2002); or weak institutions and elite capture where extractive institutions persist and elites maintain power (Acemoglu and Robinson, 2008), among others. Recently, Manysheva et al. (2025) analyzed the persistent economic inequality in South Africa and found support for it to be caused by persistent residential segregation in the post-Apartheid era. Here I propose a novel link between energy and resource scarcity and inequality in developing countries.

The paper is organized as follows. Section 2 provides an overview of the use of electricity in South Africa, the crisis of electricity supply, and an overview of the anecdotal evidence of the consequences of load shedding. Section 3 describes the data sources and the main variables used in the analysis. Section 4 describes my identification strategy and Section 5 presents the results. Section 6 discusses the robustness checks, Section 7 provides evidence of the mechanisms behind the main results, and Section 8 concludes.

2 Background

2.1 Electricity Usage and Load Shedding in South Africa

South Africa exhibits remarkably high electricity access rates compared to other Sub-Saharan African countries. According to the General Household Survey of 2023, 87% of the South African population has conventional access to the main electricity grid, and an additional 7% affirms to have access to electricity through connections to neighbors or family meters. In particular, electricity from the main grid serves as the primary energy source for lighting (88%) and cooking (77%). This remains true even for the poorest strata of the population, with only 10% of households in the lowest income quartile lacking electricity access. Connection to the grid also allows households to have access to fundamental resources in today's world like smartphones (available to 85% of households, 67% among the poorest quartile) and internet connection.

Approximately 90% of South Africa's electricity is supplied by Eskom, a vertically integrated, state-owned power company that owns and operates the national electricity grid (Energy Economics and Statistics, 2024). Eskom also serves as the principal electricity distributor across the country. Even though some large municipalities operate their own publicly-owned distribution companies, they source virtually all their power from Eskom (Budlender, 2024). In recent years, Eskom has been unable to meet the country's electricity demand due to multiple structural challenges. 80% of Eskom's power plants are coal-fired, making the utility's generating capacity heavily dependent on coal prices and availability, and susceptible to extreme weather events that can damage coal stockpiles. More critically, 80% of these power stations have reached or exceeded their mid-life cycle, requiring extensive maintenance in response to frequent plant breakdowns (Eskom, 2023).

When power plant failures prevent Eskom from producing a sufficient amount of electricity, the utility implements a system of rotational, scheduled power outages to artificially reduce demand. This system is internationally known as load shedding, and it differs from blackouts in that it is controlled and affects limited, spatially-defined areas - known as load shedding "zones"- for scheduled durations (Bhorat and Köhler, 2025). When load shedding becomes necessary, Eskom announces its implementation through major communication platforms (radio, television, social media). The system involves electricity outages lasting 2-, or 4-hour periods (plus an additional bandwidth of half an hour for power restoration), staggered throughout the day across the load shedding zones. The duration of the outage spans, as well as the total number of zones that are shed at the same time is determined by Eskom through the declaration of a load shedding "stage". Higher stages indicate greater MW requirements to be shed from the grid. Outages follow pre-existing schedules distributed by Eskom or municipalities, which specify the times each zone will lose power for each load shedding stage. The highest stage implemented to date was stage 6, meaning six different schedules (out of 16 total) would predict simultaneous power outages. Schedules are designed so that over a month, all zones experience the same number of hours of power outages, evenly distributed across different times of day, as discussed in detail in Section 4[1].

Eskom first implemented load shedding in 2007, but its use remained extremely sporadic until 2019. Beginning in 2019, the need for load shedding gradually intensified, reaching its peak in the first quarter of 2023. During 2023, load shedding was active for 332 days out of 365, and households experienced an average of 5 hours of power outages per day.

2.2 Load Shedding and Inequality

Various authors and institutions have used different methodologies to get an estimate of the costs of load shedding on the country's economy. The World Bank projected the cost to be at least $24 billion in 2022 alone, while the South African Reserve Bank (2023) estimated that load shedding reduced GDP growth by two percentage points in 2023.

The consequences of prolonged load shedding activation have been devastating for everyone in South Africa, and even more so for the poor. Anecdotal accounts in the media and

[1] Examples of schedules provided in Appendix Figure A.1.

technical reports document both direct and indirect damages of power outages on individuals, households, and businesses. Maggott et al. (2022) interviewed households in Soweto, a working-class township on the outskirts of Johannesburg, to understand how they cope with frequent power outages. The primary concern for most households relates to food storage and consumption. The inability to use refrigerators leads to food spoilage, which is not only a health hazard but also extremely costly for households relying on social grants and operating on tight budgets. Moreover, the inability to store food forces them to make daily trips to the supermarket, and the impossibility of buying in bulk causes additional financial strain. Even when power is restored, electrical appliances might be damaged by the sudden voltage changes that occur when electricity returns after load shedding, and replacing them may be prohibitively expensive. Residents further lament the lack of hot water and report that their only choice after dark is to sleep, as leaving their homes in darkness would be too dangerous. According to the Gauteng Quality of Life Survey, 60% of families residing in the poorest neighborhoods report that load shedding has significantly increased their fear of crime, compared to 35% in wealthier areas. Crime rates are extremely high and Imelda and Guo (2024) show that during power outages the incidence of crime is exacerbated by darkness and the absence of functioning streetlights.

The inability to store food and use electricity causes extreme economic damage to all those households that have established small businesses or corner shops, such as small restaurants or convenience stores (The Economist, 2023; CNN, 2023). Large businesses and factories are also suffering, particularly in the food sector, causing spikes in the prices of staples like chicken (The Economist, 2023).

Hospitals, schools, and police stations have not been exempted from power outages, and this has sparked furious debate and the intervention of the High Court of South Africa. The court forced Eskom and the government to ensure a power source for these essential buildings either through exemption from load shedding or through the provision of generators and solar panels (Rabkin, 2023). Nevertheless, even when generators have been provided, they are not powerful enough to withstand the long hours of load shedding brought about by stages 4 and 6, causing numerous surgeries and interventions to be postponed daily. At the same time, the abrupt fluctuations and voltage changes damage sensitive equipment in hospitals (Fokazi, 2023). Budlender (2024) estimates that load shedding mitigation policies statistically reduced mortality in Cape Town.

These consequences are particularly severe for the poorest segments of the population, which face significant financial constraints and cannot afford to purchase backup batteries, generators, and solar panels. Rooftop solar capacity increased by 163% between July 2022 and July 2024 (Eskom, 2025). However, while 23% of people residing in neighborhoods with the lowest poverty rates report having installed solar panels or generators, only 3% of people in poor neighborhoods have similar alternative power sources. Similarly, 76% of individuals residing in the poorest neighborhoods report that they cannot afford alternative sources of electricity.[2]

Households living in townships and poor urban areas have limited access to information about load shedding and cannot plan their days accordingly. The instability of their connection to the grid (at times illegal) makes it difficult for them to identify precisely which load shedding zone they belong to and to learn the schedule of power outages. According to the Gauteng Quality of Life Survey, 55% of households living in the poorest neighborhoods report that load shedding significantly affected the ability of scholars or students in the household to complete homeworks or study for tests and exams, compared to 35% of people residing in the richest neighborhoods.[3]

3 Data

3.1 Data Sources and Variables Construction

The dataset used in the main analysis is a panel containing daily observations for 7,274 urban sub-places between 2016 and 2023.[4] A sub-place is a census unit defined by the South

[2]Computations based on the Gauteng Quality of Life Survey 2023-2024.

[3]Wealth and income are inferred from the sub-place of residence, as the income variable is missing for 25% of the sample.

[4]There are a total of 21,589 sub-places as defined by the 2011 Census. I define urban sub-places as those that have any portion of their area classified as urban and that are not classified as "NU" (not urban) in the Census. This definition yields 7,733 sub-places. I further exclude sub-places with areas smaller than 1 sq.km, which are too small to be assigned a reliable measure of luminosity (410), and those where no household reports any income (42). For 7 sub-places in Northern Cape, schedules are unavailable.

African Statistical Office that roughly corresponds to a census tract. The average urban sub-place in the 2011 Census covers 3.57 square kilometers and has a population of 4,323 residents. The key variables in the analysis are: a measure of whether the sub-place is experiencing a power outage, a measure of poverty, and the level of luminosity.

A key challenge when estimating the differential effects of power outages between high- and low-income areas is identifying outcomes that are both geographically precise to the affected area and captured during the brief duration of the outage. I address this challenge by examining nighttime brightness as measured by satellite imagery. Specifically, I exploit the high geographic precision of the Visible Infrared Imaging Radiometer Suite (VIIRS), which orbits Earth nightly and captures light intensity at approximately 500 square meters resolution. Images are captured between midnight and 2 AM local time, and the precise timestamp of the capture is registered.[5] I average the luminosity of all pixels within a sub-place to obtain a measure at the sub-place level.

An additional major challenge in estimating the effects of interest is to precisely identify the geographical area affected by power outages.

Given the components of load shedding described in Section 2, determining when each sub-place experiences a power outage during load shedding requires combining information on: (i) load shedding activation (time series of load shedding implementation and declared stages), and (ii) load shedding schedules (time at which each zone is designated to experience power outages when load shedding is active). I obtain the time series of national load shedding stages (dates and timestamps) from the EskomSePush (ESP) app website.[6] Budlender (2024) has contributed significantly to collating this time series data and provides detailed accuracy validation against alternative sources.

I retrieve the complete set of possible outage schedules from Eskom's official website. Eskom assigns every *suburb* within a local municipality to one of 16 possible schedules. However, *suburbs* differ from sub-places and do not correspond to any administrative or geographical entity in South Africa, making their boundaries difficult to delineate.

I address this challenge by exploiting the granularity of my luminosity data based on the

[5] I access data processed by the Land Processes Distributed Active Archive Center through Google Earth Engine Data Catalog.

[6] EskomSePush is a free private mobile app created to help the South African population keep track of load shedding activation and affected areas.

principle that when a sub-place experiences an outage, its luminosity should be lower compared to days when outages are not scheduled in the area. Even in locations where the majority of households have adapted with backup power sources, load shedding switches off public lighting, creating observable differences in nighttime brightness. For each sub-place, I assign the load shedding schedule (among those available for its municipality) that best matches the observed time series of luminosity in the satellite images. Namely, the schedule that minimizes luminosity during predicted power outages. The result is an indicator variable taking value 1 if the sub-place is experiencing a power outage at the time of the satellite image capture. I validate my methodology using the City of Cape Town, which provides a map of load shedding zones for the areas directly served by the municipality. I verify that this methodology correctly assigns a power outage in 92% of the cases in which an outage is prescribed by the true schedule.[7] The application of this methodology is not limited to the South African context but could easily be adapted to any context where the areas experiencing power outages remain fairly constant over time.

Finally, I construct my measure of poverty based on the 2011 South African Census. Following the South African Statistical Office's definition of low-income individuals (Statistics South Africa, 2015), I define the share of low-income households in each sub-place as the proportion of households with annual income between 0 and 19,600 South African Rand in 2011[8], equivalent to 3,841 USD in 2024.

Additional sources of data used for robustness checks or mechanism results will be discussed when relevant.

3.2 Descriptive Statistics

Figure 1 shows the total number of hours of load shedding activated every month by Eskom since 2018. While initially infrequent, starting in 2022 the number of hours of load shedding declared sharply increased, and by the second half of the year load shedding was in place almost every day. In 2023, load shedding was active for 335 days out of 365. Not

[7]For a detailed description of the variable construction and further accuracy checks see Appendix Section A.3.

[8]The Statistics South Africa Office definition is more precisely 19,200 South African Rand, but income at the sub-place level is provided as income brackets.

only did the number of hours dramatically increase, but so did the severity of the episodes. The colors in Figure 1 represent stages; by 2023 the number of hours of stages 4, 5, and 6 comprised the majority of the hours, indicating an increase in the number of zones that are shed simultaneously when load shedding is active. In March 2024, three months before the national election, load shedding abruptly stopped and has not been reactivated for the entirety of 2024. There is discussion over what enabled Eskom to overcome the need for it (Siluma, 2024).

An increased number of hours of load shedding in place translates directly into a higher number of hours of power outages scheduled. Table 1 shows the number of hours of outages experienced by sub-places according to the schedules assigned using the methodology described in Section 3. In 2023, the average sub-place experienced 1,545 hours without electricity and experienced power outages on 315 days over 365, corresponding to almost 5 hours per day on average. The hours more than doubled with respect to 2022, which in turn were almost 5 times those experienced in 2021.

Notice also that the dispersion is quite low: the standard deviation in 2023 is only 10.40 and the gap between the minimum and maximum hours is 50, over a total of more than 300 days, meaning a difference of an average of 2 hours per month. This provides support for an even distribution of outage hours.

The distribution of the poverty measure is plotted in Figure 2.Sub-places tend not to be entirely segregated, with the median sub-place having 28.2% of households defined as low-income. The first quartile of the distribution comprises sub-places with less than 15.6% of low-income households, and the top quartile includes sub-places where more than 47.5% of families are low-income.

Descriptive statistics for luminosity are reported in Table 2, divided by the quartile of share of low-income households living in the sub-place.First, we notice how average luminosity is negatively correlated with the share of low-income households residing in the sub-place: the average luminosity for the sub-places with the lowest share of low income households is 16.18 against an average luminosity of 10.71 for sub-places with the highest share of low-income households. Second, average luminosity during power outages is lower then luminosity in days without outages for all the quartiles.

4 Empirical Strategy

Analyzing the differential impact of power outages across socioeconomic groups presents two fundamental empirical challenges: data limitations and causal identification. As discussed in Section 3, I address the first challenge through high-frequency satellite luminosity data combined with a novel methodology for identifying power outage occurrence at fine geographical scales. In this section, I describe how my empirical strategy exploits the randomness of power outages created by the interaction of schedules and load shedding activation to establish the causal impact of power outages.

The primary threat to causal identification stems from potential selection in both where and when power outages are more likely to occur. Unplanned blackouts may disproportionately affect low-income areas due to deteriorated electrical infrastructure and system overload caused by informal connections to the grid (McRae, 2015). Moreover, power outages typically occur during periods of peak demand, which may coincide with economic conditions that independently affect the outcomes of interest.

South Africa's load shedding system provides a unique setting that mitigates these identification concerns. Outages follows predetermined schedules that are applied uniformly across the country, regardless of local socioeconomic characteristics. When load shedding is activated nationally due to supply constraints, the pre-existing schedules determine which specific areas experience outages at any given time. This creates quasi-experimental variation: for every day when load shedding is active, some sub-places experience scheduled outages while others do not, and this variation is determined by the interaction of the timing of national activation decisions with assigned schedules rather than area-specific characteristics.

To understand how the effects of power outages differ by socioeconomic strata of the population, I estimate the simple OLS heterogenous effects model below:

$$\text{Log(Lum)}_{sd} = \alpha + \beta_1 \text{Outage}_{sd} + \beta_2 \text{Outage}_{sd} \times \text{Sh. Low Income}_s + \theta_s + \gamma_d + \varepsilon_{sd} \quad (1)$$

Where s denotes sub-place and d denotes a day in which load shedding was active between 2016 and 2023. Log(Lum)_{sd} is the logarithm of average light intensity for sub-place s on date d. Outage_{sd} is my measure of load shedding exposure and is a dummy variable taking value 1 if the load shedding schedule assigned to s by my algorithm predicts a power outage *and* load shedding has been activated by Eskom at the time of the satellite image capture. Sh. Low Income_s is the share of low-income population living in sub-place s. θ_s and γ_d are sub-place and day fixed effects, respectively. Additional controls are discussed when I present the results.

Taking the logarithm of light intensity is common practice in the literature (Mahadevan, 2024), and it allows me to examine relative effects. It is important to notice that luminosity never takes a value less than or equal to 0.

The coefficient of interest, β_2, captures the differential effect of load shedding associated with the share of low-income individuals in the sub-place. A negative coefficient, $\hat{\beta}_2 < 0$, indicates that a higher share of low-income households amplifies the adverse effects of power outages. In other words, the poorer the sub-place, the greater the decrease in luminosity when experiencing a power outage.

Conceptually, my empirical strategy compares luminosity of a sub-place during a power outage to the same sub-place's luminosity when the country is experiencing load shedding (thereby holding constant external conditions) but the sub-place is not scheduled for an outage. The fact that schedules assign power outages across all socioeconomic strata enables me to identify distributional effects.

Causal interpretation of β_2 relies on two main assumptions. First, that the estimation of power outages is accurate, as discussed in Section 3. The second assumption is that power outage occurrence is as good as random, or that load shedding activation in a specific sub-place is uncorrelated with sub-place socioeconomic characteristics. The main violation of this assumption would be the case in which schedules are attributed based on the income of the load shedding zone. If this was the case, we would observe poor sub-places having power outages at systematically different times than the rich ones and this might bring us back into the time selection issue. In an even more problematic case, Eskom could decide to activate load shedding only when low income areas are scheduled for an outage.

I provide two pieces of evidence against this violation. First, in each row of Figure 3 I plot the coefficient of a regression of a dummy variable for whether the sub-place is assigned to each of the schedules over the share of poverty in the sub-place and municipality fixed effects. The figure shows no systematic correlation between poverty and schedule assignments. Figure 3 focuses on municipalities where electricity is directly distributed by Eskom. To verify that this trend is common to all municipalities, Table 3 shows the correlation between the share of poverty of a sub-place and the number of hours of power outages experienced over different time intervals at the monthly level. Column (1) shows that the share of low income households residing in the sub-place has no correlation with the total number of hours of power outages experienced in a month. Column (2) focuses on the total number of hours experienced during weekdays (vs. weekends), and Columns (3)-(8) look at the total number of hours of outages experienced in a month between midnight and 4am, 4m and 8am etc. While the coefficient in some of the columns is significant the magnitude is negligible. Taking Column (3) as an example, moving from a sub-place at the 25th percentile of the share of low income to one in the 75th percentile is correlated to an additional 1.2 minutes of power outages between midnight and 4am per month.

5 Results

Results from Equation 1 are presented in Column (1) of Table 4. Experiencing a power outage during load shedding decreases luminosity by 35% for every sub-place. In addition, for every percentage point increase in the share of low income in the sub-place, luminosity further decreases by 0.05%. In other words, if we consider a sub-place with 50% share of low-income population (corresponding to around 75th percentile of the distribution), a power outage further decreases luminosity by 27% (0.5×0.54). This is consistent with high income households adapting to power outages and installing alternative energy sources.

We might be concerned that the results are confounded by regional time trends or municipal policies that evolve over time. For example, if wealthier municipalities systematically invest in improved street lighting or public infrastructure over the years, for example by expanding lighting coverage, this would increase baseline luminosity in richer areas relative to poorer ones. Such differential infrastructure investment could artificially amplify the inequality effects of load shedding, as wealthier areas would have more lighting to lose during outages.

Conversely, if poorer municipalities experience infrastructure degradation or reduce public lighting due to budget constraints, this would similarly bias the poverty interaction coefficient upward. To address these concerns, Columns (2) and (3) control for time trends common to provinces and municipalities, respectively, by including province $\times$ year and municipality $\times$ year fixed effects. Results remain unchanged across these specifications. Column (4) additionally controls for baseline luminosity levels interacted with year fixed effects, allowing areas with different initial light intensity to follow distinct time trajectories.

Finally, sub-places are usually smaller units than a load shedding zone, therefore, if a sub-place is experiencing a power outage it is very likely that the sub-places surrounding it are also experiencing one. Similarly, areas that are surrounded by brighter neighbors might capture part of the luminosity if the boundaries of the sub-places do not precisely correspond to the pixel divisions. To address this concern in column (5) I control for the average luminosity within 10km of the sub-place centroid. While I do observe a decrease in the effect of load shedding for everyone and luminosity now decreases by 18% as a result of power outages, the differential effect between rich and poor remains unchanged.

Table 5 presents distributional results using quartiles of low-income share rather than the continuous variable. The effects increase monotonically with the share of low-income households in the sub-place. Sub-places in the fourth quartile (with more than 47.5% low-income population) experience an additional 28% decrease in luminosity beyond the 38% reduction already experienced by sub-places in the first quartile (with less than 15.6% low-income population).

The sample in Table 4 is restricted to exclude a few municipalities. First, I exclude the City of Cape Town, where the part of the municipality which is directly served by the municipal distributor rather than directly distributed by Eskom was able to experience a mitigated load shedding given the availability of a pumped-storage hydroelectric plant. The part of the municipality which is directly distributed is selected in terms of health and income (Budlender, 2024). I further exclude municipalities that are known to have experienced exceptional circumstances or maintained some degree of distribution autonomy. This includes eThekwini (which suffered flooding and was exempted from load shedding in 2022), Nelson

Mandela Bay, Buffalo City, and Polokwane (Budlender, 2024). Appendix Table A.1 shows that the results point to the same direction when I lift this restriction. Not surprisingly, results including these municipalities are mitigated with respect to our main sample as in many instances I would be attributing outages to times in which load shedding was inactive in the area causing classical measurement error issues. Moreover, Column (4) shows results obtained by excluding all those municipalities that directly distribute electricity, in case they are deviating from load shedding in some other ways I am not aware of.

5.1 Magnitude benchmarking

To contextualize my findings, I provide back-of-the-envelope calculations comparing my results to those in the existing literature that use similar measures. These comparisons should be interpreted cautiously, as I examine temporary rather than permanent changes in luminosity. Moreover, I am using VIIRS satellite imagery, which provides measures on a different (and more accurate) scale than previous imagery used in the literature, making direct comparisons rely on heavy assumptions.

Beyer et al. (2022) uses VIIRS satellite data to measure the elasticity between nighttime luminosity and quarterly economic activity, estimating a value of 1.55 for emerging markets and developing economies. This implies that a 1.55% decrease in luminosity is associated with a 1% decrease in GDP. Applying this relationship, my estimated 28% additional decrease in luminosity in the poorest quartile corresponds to 18.06% additional decrease in GDP relative to wealthy areas.

The majority of previous literature relies on DMSP-OLS satellite data, which measured luminosity on a 0-63 scale. Machemedze et al. (2017) estimates that in rural South Africa, connecting 200 households to electricity increases luminosity by 20% of the baseline. Assuming a linear relationship holds with VIIRS data, the 28% decrease observe in my context corresponds to approximately 280 fewer grid-connected households.

Similarly, Min et al. (2024) finds that a 1-unit increase in brightness in Vietnamese villages corresponds to 60 public streetlights or 240-270 electrified homes. Given their sample's average luminosity of 11.6 units, a 1-unit change represents a 9% variation. My 28% differential effect ($28/9 = 3.11$) thus corresponds to switching off approximately 187 (60×3.11) streetlights or removing electricity from 746-840 ($240\text{-}270\times3.11$) households.

Burlig and Preonas (2024) show that in rural India, a 0.25-unit increase in luminosity (6% of the control group mean) corresponds to a 10 percentage point increase in the share of households with electric lighting (equivalent to a 22% increase given the pre-treatment baseline of 46%). The 28% additional effect for poor households in our case is approximately 4.7 times this magnitude, suggesting a 103% decrease in the number of households with electricity access during power outages.

To provide additional context, I compare my results to seasonal electricity consumption patterns. Nighttime luminosity exhibits strong seasonality, with average winter luminosity approximately 16% higher than the rest of the year.[9] This seasonal variation corresponds to a 28% increase in electricity expenditure during South Africa's winter quarter (Statistics South Africa, 2016). The additional impact for the poorest sub-places during power outages (28%) is thus approximately 1.75 times the seasonal variation in luminosity, corresponding to a reduction of 49% in energy expenditure.

6 Robustness

Table 6 shows the results for different robustness exercises that I perform on the baseline results and that I describe below.

City of Cape Town The City of Cape Town directly distributes electricity to portions of its population and can mitigate load shedding intensity through additional electricity sources beyond Eskom's supply. It presents a unique case for validation as, for municipally-served areas, Cape Town provides detailed maps of load shedding zones with corresponding schedules and activation time series, resolving the challenge of identifying zone boundaries that exists elsewhere in the country.

Column (1) of Table 6 presents results estimated for Cape Town using the official schedules.

[9] Results from regressing the logarithm of light intensity on a dummy for winter months (July, August, and September), with sub-place and year fixed effects. Sample includes sub-place-day observations from 2016-2018.

While the population in municipally-served sub-places tends to be wealthier on average than the rest of the city and country (Budlender, 2024), and the results are correspondingly smaller in magnitude, there remains a strong and statistically significant additional effect of power outages on the poorest segments of the population. Column (2) shows results for the same Cape Town sample but with power outage incidence estimated using the luminosity-based methodology described in Section 3. The fact that results are nearly identical not only confirms that the power outage estimation methodology successfully captures true outage occurrence, but it also and demonstrates that the main results are unlikely to be artifacts of the estimation approach.

Schedule Assignment by EskomSePush As an additional robustness check, I validate my luminosity-based methodology using schedules directly assigned by the EskomSePush app, the primary tool used by South Africans to receive load shedding notifications. When users geolocate themselves, the app provides up to 10 possible schedules that might correspond to the one affecting their location.[10] I query the EskomSePush API for all 10 possible schedules at each sub-place centroid and assign the modal schedule to each location. This exercise is restricted to municipalities served exclusively by Eskom to ensure reliability. Column (3) of Table 6 presents results using ESP-assigned schedules, which show similar significance levels and magnitudes to the main findings.

Falsification Exercise Column (4) demonstrates results for a falsification test where schedules are randomly assigned to sub-places. The absence of any significant effects when using random schedule assignments confirms that the main results are not driven by pre-existing differences between areas or spurious correlations.

[10] The fact that even this specialized local app cannot provide a single definitive schedule for any given location reinforces the hypothesis that load shedding zones do not correspond to standard geographical entities and are inherently difficult to identify.

7 Mechanism: Adaptation

The differential impact of power outages across income groups is consistent with high-income households mitigating the impact of load shedding by installing off-grid power sources, while poor households cannot afford similar means of adaptation. In this section I provide evidence supporting this mechanism.

Households can adapt to power outages in different ways, requiring varying levels of investment. The cheapest options include candles and flashlights, which provide basic lighting but leave appliances and other electrical needs unmet during outages. More comprehensive solutions include generators, battery systems with inverters, and solar panels, but these require substantial upfront investments. A small residential solar system costs between R70,000 and R150,000, an inverter system costs R30,000-R90,000, and a generator requires an initial investment of R15,000-R30,000 plus ongoing fuel costs. Given that the median annual household income in South Africa was R63,084[11] in 2023 and unemployment stood at 32%, these backup power sources are unaffordable for a large share of the population.

This financial constraint is reflected in household survey data. According to the 2023 General Household Survey, when experiencing power outages, 4% of households use solar panels, generators, or inverters as their main lighting source, while 39% rely on flashlights and 44% use candles. These statistics mask significant heterogeneity across income levels. Among households in the bottom income quartile, 1% use generators or solar systems, 25% use flashlights, and 58% use candles. In contrast, among top-quartile households, 10% use backup power systems, 60% use flashlights, and 22% use candles (Appendix Table A.4).

The Gauteng Quality of Life Survey provides more detailed adaptation measures, though the sample is limited to Gauteng province, the wealthiest province in the country (Statistics South Africa, 2023). In this sample, 16% of households have invested in backup power, with 30% using generators and 40% using solar systems. When asked why they have not invested in alternative energy sources, 76% of households in the poorest quartile cite affordability constraints, compared to 40% in the richest quartile. I now provide empirical evidence supporting these patterns for generator and solar panel adoption.

[11] Computation based on 2023 General Household Survey.

7.1 Solar Panels

Rooftop solar capacity increased by 163% in South Africa between 2022 and 2024 (Eskom, 2025).

According to the General Household Survey, in 2015 0.44% of low-income households[12] owned a generator against 2.30% among high-income households. In 2024, this percentage has rose to 7.62% for high income households but only to 0.71% for low income.

In Figure 4 we can observe the evolution of this share over time for low- and high-income households. While the difference remained stable until 2019, starting in 2022 we observe a clear divergence between the patterns of high- and low-income households.

7.2 Generators

According to the Gauteng Quality of Life Survey, 30% of households who own back-up power sources own a petrol or diesel generator. If high-income households are indeed more likely to adapt by purchasing generators, we should observe a decrease in the additional effect of power outages on low-income households when diesel prices are high. When fuel prices increase, operating generators becomes more costly, leading to reduced electricity generation during power outages.

To test this hypothesis, I use the time series of basic fuel prices from Statistics South Africa. The basic fuel price reflects the cost of purchasing petroleum from international markets and shipping it to South Africa. I then estimate a triple interaction model on the basis of Equation 1 by adding interactions with fuel prices. For ease of interpretation, I present results using quartile indicators for the share of low-income households rather than the continuous variable.

[12] Here low-income household is defined as a household in the bottom 25% of the income distribution, and high-income households are in the top quartile of the distribution.

$$
\begin{aligned}
\text{Log(Lum)}_{sd} = \alpha &+ \beta_1 \text{Outage}_{sd} + \beta_2 \text{Fuel Price}_{m-1} + \beta_3 \text{Outage}_{sd} \times \text{Fuel Price}_{m-1} \\
&+ \sum_{q=2}^{4} \beta_{4q} \text{Outage}_{sd} \times Q_q \text{ of Sh. Low Income}_s \\
&+ \sum_{q=2}^{4} \beta_{5q} \text{Fuel Price}_{m-1} \times Q_q \text{ of Sh. Low Income}_s \\
&+ \sum_{q=2}^{4} \beta_{6q} \text{Fuel Price}_{m-1} \times Q_q \text{ of Sh. Low Income}_s \times \text{Outage}_{sd} \\
&+ \theta_s + \gamma_d + \varepsilon_{sd}
\end{aligned} \tag{2}
$$

where Fuel Price_{m-1} is the monthly real fuel price (in thousands of South African Rands) lagged by one month, and Q_q of Sh. Low Income_s is a dummy variable equal to 1 if sub-place s belongs to the q^{th} quartile of the share of low-income households distribution. The remaining variables are defined as in Equation 1. The coefficients of interest are β_{6q}, which capture how fuel price changes affect the differential impact of outages for each quartile relative to the wealthiest areas.

The intuition is as follows. Higher fuel prices reduce generator affordability for all households, but the effects may vary across the income distribution. Extremely poor households are unlikely to own generators regardless of fuel prices, so we expect the differential impact between wealthy households (who reduce generator usage when fuel is expensive) and the poorest households (who never had generators) to diminish. However, households that could barely afford generators may be more sensitive to price changes than wealthier households or those who invested in costlier alternatives like solar panels. For these marginal generator owners, the additional impact of power outages relative to the richest sub-places may actually increase.

Table 7 presents the results. Households in the second and third quartiles of low-income share are negatively affected by fuel price increases, experiencing greater luminosity decreases during outages when fuel is more expensive. In contrast, households in the poorest sub-places (fourth quartile) show a positive and statistically significant coefficient, indicating that higher fuel prices reduce the luminosity gap between the poorest and richest households during power outages.

These findings are consistent with a narrative where wealthier households adapt to power outages through backup generation while the poorest households bear the full burden of electricity disruptions.

8 Conclusion

This paper examines how power outages exacerbate economic inequality, exploiting South Africa's energy crisis as a natural experiment. In a context where rotating power outages have been implemented at near-daily frequency since 2022, I find that the poorest areas experience disproportionately severe impacts despite the ostensibly equitable design of the load shedding system. Sub-places in the highest quartile of poverty experience an additional 28% decrease in luminosity during outages compared to the wealthiest areas, suggesting that while the timing and duration of outages are distributed fairly, their economic consequences are decidedly unequal.

These findings are consistent with wealthy households and businesses adapting to unreliable electricity supply through costly private alternatives, while low-income populations face binding credit constraints that prevent similar adaptation. Indeed, when fuel prices are high, and high income households are less likely to use generators, the difference between the impact on sub-places in the first and fourth quartile of share of low income decreases.

The results demonstrate that even well-intentioned policies designed to distribute burdens equitably can inadvertently widen inequality when adaptive capacity varies systematically across socioeconomic groups. My findings are robust to alternative measures of power outage identification.

The policy implications extend beyond South Africa's specific context. As developing countries worldwide grapple with inadequate electricity infrastructure and growing demand, my results suggest that policymakers should consider not only the fairness of rationing mechanisms but also differential adaptive capacity when designing crisis responses. Load reduction strategies that preserve baseline electricity access for essential services, rather than complete outages, may better serve equity objectives. Additionally, complementary policies that subsidize backup power for low-income households could help maintain the intended distributional neutrality of rationing systems.

I am currently expanding this analysis using smartphone geolocation data, which will provide direct evidence of how power outages affect individual mobility and economic activity differently across socioeconomic strata.

Further research is needed to understand the long-term implications of prolonged exposure to unreliable electricity supply, particularly whether temporary inequality effects become entrenched through differential human capital accumulation and business development.

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Tables

Table 1: Load shedding Hours - Descriptives

	2018	2019	2020	2021	2022	2023
Total hrs. outage	13	83	110	157	737	1,545
Std. Dev.	1.95	2.33	3.83	5.37	4.29	10.40
Min.	10	77	103	147	729	1,524
Max.	18	87	118	165	749	1,571
Number of days of LS	6	25	39	55	172	315
Std. Dev.	1.35	1.77	1.99	2.60	2.76	3.61
Min.	4	22	36	51	167	306
Max.	9	28	44	59	180	321
Avg. hrs of outage per LS day	2.15	3.34	2.82	2.84	4.30	4.90
Std. Dev.	0.28	0.20	0.10	0.08	0.06	0.04
Min.	1.75	2.96	2.57	2.70	4.09	4.81
Max.	2.75	3.77	3.00	3.00	4.43	4.99
Obs.	7,274	7,274	7,274	7,274	7,274	7,274

Observations are at the sub-place level. The sample is limited to urban sub-places. Years 2016 and 2017 are part of the sample but have no load shedding episodes.

Table 2: Luminosity - Descriptives

	Luminosity		
	Avg.	Outage	No Outage
1st Quartile Sh. Low Income	16.181	10.509	16.403
	(13.178)	(10.028)	(13.237)
Obs.	5,028,776	189,494	4,839,282
N. Sub-places	1,821	1,821	1,821
N. Days	2,887	513	2,887
2nd Quartile Sh. Low Income	14.682	9.408	14.887
	(13.768)	(10.217)	(13.847)
Obs.	5,063,034	189,687	4,873,347
N. Sub-places	1,835	1,835	1,835
N. Days	2,887	513	2,887
3rd Quartile Sh. Low Income	14.342	8.004	14.592
	(14.102)	(9.309)	(14.199)
Obs.	5,016,645	189,824	4,826,821
N. Sub-places	1,821	1,821	1,821
N. Days	2,889	514	2,889
4th Quartile Sh. Low Income	10.712	6.257	10.887
	(11.077)	(7.587)	(11.156)
Obs.	4,947,485	187,321	4,760,164
N. Sub-places	1,797	1,797	1,797
N. Days	2,889	514	2,889

Notes: An observation is a sub-place and a day. The sample cover years 2016-2023. Standard error of the mean in parentheses.

Table 3: Load shedding Hours - Correlations with Measures of Poverty

	Hours of Outage							
	Month	Weekdays	12am-4am	4am-8am	8am-12pm	12pm-4pm	4pm-8pm	8pm-12am
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sh. Low Income	-0.010	-0.006	0.065***	0.027*	-0.010	-0.028**	-0.061***	-0.003
	(0.007)	(0.009)	(0.020)	(0.016)	(0.013)	(0.013)	(0.017)	(0.020)
Obs.	523,728	523,728	523,728	523,728	523,728	523,728	523,728	523,728
Mean of dep. var.	36.764	27.600	6.020	5.249	5.257	5.475	7.474	7.290

Notes: Observations are at the sub-place monthly level. The outcome variable is the total number of hours of power outages experienced in a month for column (1), the total number of hours experienced per month during weekdays for column (2) and the total number of hours experienced per month in the time interval in the column title for columns (3)-(9). Standard errors clustered at the sub-place level in parentheses.

Table 4: The Effect of Load Shedding on Luminosity

	(1) Lum. (Log)	(2) Lum. (Log)	(3) Lum. (Log)	(4) Lum. (Log)	(5) Lum. (Log)
Outage	-0.347***	-0.345***	-0.345***	-0.346***	-0.181***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.020)
Outage × Sh. Low Income	-0.543***	-0.547***	-0.548***	-0.546***	-0.579***
	(0.066)	(0.066)	(0.066)	(0.066)	(0.049)
Observations	2,740,176	2,740,176	2,740,176	2,740,176	2,634,919
SP FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
Prov × Year FE	N	Y	N	N	N
Mun × Year FE	N	N	Y	N	N
Avg.Lum.2016 × Year FE	N	N	N	Y	Y
Lum in 10km	N	N	N	N	Y
Mean of dep. var.	10.58	10.58	10.58	10.58	10.88

Observations are at the sub-place day level. The sample is limited to days in which load shedding was active, and to sub-places which never experienced load shedding mitigation (see text for details). Standard errors clustered at the schedule level in parentheses.

Table 5: The effect of Load Shedding on luminosity - Quartiles

	(1) Lum. (Log)	(2) Lum. (Log)	(3) Lum. (Log)	(4) Lum. (Log)	(5) Lum. (Log)
Outage	-0.378***	-0.377***	-0.377***	-0.377***	-0.220***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.020)
Outage × Sh. Low Inc. 2nd Qtile	-0.059**	-0.060***	-0.059***	-0.059***	-0.066***
	(0.021)	(0.022)	(0.021)	(0.022)	(0.013)
Outage × Sh. Low Inc. 3rd Qtile	-0.220***	-0.221***	-0.221***	-0.220***	-0.213***
	(0.023)	(0.023)	(0.022)	(0.022)	(0.016)
Outage × Sh. Low Inc. 4th Qtile	-0.283***	-0.286***	-0.285***	-0.285***	-0.302***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.024)
Observations	2,740,176	2,740,176	2,740,176	2,740,176	2,634,919
SP FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
Prov × Year FE	N	Y	N	N	N
Mun × Year FE	N	N	Y	N	N
Avg.Lum.2016 × Year FE	N	N	N	Y	Y
Lum in 10km	N	N	N	N	Y
Mean of dep. var.	10.58	10.58	10.58	10.58	10.88

Observations are at the sub-place day level. The sample is limited to days in which load shedding was active, and to sub-places which never experienced load shedding mitigation (see text for details). Standard errors clustered at the schedule level in parentheses.

Table 6: Robustness Checks

	(1)	(2)	(3)	(4)
Sample:	CPT - True	CPT - Est.	ESP API	Random
	Lum. (Log)	Lum. (Log)	Lum. (Log)	Lum. (Log)
Outage	-0.139***	-0.121***	-0.247***	0.009
	(0.030)	(0.035)	(0.047)	(0.011)
Outage × Sh. Low Income	-0.298***	-0.300***	-0.520***	-0.030
	(0.088)	(0.099)	(0.098)	(0.027)
Observations	1,548,998	1,548,998	1,427,265	2,728,005
SP FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Mean of dep. var.	24.42	24.42	6.40	10.60

Observations are at the sub-place day level. The sample is limited to days in which load shedding was active. Column (1) presents the results for the area where electricity is directly distributed for the City of Cape Town, and power outages are assigned following the true schedules. Column (2) uses the same sample as (1) but assigns power outages using the estimating methodology. Column (3) assigns power outages based on the schedules assigned by the EskomSePush App, sample is restricted to municipalities where electricity is directly distributed by Eskom. Column (4) assigns power outages based on random assignment of schedules. Standard errors clustered at the schedule level in parentheses.

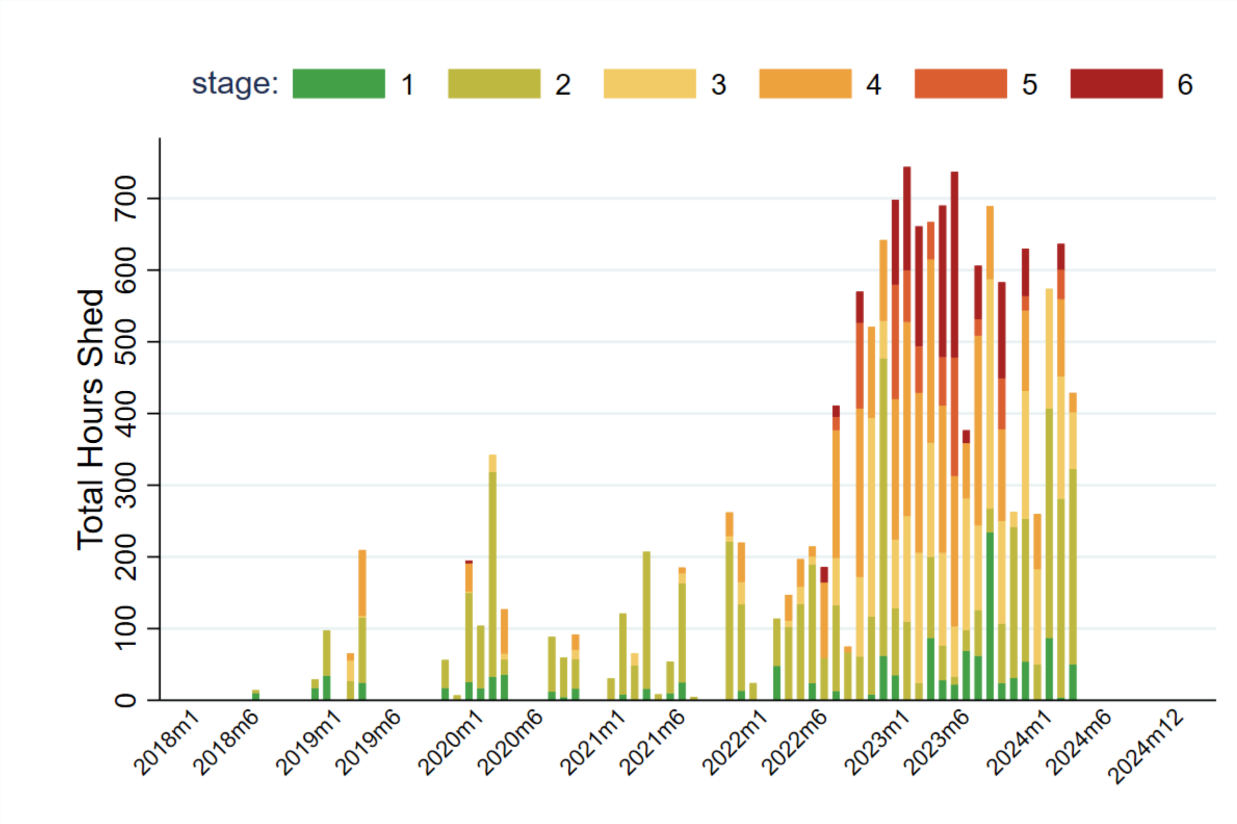
Table 7: Mechanism: Fuel Prices

	(1)
	Lum. (Log)
Outage	-0.275***
	(0.019)
Fuel Price	-0.727***
	(0.128)
Fuel Price × Outage	-0.074***
	(0.012)
Outage × Sh. Low Inc. 2nd Qtile × Fuel Price	-0.015
	(0.017)
Outage × Sh. Low Inc. 3rd Qtile × Fuel Price	-0.049***
	(0.018)
Outage × Sh. Low Inc. 4th Qtile × Fuel Price	0.053***
	(0.019)
Observations	2,841,503
SP FE	Y
Date FE	Y
Mean of dep. var.	10.65

Observations are at the sub-place day level. The sample is limited to days in which load shedding was active, and to sub-places which never experienced load shedding mitigation (see text for details). Fuel prices is the official price of fuel in South Africa the month before the capture was taken, measured in real terms and thousands of dollars. Standard errors clustered at the schedule level in parentheses.

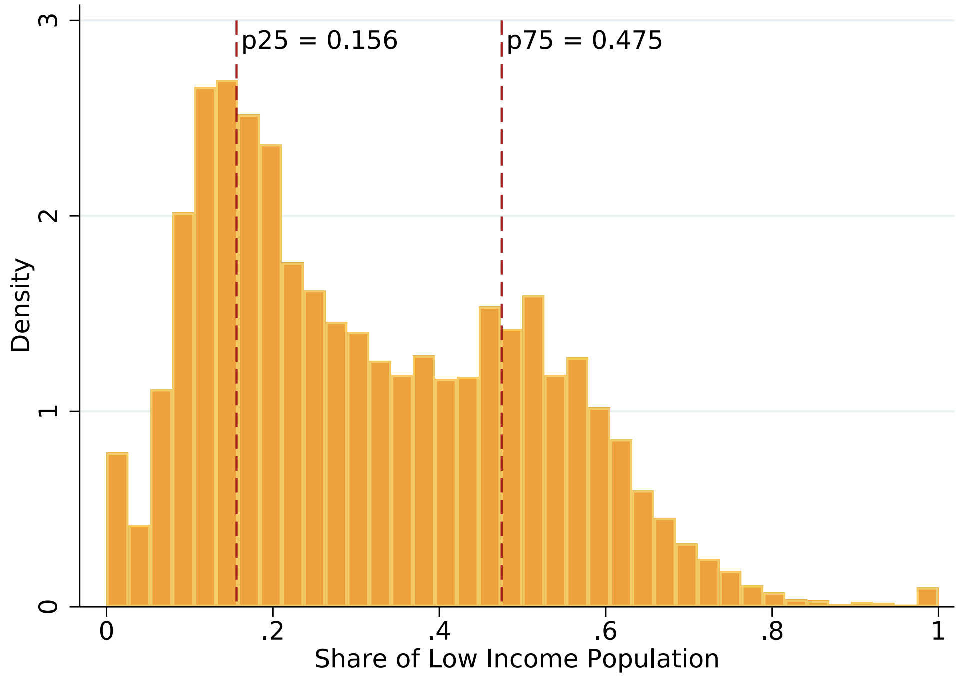
Figures

Figure 1: Hours of Load Shedding Activated by Eskom



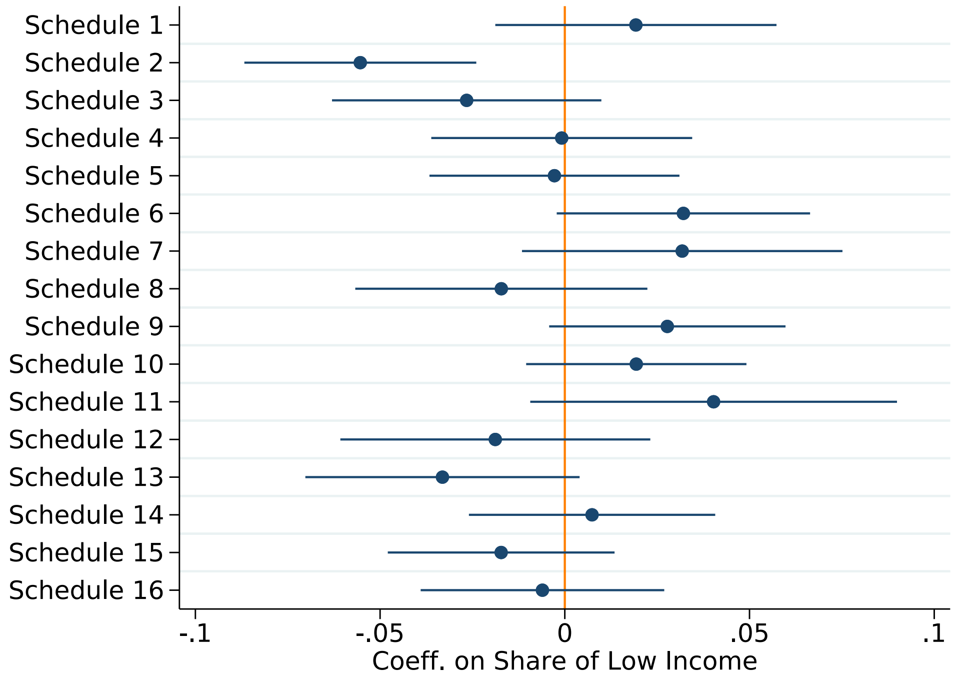
Note: This figure shows the total number of hours of load shedding activated per month in South Africa, the colors represent the stage of load shedding declared according to the legend above. The data is collected from the EskomSePush website and covers the period from January 2018 to December 2024.

Figure 2: Share of Low Income Population by Sub-Place - Distribution



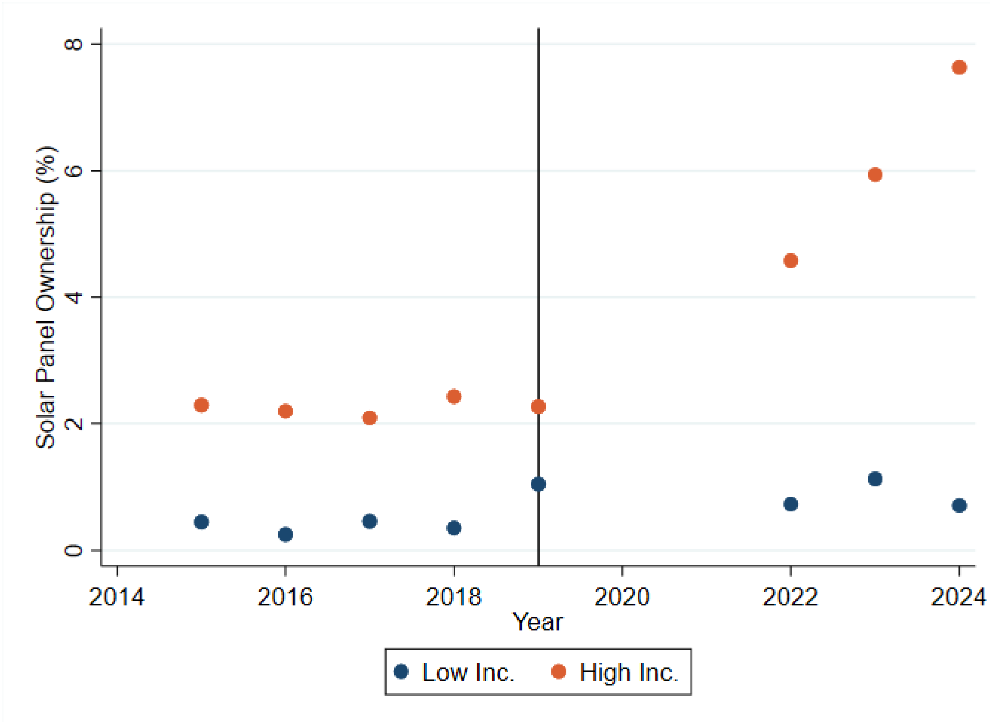
Note: This figure shows the distribution of the share of low income households in the sub-places in the sample, according to the 2011 South African Census. The dashed lines represent the 25th and 75th percentile, respectively.

Figure 3: Correlation Between Schedule Assignment and Share of Poverty



Note: Each row of this figure represent the coefficient for a regression of a dummy variable for the assignment to the schedule in the row title over the sub-places share of low-income population, and municipality fixed effects.

Figure 4: Time Series of Solar Panel Ownership



Note: Each dot represents solar panel ownership for low- and high-income households. Low- (High-) income households are those in the bottom (top) quartile of the income distribution. Precise income bracket depend on year.

A Appendix

A.1 Appendix Tables

Table A.1: The Effects of Load Shedding on Luminosity - Different Samples

	(1) Lum. (Log)	(2) Lum. (Log)	(3) Lum. (Log)	(4) Lum. (Log)
Outage	-0.393***	-0.332***	-0.360***	-0.463***
	(0.042)	(0.036)	(0.038)	(0.050)
Outage × Sh. Low Income	-0.356***	-0.465***	-0.530***	-0.416***
	(0.080)	(0.069)	(0.064)	(0.099)
Observations	3,574,981	3,184,698	2,793,408	1,546,002
Sample	All	No Cape Town	No Mitigation	No Direct Dist.
SP FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Mean of dep. var.	11.80	10.69	10.53	6.427

Observations are at the sub-place day level. The sample is limited to days in which load shedding was active for all columns. Column (1) presents the results for the full sample of sub-places. Column (2) presents results excluding the municipality of the City of Cape Town. Column (3) excludes the municipalities of Cape Town, Buffalo City, Nelson Mandela Bay, eThekwini, and Polokwane. Column (4) excludes municipalities that have direct distribution of electricity. See Section 5 for a discussion. Standard errors clustered at the schedule level in parentheses.

Table A.2: The Effects of Load Shedding on Luminosity - All days

	(1) Lum. (Log)	(2) Lum. (Log)	(3) Lum. (Log)	(4) Lum. (Log)	(5) Lum. (Log)
Outage	-0.325***	-0.321***	-0.320***	-0.308***	-0.147***
	(0.034)	(0.033)	(0.032)	(0.034)	(0.020)
Outage × Sh. Low Income	-0.610***	-0.624***	-0.626***	-0.662***	-0.752***
	(0.073)	(0.068)	(0.064)	(0.071)	(0.063)
Avg. Lum. within 10km					0.068***
					(0.003)
Observations	15,350,762	15,350,762	15,350,762	15,350,762	14,755,163
SP FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
Prov × Year FE	N	Y	N	N	N
Mun × Year FE	N	N	Y	N	N
Avg.Lum.2016 × Year FE	N	N	N	Y	Y
Lum in 10km	N	N	N	N	Y
Mean of dep. var.	12.73	12.73	12.73	12.73	13.10

Observations are at the sub-place day level. The sample is limited to sub-places which never experienced load shedding mitigation (see text for details). Standard errors clustered at the schedule level in parentheses.

Table A.3: The Effects of Load Shedding on Luminosity - Levels

	(1) Luminosity	(2) Luminosity	(3) Luminosity	(4) Luminosity	(5) Luminosity
Outage	-3.837***	-3.832***	-3.837***	-3.834***	-1.929***
	(0.494)	(0.496)	(0.495)	(0.497)	(0.271)
Outage × Sh. Low Inc.	0.190	0.175	0.185	0.178	-0.267
	(0.600)	(0.605)	(0.602)	(0.605)	(0.462)
Observations	2,793,408	2,793,408	2,793,408	2,793,408	2,684,221
SP FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
Prov × Year FE	N	Y	N	N	N
Mun × Year FE	N	N	Y	N	N
Avg.Lum.2016 × Year FE	N	N	N	Y	Y
Lum in 10km	N	N	N	N	Y
Mean of dep. var.	10.53	10.53	10.53	10.53	10.83

Observations are at the sub-place day level. The sample is limited to days in which load shedding was active, and to sub-places which never experienced load shedding mitigation (see text for details). Standard errors clustered at the schedule level in parentheses.

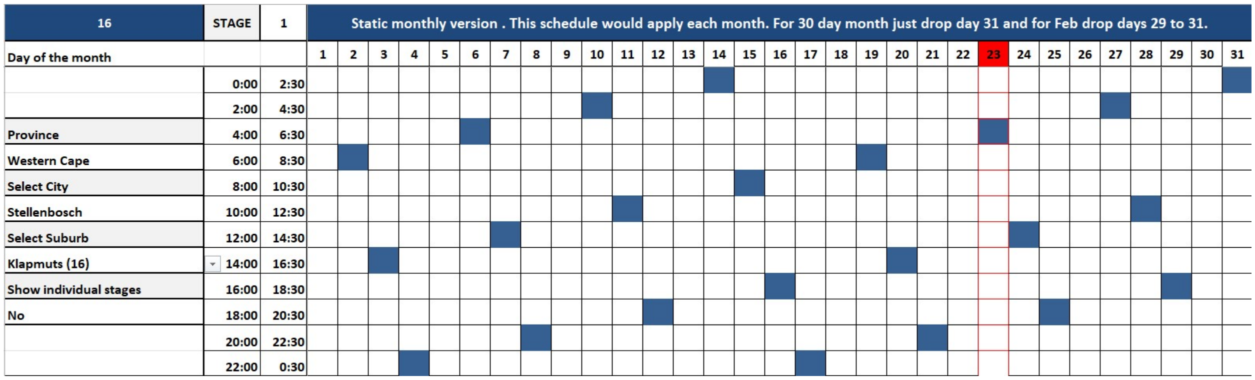
Table A.4: Means of Adaptation - GHS 2023

Main source of light during outages	All	High-Income (> R155,520)	Low-Income (< R29,760)
Back-up system (e.g. solar panels, inverters)	0.044	0.101	0.014
	(0.205)	(0.301)	(0.116)
Flashlights	0.385	0.594	0.250
	(0.487)	(0.491)	(0.433)
Candles	0.441	0.216	0.579
	(0.497)	(0.412)	(0.494)
Others	0.119	0.083	0.142
	(0.324)	(0.276)	(0.349)
N	20,927	5,132	5,158

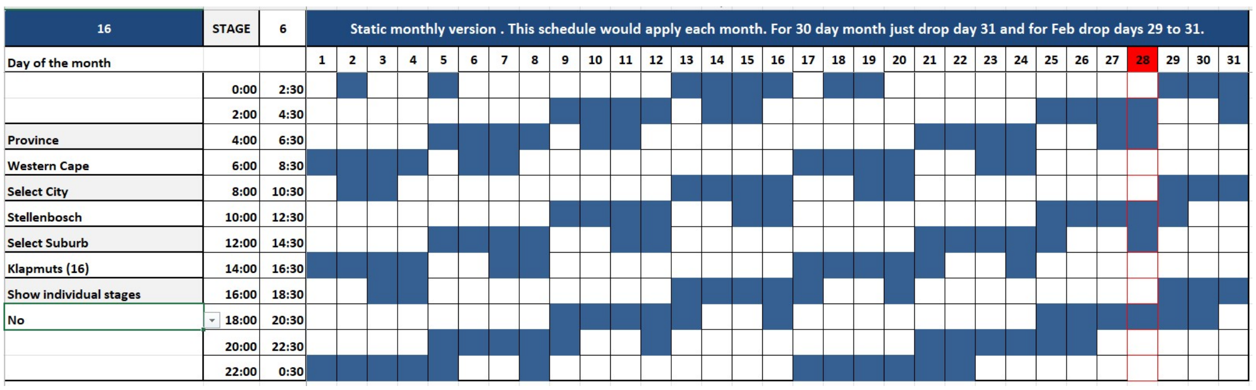
Data are from the 2023 General Household Survey. High-incomes is the sample of households in the top quartile of the income distribution (annual income above R155,520). Low-income is the sample of households in the bottom quartile if the income distribution (annual income below R29,760). Standard errors in parentheses.

A.2 Appendix Figures

Figure A.1: Examples of Eskom Load Shedding Schedules in Stellenbosch



Stage 1



Stage 6

Note: These are the schedules for a suburb in Stellenbosch, the blue cells are the moments in which a power outage is expected if load shedding is active. The top figure shows the outages for Stage 1 while the bottom one shows the outages for Stage 6. Schedules for suburbs directly served by Eskom are available at: `https://www.eskom.co.za/distribution/customer-service/outages/downloadable-loadshedding-spreadsheets-for-eskom-customers/`.

A.3 Description of Power Outages Assignment Algorithm

A.3.1 Methodology

The primary empirical challenge in studying load shedding effects lies in identifying a measure of load shedding at the sub-place level. As discussed in Section 3, Eskom assigns load shedding schedules at the *suburb* level, an administrative unit with no corresponding geographical boundaries. To address this challenge and determine when a sub-place experiences outages, I exploit luminosity data based on the principle that when a sub-place experiences an outage, its luminosity should be lower compared to days when load shedding is not prescribing an outage in that area. Even in locations where many households have adapted with backup power sources, load shedding switches off public lighting, creating observable differences in nighttime brightness. I combine this information to assign each sub-place to the schedule that best matches its observed luminosity patterns—namely, the schedule that assigns load shedding during days and times when the lowest luminosity levels are observed.

Specifically, the methodology proceeds as follows:

1. For each sub-place, I consider all possible load shedding schedules and merge them with the time series of load shedding activation, which indicates when load shedding was active. Therefore, for every possible schedule, I obtain a time series of whether it predicted a power outage for every hour of every day in my sample.

2. For each sub-place, I also construct the time series of luminosity data. For every day between 2022 and 2023 (the previous years in my sample have no instances of load shedding), I construct a time series with the level of luminosity in the sub-place and the specific time of capture. I remove observations below the 1^{st} and above the 99^{th} percentiles of luminosity distribution to make sure to remove all outliers due to maintenance of the satellite or meterological conditions.

3. For every possible schedule in step 1., I compute the average luminosity on days when the schedule predicts an outage and load shedding has been activated—namely, days when I expect a blackout in the sub-place if it follows such a schedule.

4. For every sub-place, I assign the schedule that corresponds to the minimum average luminosity during predicted outage periods.

A.3.2 Validation and Accuracy

The City of Cape Town provides a useful opportunity to validate this methodology. Unlike other municipalities, Cape Town supplies a detailed map showing suburbs and their respective assigned schedules, allowing me to know precisely the geographic extent of load shedding zones. First, this map reveals that suburbs are typically much larger than sub-places, which supports the approach of assigning schedules at the suburb level without concern that individual sub-places span multiple load shedding zones. Second, limiting my sample to Cape Town, I apply my algorithm to identify sub-place schedules and compare the results against the true schedule assignments. The algorithm correctly identifies 92% of power outages during load shedding events. Importantly, the accuracy level depends on the population size of the sub-place but does not vary systematically with income quartile.