Smart Rationing: Designing Shortage Mechanisms for Extreme Events

Mar Reguant Mayra Wagner Dorian Weber*

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Abstract

As shortages of resources like water and electricity due to extreme weather events become more frequent, high prices alone often fail to curb demand, making non-price interventions necessary. We propose a partial rationing policy for residential electricity consumption to limit consumption to avoid traditional rolling blackouts. Using smart meters, we find that consumption limits can provide equivalent savings to large rolling blackouts, even when generous. Additionally, due to selection, partial rationing policies reduce the number of households impacted by a shortage event. We conclude by discussing the welfare consequences of rationing mechanisms and their heterogeneous impacts across households.

*Mar Reguant: IAE-CSIC (ICREA) and Northwestern University, mar.reguant@northwestern.edu. Mayra Wagner: mayra.wagner@bse.eu. Dorian Weber: Compass Lexecon. DWeber@compasslexecon.com. We are thankful for comments and feedback received at several seminars and conferences. This project has received support from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No 101001732-ENECML).

1 Introduction

When the supply of essential goods like water, food or electricity falls short of demand and cannot be quickly increased, prices can fail to clear the market. In times of scarcity, high prices often do not sufficiently curb demand (Labandeira et al., 2017; Zhu et al., 2018; Romero-Jordán et al., 2014), particularly when consumers are unable or slow to adjust their consumption, or when demand surges unpredictably (Joskow and Tirole, 2007; Borenstein et al., 2023). In these cases, non-price interventions are often necessary to mitigate the burden on vulnerable populations. One possible intervention is quantity rationing. Rationing has been applied in a variety of scarcity situations in the past, may it be limited gasoline access during the oil crisis in 1973 (Horowitz, 1982), reducing access to water during droughts (Renwick and Green, 2000; Ryan and Sudarshan, 2020; Abajian et al., 2024) or cutting off households from the electricity supply during extreme weather events (Hunt. et al., 2018).

Looking forward, climate change poses a growing threat to ensuring the provision of basic necessities, particularly during extreme events. According to the IPCC, the increasing frequency and intensity of extreme weather events such as heatwaves, storms, and wildfires exacerbate the risk of blackouts, while the presence of extended droughts and persistent extreme temperatures threaten access to water and food (Pörtner et al., 2022; Stone et al., 2021).[1] Regions dependent on hydropower or thermoelectric power plants face particular risks due to climate change, as these systems depend heavily on water availability and temperature for cooling (Byers et al., 2020; Haes Alhelou et al., 2019).[2] Such conditions not only threaten energy supplies but also compound water shortages for agricultural and residential users.[3] Due to the significant costs and distributional implications of shortages for essential goods, regulators need to prepare for unexpected emergencies in which the price mechanisms alone may not be an effective tool to clear the market due to the need to ensure access for critical goods (Levin et al., 2022; Renwick and Green, 2000; Joskow and Tirole, 2007).[4] Improvements in rationing schemes have the potential of ensuring access to basic goods during extreme shocks.

A recent example of shortages triggered by extreme events is the Texas winter storm in February 2021, when the power supply chain experienced significant failures and was unable to meet the high demand (Wolak, 2022). To ensure that the grid was operational, the Southwest Power Pool and the Electric Reliability Council of Texas ordered rolling blackouts, leaving millions of households without electricity, some for consecutive days.[5] The Texas shortages occurred even in the presence of a high price \$9,000/MWh cap in the market, which did not incentivize more generation due to the failure of the physical supply chain of natural gas. Rather than increasing the price cap for future events, the Public Utility Commission (PUC) of Texas has since limited the price cap to \$5,000/MWh, due to the ripple effects on retailer bankruptcies and household

[1] Pörtner et al. (2022) reports increasing human and economic losses from climate-related events, including cascading impacts like blackouts caused by flood-damaged energy infrastructure. According to Stone et al. (2021), the potential for blackouts in the US during extreme weather events is rising. Blackouts of at least one hour that impact 50,000 or more utility customers increased by 60 percent in the years before 2021.

[2] In the U.S. and Europe, the likelihood of extreme reductions in thermoelectric power generation is projected to triple. Studies suggest that, during summer, power plant capacity could decrease by 6-19 percent in Europe and 4-16 percent in the U.S., depending on the cooling technology and climate scenario (Vliet et al., 2012; Yalew et al., 2020).

[3] A recent example is the case of Ecuador, which is undergoing extreme drought, leading to problems of energy, water, and food supply in many parts of the country. See `https://www.wired.com/story/ecuador-energy-crisis-water-shortage-hydro/`.

[4] A recent discussion on these issues has emerged in Europe due to the increasing costs of energy in the wake of the gas crisis with Russia (Nasr and Eckert, 2022).

[5] This winter storm became Texas' most costly natural disaster, with estimated damages of \$195 billion and over 240 cold-related deaths, highlighting significant societal and economic impacts (Hellerstedt, 2021; Austin-Travis County, 2021). Further studies, such as those by Lee et al. (2022) and Peterson et al. (2024), have shown that low-income and ethnic minority groups, along with households with children and those with disabilities, were disproportionately affected, indicating existing inequalities in the distribution of power outages in Texas.

bills, highlighting the potential limitations of the price mechanism when dealing with essential goods during extreme events in otherwise well-functioning markets.[6]

Rather than relying on price mechanisms alone, which can fail during extreme events, we focus on improving quantity-based interventions for residential electricity households, and that nowadays typically leads to households losing access to electricity in the form of rolling blackouts. Rather than relying on blackouts to reduce demand, which is an extreme form of rationing, we study partial rationing using smart meters. The mechanism, also known as load limiting, uses the capabilities of smart meters to limit households' consumption in a dynamic fashion, depending on the severity of the shortage. Rather than exposing entire neighborhoods to the dark for several hours with rolling blackouts, the mechanism limits consumption at each home and provides access to essential appliances such as refrigerators, lights, and communication devices. Because the limits apply to homes, one can also maintain public uses of electricity (e.g., from street lights to community elevators), minimizing some of the costs of rolling blackouts such as increased crime (Imelda and Guo, 2024).

While it seems intuitive that partial rationing should generate substantial value to households in expectation, as it provides guaranteed access to electricity, intuition suggests that it may impact a greater number of households. Yet, we theoretically show that there exist quite general conditions under which partial rationing leaves *fewer* households affected by the rationing event, making the acceptability of partial rationing even more viable. The result works via *selection*. By setting consumption limits, the high energy users are the ones contributing to demand reductions, which can disproportionately contribute to demand reductions if the distribution of electricity consumption is heavy-tailed. For the rationed households, we highlight the risk reduction properties of the mechanism and show conditions under which partial rationing is an ex ante Pareto improvement to risk-averse households. These conditions depend on the preferences for risk under standard utility functions (sufficiently risk averse). We find that, under reasonable theoretical parameters, partial rationing is a "no-brainer." This result applies to the rationing of any good whose distribution is heavy tailed, such as the log-normal distribution, which is common in essential goods.

Empirically, using data from over a million Spanish households provided by a regulated distribution company, we analyze how adjusting household consumption limits in anticipation of a blackout could improve rationing schemes.[7] Specifically, we compare the effectiveness of setting household consumption limits versus implementing full blackouts in terms of the number of households affected. Simulating random rationing under varying uniform power limits, we empirically confirm that limiting consumption not only mimics the electricity reduction effects of a blackout but also impacts *fewer* households. We also apply our theoretical welfare results and examine, empirically, under which conditions the mechanism can be a Pareto improvement.

What are the welfare implications of using the mechanism? We complement our data with individual measures of income and HVAC mode from Cahana et al. (2022). This allows us to assess first if the rationing mechanism appears to be regressive, and second how it may conflict with heating and cooling needs during extreme events. We find that high-consumption households, which tend to be higher-income in our data, are most affected by partial rationing. Thus, the approach could offer a more equitable method of rationing electricity, lessening the burden on lower-income households who consume less power and may be

[6] The PUC justified the change to "help ensure prices remain affordable during the upcoming winter season and lessen the financial risk to customers during scarcity events." See https://www.reuters.com/markets/commodities/texas-cuts-9000-power-price-cap-after-february-freeze-2021-12-03/.

[7] By 2018, 99 percent of Spanish households were equipped with smart meters. These smart meters allow electricity providers to set a maximum amount of electricity a household can consume at any given time, known as the contracted power. Therefore, in the case of Spain, power limits can be implemented without the need of capital investments.

less equipped to handle complete outages (Peterson et al., 2024; Ganz et al., 2023). These findings remain robust even when extending blackout periods over multiple hours. Secondly, rationed households also tend to be using HVAC equipment in hot and cold days. While some of the higher limits that we consider may allow the use of this equipment, other households might be more restricted. Therefore, future work will need to consider how to evaluate these trade-offs in practice.

In summary, we highlight the new avenues for shortage mechanisms that smart meters open and provide a framework to assess its benefits. In many countries, these mechanisms could be readily implemented for resilience preparedness. Indeed, France has already piloted a mechanism for 115,000 consumers in 2024, leveraging their existing smart meter technology.[8] Apart from the case of extreme weather, rapidly growing energy demand or underinvestment in energy infrastructure in emerging economies forces utilities to implement rolling blackouts on a regular basis in many geographies, as seen in countries like India, Vietnam, and South Africa. In South Africa, to better manage blackouts, in 2023, the state-owned power utility proposed installing two-way communication smart meters in all South African households over the next four years (Dludla, 2023). The utility is already piloting these smart meters, which use load-limiting technology as the one explored in our work to help manage electricity consumption during blackouts (Jacobs, 2023). This highlights the importance of understanding these mechanisms, which will become more commonplace in the future.

Related Literature While prices are often argued to be efficient, by allocating goods to those willing to pay, they may not be equitable for essential goods, where needs are relatively uniform across income levels. Weitzman (1977) argues that for certain essential goods like healthcare or electricity, prices may not fully capture the true necessity of the good, specifically in situations where some households are constrained in their income, leaving the essential good to be allocated to higher-income households. Apart from distributional concerns, questions arise if prices will sufficiently reduce demand, when demand spikes or supply side losses are extreme. Although price increases during shortages can reduce consumption (Grafton and Ward, 2008), the reduction is usually moderate, leaving prices insufficient to significantly lower demand (Renwick and Green, 2000).

For residential demand, studies have explored alternative market interventions such as price caps, rationing, political campaigns aimed at reducing demand (He and Tanaka, 2023), or combinations of these approaches. Tokarski et al. (2023) introduce a threshold-based price cap that caps rates up to a consumption limit based on household characteristics. This targeted approach is more equitable, as it encourages wealthier households to subsidize the energy needs of lower-income ones, unlike uniform price caps. However, price-cap policies have limitations when consumer price responsiveness is low. To address these concerns, Gerlagh et al. (2022) propose a policy that addresses inefficiencies in electricity pricing during persistent supply shocks with a temporary, time-varying price cap. This cap adjusts with demand changes, balancing consumption between price-responsive and non-responsive consumers, an extension of Joskow and Tirole (2007). We differ by focusing on mechanisms that are invoked under extreme situations (blackouts and its alternatives) even when the price cap is allowed to be quite large.

Other studies have explored targeted short-run blackouts as an improved response to substantially reduce electricity consumption. For instance, using a household production function approach based on Becker (1965), de Nooij et al. (2009) examined rolling blackouts versus efficient rationing at the municipal level in the Netherlands, demonstrating that targeting municipalities with lower social costs reduces overall social

[8] See `https://www.tf1info.fr/economie/exclusif-limitation-de-puissance-des-compteurs-linky-les-resultats-de-l-experimentation-d-enedis-2301249.html`.

costs. Similarly, Wolf and Wenzel (2015) estimate the cost of short-run blackouts on the county level in Germany using the production function approach and use these estimate to compare four different rationing regimes: random rationing, and minimizing total social costs, per capita damage, and the number of people affected. Their analysis found that strategies focused on minimizing social costs and on impacting fewer individuals tend to reduce damages more effectively, reinforcing our focus on the number of households as a key objective. Instead of applying blackouts across entire areas, our approach effectively targets high-consumption households across wider sets of areas.

While we focus on quantity-only mechanisms, smart meters are already used in many countries in Europe to limit the maximum consumption of homes, as it translated into the fixed cost of their contracts. In future work, we plan to also explore emergency-contingent capacity contracts, akin to those used in industrial settings and formally studied in the priority service literature (Chao and Wilson, 1987). However, it is important to keep in mind that such a mechanism may not be politically viable under extreme conditions. The burden on low-income households may not be socially acceptable and the highest income consumers may still be needed to achieve the desired targets. However, these contracts may be attractive to increase demand response in the presence of renewable intermittent sources (Chao et al., 2022).

In summary, this study contributes to the existing literature in three key ways. To our knowledge, this is one of the first papers to explore the use of smart meters to dynamically limit households' consumption as a last-resort measure for reducing energy demand during extreme events. Second, it adds to the literature on the distributional impacts of rationing, examining how income distribution and households consumption characteristics influence the effects of rationing policies. Last, it contributes to the broader discussion on using prices or quantities for managing scarce resources.

2 A Framework for Partial Rationing

Consider the following individual net utility from electricity (Weitzman, 1977):

$$w_i(p; \lambda_i, \epsilon_i) \;\equiv\; u_i(x_i(p); \epsilon_i) - \lambda_i \; p \; x_i(p),$$

where u_i stands for individual utility dependent on the amount of electricity x_i at price p and the need for electricity ϵ_i. The net utility can thus be expressed as the difference between the utility and the cost of electricity, with the cost expressed as the amount of electricity at a given price, normalized by the opportunity costs of foregone income.

We consider situations in which the price mechanism fails to clear the market, and thus demand curtailment, also called load shedding, is required. More concretely, we consider a situation in which, at $\overline{p}$, $D(\overline{p}) \equiv \sum_i x_i(\overline{p}) \gg S(\overline{p})$. For the purposes of this short paper, we assume that this price limit binds, and therefore drop the price in the rest of the notation.

Due to the need to curtail demand, the consumption of households will be limited by a rationing mechanism that sets a maximum limit $\kappa \in [0, \overline{\kappa}]$ to their consumption, such that

$$x_i(\kappa) = \min\{x_i, \kappa\}.$$

When $\kappa = 0$, consumers cannot use any power, i.e. there is full rationing (a "blackout"). As a normalization, for $\kappa = \overline{\kappa}$, there is no rationing.[9] Intermediate values of κ may ration some consumers, but not all.

[9] In practice, we will let κ be the allowed consumption at the household level, with $\kappa = 0$ being equivalent to a blackout and

2.1 Random access

Under traditional rolling blackouts, a fraction α of consumers gets selected for a blackout and gets zero power ($\kappa = 0$), while the rest remains with provision of service ($\kappa = \overline{\kappa}$). Under *random* rationing, total welfare equals

$$W^B(\alpha) = \alpha W(0) + (1-\alpha)W(\overline{\kappa}),$$

where W represents aggregate welfare, i.e., $W(\kappa) = \int_i w_i(\kappa)di$.

Notice that α might be small, but the costs to selected consumers can be large if the blackout is severe under plausible utility functions.

2.2 Random limits

Smart meters allow for individual-specific power limits that are above zeros and can be digitally adjusted during an extreme event. This is in contrast with traditional meters, for which, even if they have the ability to limit consumption, their limit that cannot be easily adjusted. While limits can be flexibly set, rules might need to be simplified in practice due to information asymmetries. Furthermore, there might be social consideration on what policies might be considered acceptable, beyond those reflected by the utility function.

For the purposes of this paper, we consider a special case of a rationing rule in which households are randomly selected into rationing with some probability β and, conditional on rationing, they get their consumption limited to a common threshold $\kappa \in (0, \overline{\kappa})$. This simple rule can be easily conveyed to households, as it does not entail targeting or customization, and it is simple to implement.

Under partial rationing with a limit κ, welfare becomes:

$$W^P(\beta, \kappa) = \beta w(\kappa) + (1-\beta)w(\overline{\kappa}).$$

Definition 1. *An α-**equivalent power-limit policy** is a combination of β^* and κ^* that is equivalent in expectation to a blackout of size α, i.e.,*

$$\beta^*, \kappa^* \ \ s.t. \ \ \beta^* D(\kappa^*) + (1-\beta^*)D = (1-\alpha)D$$

where $D(\kappa) \equiv \sum_i x_i(\kappa)$.

Under this policy, households get a consumption limit of κ so that total demand is equivalent to a share $(1-\alpha)$ of D.

While this rule is not tailored, it can still provide substantial welfare improvements, as households do not lose their access to power completely. Additionally, one can maintain electricity for public goods such as street lights, something that is not modeled explicitly in the framework but is likely to benefit all households.

Maximizing κ can be a natural benchmark under a declining marginal utility of consumption. A special case that might be appealing is one that maximizes the limit κ by setting $\beta = 1$. Setting $\beta = 1$ also provides a sense of the maximum power reductions that can be achieved for a given κ. Under such a rule, all households are being selected for rationing and the potential maximum rationing for a given limit κ is achieved.

Definition 2. *The **maximum rationing** that can be achieved by a rationing policy with limit $\kappa > 0$ and $\beta = 1$, achieves a blackout of size,*

$$\overline{\alpha}(\kappa) = 1 - \frac{D(\kappa)}{D} < 1.$$

$\kappa = \infty$ being equivalent to no rationing policy.

This maximum blackout size can be useful to assess the extent to which partial rationing policies can mimic the demand-reduction impact of rolling blackouts, which will be determined by the distribution of electricity consumption.

2.3 Effectively rationed households

It seems intuitive that a random power limit should be preferred to rolling blackouts, as it does not leave any household completely in the dark. However, it can severely limit the consumption and it can potentially leave many more households affected by the adverse event

Definition 3. *Denote $\delta \equiv \beta/\alpha$, i.e., the number of households that need to be selected under a partial rationing mechanism to achieve a blackout of size α. Naturally, for any α-equivalent policy with $\kappa > 0$, it needs to be that $\delta \geq 1$.*

As we will show, many of the results will depend on this ratio. It is important to note that β is endogenously determined as a function of κ and the distribution of demand.

To understand the welfare trade-off between the two mechanisms, it is useful to define not only the share of households that need to be selected, but the share of affected households that are actually affected.

Definition 4. *We say that consumers are **effectively rationed** under a power limit κ if $x_i > \kappa$. The share of effectively rationed households is $\phi \equiv \beta Pr(x_i > \kappa)$. The rest of households, $1 - \phi$, do not get their consumption rationed, even if they have been selected.*

We find that it is not necessarily the case that the number of effectively rationed households is larger under a rationing rule. More concretely, we observe that the number of households that are *effectively* affected by a power limit (ϕ) might be *less* than under a blackout (α) for quite general conditions if the distribution of demand is sufficiently skewed, which we summarize in Results 1 and 2.

Result 1. *Effectively rationed consumers ϕ under an α-equivalent policy are less than those selected by a blackout of size α as long as,*

$$E[x_i|x_i > \kappa] - \kappa > E[x_i].$$

As this statement makes clear, whether the partial rationing event needs many consumers to limit their consumption depends on the shape of the distribution of consumption and its tailed nature. For example, under a bounded distribution such as the uniform, this condition can never hold and $\phi > \alpha$.[10] However, it is likely to be satisfied by other distributions, which we characterize below.

Result 2. *Under the **exponential distribution**, $E[x_i|x_i > \kappa] - \kappa = E[x_i]$, i.e. the number of households affected under partial rationing and blackouts is the same in expectation. Therefore, **heavy-tailed distributions** lead to fewer consumers effectively rationed than under a full blackout.*[11]

Thus, depending on the distribution of electricity consumption at a given point in time, there could be situations in which partial random limits not only avoid blackouts but also effectively bother fewer people. This condition is satisfied by familiar distributions such as the log-normal distribution or the t-student.[12]

While the number of households that are affected by the rationing event is the same (or even lower), it is important to highlight that these are *different* households. By setting a power limit, the partial rationing

[10] Under the uniform $U(a, b)$, $E[X \mid X > \kappa] - \kappa - \mu = \frac{b+\kappa}{2} - \kappa - \frac{b+a}{2} = -\frac{\kappa+a}{2} < 0$.

[11] Heavy-tailed distributions are those that are heavier-tailed than the exponential distribution.

[12] Note that this is a sufficient but not necessary condition.

rule finds the heavy users among a larger set of randomly selected households β. This selection effect is correlated with their consumer characteristics ϵ_i and λ_i, which we explore in the empirical section.

Extension to multiple periods When the rationing event lasts more than one period, then it is important to consider the impact on households for blackouts vs. power limits. Due to the stochastic nature of electricity consumption, some households might not be affected by the power limit in some hours but might need to reduce their power in others, being thus effectively rationed during a subset of hours.

From a mathematical point of view, we can interpret this increased probability of being effectively rationed as a function of the multi-dimensional distribution of electricity consumption during the day. A household is "effectively bothered" if the first order statistic of x_i is larger than κ. The probability of being rationed *at least* one hour can be substantially larger than the probability of being bothered in a single hour.

The extent to which partial rationing will affect many households under these broader interpretation is an empirical question, and it will depend on the within-household vs. the across-household variation in consumption. If electricity consumption is persistent within a households, then the affected consumers are likely to be correlated. However, if electricity consumption is quite random at the household level, then the households contributing to demand reductions will change during the day, spreading the burden across consumers depending on the hour of the day.

2.4 Welfare considerations

Given the severity of blackouts, which provide a consumption of zero to households during the event, it is reasonable to expect partial blackouts to improve overall average welfare. In fact, this is true by construction, at least weakly, as it increases the degrees of freedom of the operator.

An additional question is under which conditions a partial blackout can be a Pareto improvement. For households with consumption below the limit, a partial blackout is a strict improvement, as they are unaffected by the event. For the rest of households, their welfare change will be determined by the concavity of the utility function, which determines the aversion of households to a blackout.

More precisely, for households with $x_i > \kappa$, whether they are better off under a partial ratioining scheme will depend on their consumption and risk tolerance. Households will be better off as long as,

$$\beta U(\kappa) + (1-\beta)U(x) > \alpha U(0) + (1-\alpha)U(x).$$

Notice that, if $U(0) \to -\infty$, all households prefer the partial blackout. For example, with a constant relative risk aversion (CRRA) utility function, $U(c) = \frac{c^{1-\gamma}}{1-\gamma}$, partial blackouts are a Pareto improvement for all households as long as $\gamma \geq 1$, as highlighted by Result 3 below.

One can also work with a utility function that is bounded below, such as the constant absolute risk aversion (CARA) utility function, $U(c) = -e^{-\rho c}$. The CARA utility function is, however, bounded above by zero. Therefore, under plausible risk aversion parameters, one can also conclude that all households are better off, due to the substantial declining marginal utility of electricity consumption. This leads to predictable conditions under which a partial blackout is a Pareto improvement.

Result 3. *Under CRRA utility function and $\gamma \geq 1$, all households are better off with partial rationing. Under CARA utility function and for an α-equivalent power limit policy $\{\beta, \kappa\}$, there exists a risk aversion parameter $\overline{\rho}$ above which all households are better off, given by $\overline{\rho} = \frac{\log(\delta)}{\kappa}$.*[13]

[13] The result for the CARA utility function derives from noting that the utility limits to zero as consumption goes to infinity.

Intuitively, a large κ will make the risk aversion limit lower, as consumption gets censored where its marginal utility has declined. Contrarily, a higher β relative to α, i.e., higher δ, will make the needed limit higher, as households are penalized more often. In equilibrium, β and κ are jointly determined, and which of the two effects dominates will depend on the distribution of consumption.

In addition to examining general conditions on the risk aversion parameters under which all households are better off, one can also consider the level of consumption that makes a household indifferent, holding the level of risk aversion constant, which we calculate in Result 4. We solve for the limit under which households are indifferent between a blackout or partial rationing for CRRA and CARA preferences.

Result 4. *Under CRRA utility function and $\gamma < 1$, households with consumption $\overline{c}_{CRRA} = \left(\frac{\delta}{\delta-1}\right)^{\frac{1}{1-\gamma}} \kappa$ experience a Pareto improvement. Under CARA utility, for a given level of risk aversion ρ, households with consumption below $\overline{c}_{CARA} = \frac{1}{\rho}\log\left(\frac{1-\delta}{1-\delta e^{-\rho\kappa}}\right)$ experience a Pareto improvement.*

In both cases, the limit is increasing with risk aversion, as households are more willing to be partially rationed, even if they give up a substantial share of their consumption. In relative terms, one property of the CRRA function is that the consumption at which households are indifferent is always proportional to the consumption limit κ, i.e., $\overline{c}_{CRRA}/\kappa$ is constant. However, whether the consumption limit is increasing or not in κ in absolute terms, holding γ constant, depends on the values of δ and κ, which are jointly determined. Under the CARA function, we find that the consumption limit is increasing with κ, but decreasing in δ, leading to a similar tension.

We bring these conditions to the data, to assess the potential welfare implication of the partial rationing mechanism for households with high levels of consumption.

3 Empirical assessment

We use smart meter data from nearly 1.6 million Spanish households to compare power limits to rolling blackouts.[14] The data include hourly consumption (in kWh) and the contracted power for each household served by the utility . We combine these data with estimates of household-specific income and heating and cooling mode (HVAC) derived in Cahana et al. (2022). We use these measures as a proxy for λ_i (income) and ϵ_i (HVAC) to explore the heterogeneous impacts of the proposed mechanism.

Table 1 summarizes the electricity consumption data across HVAC modes and income quintile. Households with both heating and cooling systems demonstrate the highest average consumption and maximum daily consumption, while those without such systems have the lowest, reflecting higher contracted power and greater energy needs for households with HVAC. Examining income heterogeneity, both average consumption and contracted power gradually rise from the lowest to the highest income quintile, indicating a positive correlation between income, energy usage, and contracted power.

3.1 Equivalent frontier between mechanisms

To study the effect of different rationing rules, we look at a range of consumption limits, $\kappa \in \{0, 0.25, 0.5, 1, 2\}$, in kWh per hour. Here, $\kappa = 0$ represents a blackout, while values greater than 0 indicate partial rationing.

therefore, the condition is satisfied when $\alpha U(0) = \beta U(\kappa)$, which leads to $-\alpha = -\beta \exp^{-\rho\kappa}$.

[14] The data covers the period from January 1st, 2016, to April 30th, 2017 and it was provided to us by Naturgy, one of the largest Spanish utility companies. Households in our sample mostly reside in Madrid, although they are scattered throughout Spain. The geographic distribution of households is shown in the Appendix in Figure A.1.

Conditional on being selected for rationing at limit κ, we assume that household i's consumption at time t is then given by $D^r_{it}(\kappa) = \min\{D_{it}, \kappa\}$, where D_{it} denotes the observed consumption.[15]

For each rationing limit, we compute how many people need to be selected for partial rationing to achieve an equivalent full blackout if households are allowed to consume up to κ, i.e., δ. The results are shown in the light bars in Figure 1. The bar is equal to one by construction for the case of a blackout ($\kappa = 0$). For the case of $\kappa = 2$, an average of twelve households would need to be selected, for each household experiencing a blackout, to achieve the same reduction in electricity. One can see that δ grows more than linearly as a function of the limit, denoting that selection increases.

Indeed, being selected for rationing does not mean all households are fully rationed; it is only binding if their usage exceeds κ. This is shown with the dark bars in Figure 1. As κ increases, while more households need to be selected for rationing, fewer are effectively rationed. For $\kappa = 2$, for each twelve households selected, much less than one is actually impacted by rationing. The reasoning is as follows: as κ rises, fewer households are affected by rationing. To reach a targeted savings level, more households need to be selected, increasingly targeting those with higher consumption. As a result, the average consumption of rationed households rises, since low-consuming households exit while higher consumers enter, concentrating savings among a smaller, more heavily rationed group.

Introducing daily rationing, in which households are selected for all hours of one day, naturally increases the probability of effective rationing in at least in one hour of the day. However, not all hours within a day are affected by the rationing limit. For instance, with a rationing limit of $\kappa = 0.25$, effective rationing only encompasses about 34 percent of all hours in a day, as displayed by the red circles, and this number goes further down as the limit increases. The number of households affected during a daily partial limit tend to increase under mid-range rationing rules, as variance in consumption within a household will tip them over the limit at some point during the day. As the limit grows, when $\kappa = 2$, the number of households necessary for an equivalent blackout decreases again, as a larger proportion of households remain unaffected by the limit throughout the day. This trend aligns with the findings observed in the hourly rationing analysis.

Finally, the diamond-shaped markers in Figure 1 indicate the maximum percentage of energy that can be saved at each limit when every household is selected for rationing. Following from the example above, the maximum size of a blackout that can be achieved when $\kappa = 2$ is around 8 percent. A reduction of this magnitude, even if small, represents a substantial reduction in energy consumption while allowing household to use a significant amount of power.

3.2 Indifference frontier for the mechanism

Using the estimated rationing probabilities derived from Figure 1, we estimate the risk-aversion consumption frontier at which households are indifferent between experiencing a blackout and being rationed, given a specific power limit κ. We plot the consumption indifference frontier between these two scenarios (blackout vs. partial rationing) for different values of κ in Figure 2.

Figure 2a depicts the consumption frontier for the CRRA utility function for values of risk aversion below one. We observe that the frontier for the different limits follows a similar pattern. The consumption indifference point is close to the limit when households are not risk averse, but it exponentially grows as households approach one. We find that the consumption frontier expands faster for lower consumption

[15] Note that this provides a conservative amount of rationing, as in practice most households would default into consumption substantially smaller than κ. However, it presents a best-case scenario for welfare, as households are able to get their maximum constrained utility under partial rationing.

limits, which is driven by the fact that the burden is spread across more households and, thus, the additional sampling of households compared to a blackout (δ) is lower. When households are more actively selected with higher limits, the remaining effectively rationed households require a higher risk aversion to find that the partial rationing mechanism provides a Pareto improvement.

Figure 2b depicts the same frontier for the CARA utility function. Households with higher risk aversion derive significant utility from securing guaranteed access to electricity, even if that access is limited, with indifference consumption substantially above the limit. Conversely, individuals with higher consumption levels and lower risk aversion tend to prefer blackouts over rationing, as their utility function is less concave. For households that are not risk averse, the frontier converges to κ, households would prefer a lower probability of a blackout than being selected more often.

As introduced earlier, for the CARA utility, there exists a value ρ above which all households prefer being partially rationed. As κ increases, the value of ρ for which all households prefer rationing over blackouts decreases. Thus, households need to be less risk-averse in order to still prefer rationing over blackouts. This is because the selection channel dominates. Conditional on being rationed, they are selected more often when the limit is high (i.e., the increase in the ratio δ dominates).

Overall, these simulations suggest that rationing, by guaranteeing a minimum level of consumption, mitigates the extreme utility losses associated with having no electricity during blackouts and can provide substantial benefits to a large share of households.

3.3 The role of income and HVAC

We calculate the probability of being rationed along the income distribution and different HVAC modes. As Figure 3 shows, higher-income households are more likely to be rationed than lower-income households. In fact, rationing is progressive across all values of κ and HVAC modes. The probability of being rationed is lowest for households without heating or cooling appliances. However, in this scenario, high-income households are significantly more likely to be rationed compared to lower-income households, with this income disparity being more pronounced than in scenarios where heating and/or cooling appliances are present. For example, when $\kappa = 0.25$, the highest income quintile is more than 1.4 more likely to be rationed than the lowest income quintile (see Figure A.2). This outcome may reflect that, in the absence of HVAC systems, higher-income households can display less energy-efficient behaviors than lower-income households.[16]

For households equipped with heating and cooling appliances, rationing probabilities are approximately three times higher compared to households without these appliances, reflecting the considerable share of electricity consumption these systems represent (Kotsila and Polychronidou, 2021). As seen in Figure 3(c), income-related differences in rationing probabilities are less pronounced among households with heating, possibly because higher-income households in Spain often use natural gas for heating, while lower-income households rely more on electric heating, increasing their likelihood of rationing (Ortega-Izquierdo et al., 2019).

The external validity of these results relies on the observed positive correlation between income and high electricity consumption. Although higher income is generally linked to greater electricity use (Kotsila and Polychronidou, 2021; Huang, 2015; Romero-Jordán et al., 2014), as our findings also suggest, other factors such as household size, energy efficiency, appliance use, and insulation can play crucial roles in influencing

[16] Additional research might also consider other potential contributing factors, such as ownership of other electrical appliances, household size, or lifestyle.

consumption. As noted by Borenstein (2024), policies aimed at high consumers may not necessarily target high-income households, as consumption patterns can vary regionally, can change with the adoption of solar rooftops by wealthier households or be influenced by other non-income factors. Therefore, the rationing scheme could be further refined with observable attributes of households, such as household size or type of heating, similarly to how non-linear electricity rates can depend on heating mode in states like California.

4 Conclusions

We develop and analyze a novel partial rationing mechanism, leveraging smart meter technology to limit household electricity consumption only during periods of potential shortages. Rather than implementing full blackouts, our mechanism ensures that households retain access to essential services like refrigeration and lighting by capping electricity usage at individualized limits.

Through both theoretical modeling and empirical analysis using data from over a million Spanish households, we demonstrate that partial rationing affects fewer households and distributes the burden towards those that consume more. In addition, our findings show that, under reasonable conditions, partial rationing can be a Pareto improvement over rolling blackouts. These findings are likely to apply to other settings in which the consumption of essential goods follows heavy-tailed distributions, such as the log-normal.

Our analysis opens the door to several avenues of future research. How should more flexible rationing policies be deployed? Should the price mechanism be considered to manage rationing conditions? Should partial limits, combined with pricing schemes, be used more broadly under less severe conditions to manage renewable intermittency? We leave these questions open for future research.

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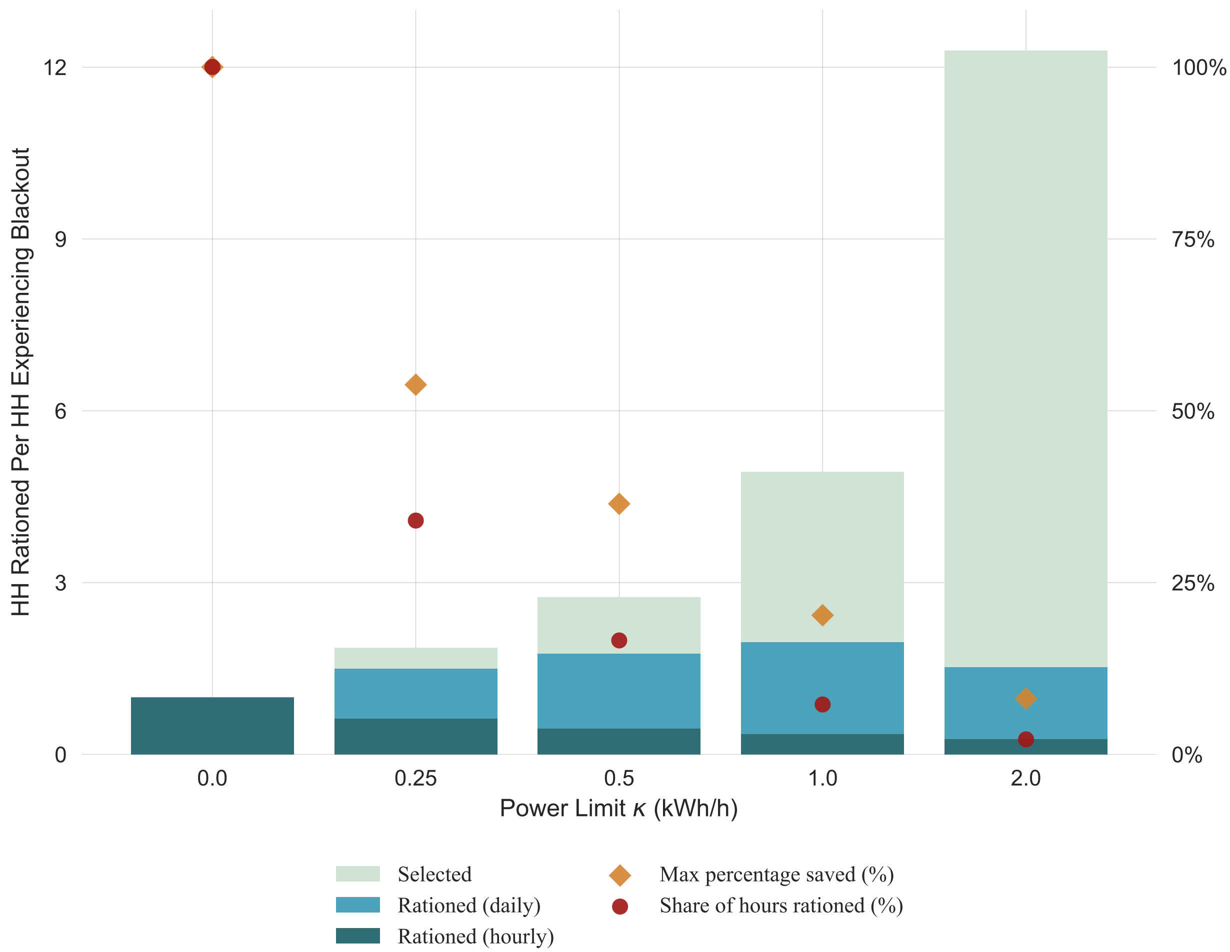
Tables and Figures

Table 1: Summary of Household Electricity Consumption

	$\bar{c}$	$\overline{\text{sd}}$	$\overline{c_{\max}}$	Contracted Power	N
Full sample	0.34	0.26	1.06	4.11	1,571,476
	(0.38)	(0.30)	(0.97)	(1.51)	
By HVAC					
No Heating or Cooling	0.24	0.18	0.79	3.88	1,052,684
	(0.21)	(0.15)	(0.57)	(1.39)	
Cooling	0.40	0.27	1.16	4.39	175,334
	(0.39)	(0.20)	(0.78)	(1.74)	
Heating	0.66	0.55	2.01	4.75	218,685
	(0.61)	(0.51)	(1.53)	(1.42)	
Heating and Cooling	0.75	0.27	2.20	5.13	53,001
	(0.61)	(0.49)	(1.54)	(1.81)	
By Income Quintile					
Q 1	0.32	0.24	0.96	3.35	306,359
	(0.09)	(0.10)	(0.36)	(1.23)	
Q 2	0.34	0.26	1.04	3.88	317,213
	(0.10)	(0.11)	(0.40)	(1.46)	
Q 3	0.34	0.26	1.06	4.16	317,792
	(0.10)	(0.11)	(0.41)	(1.51)	
Q 4	0.34	0.27	1.09	4.44	318,574
	(0.10)	(0.11)	(0.43)	(1.50)	
Q 5	0.35	0.28	1.14	4.71	311,538
	(0.11)	(0.12)	(0.46)	(1.46)	

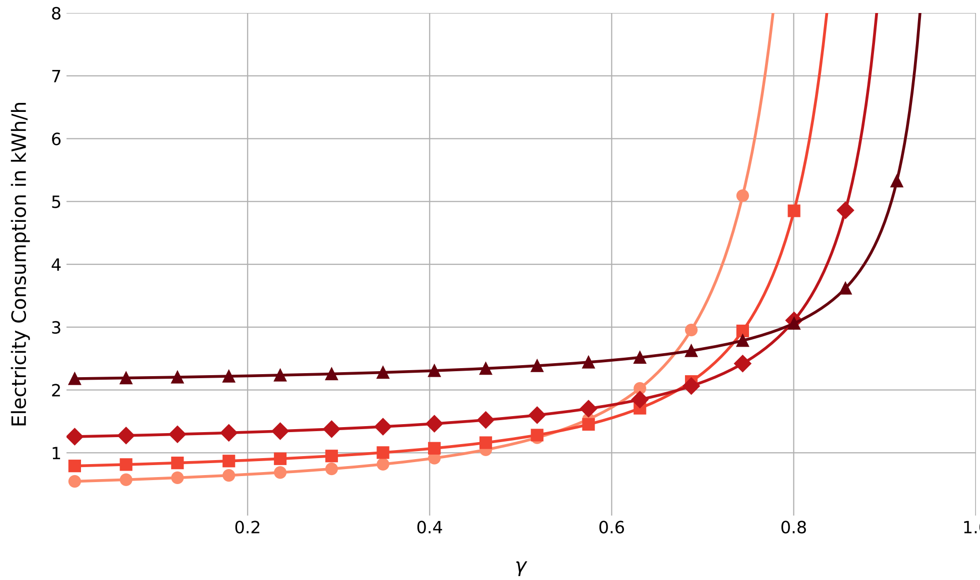
Notes: The unit of observation is a household (meter). $\bar{c}$ is the average hourly consumption, $\overline{sd}$ is the average daily standard deviation, and $\overline{c_{max}}$ is the average maximum daily (all in kWh). The contracted power represents the maximum power a household can contractually consume at any instant (in kW).

Figure 1: Comparing the performance of blackouts vs. power limits

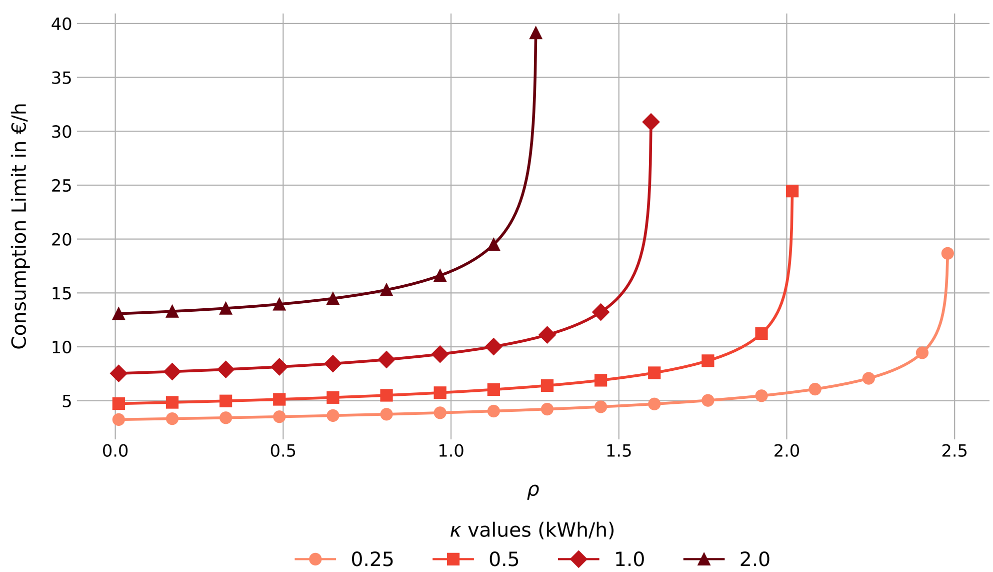


Notes: This figures shows rationing outcomes from hourly data of 1.57 million households. On the left-axis, one can see the rationed households vs. those experiencing a backout, i.e., β/α. Selected households are displayed in light green, while rationed households for a given hour are displayed in dark green and households rationed at least one hour in a day are display in teal. On the right-axis, one can see the percentage of hours that households are rationed (red circles) and the maximum attainable size of a blackout that can be achieved with a limit κ (yellow diamonds).

Figure 2: Pareto-indifference curve between a blackout and partial rationing



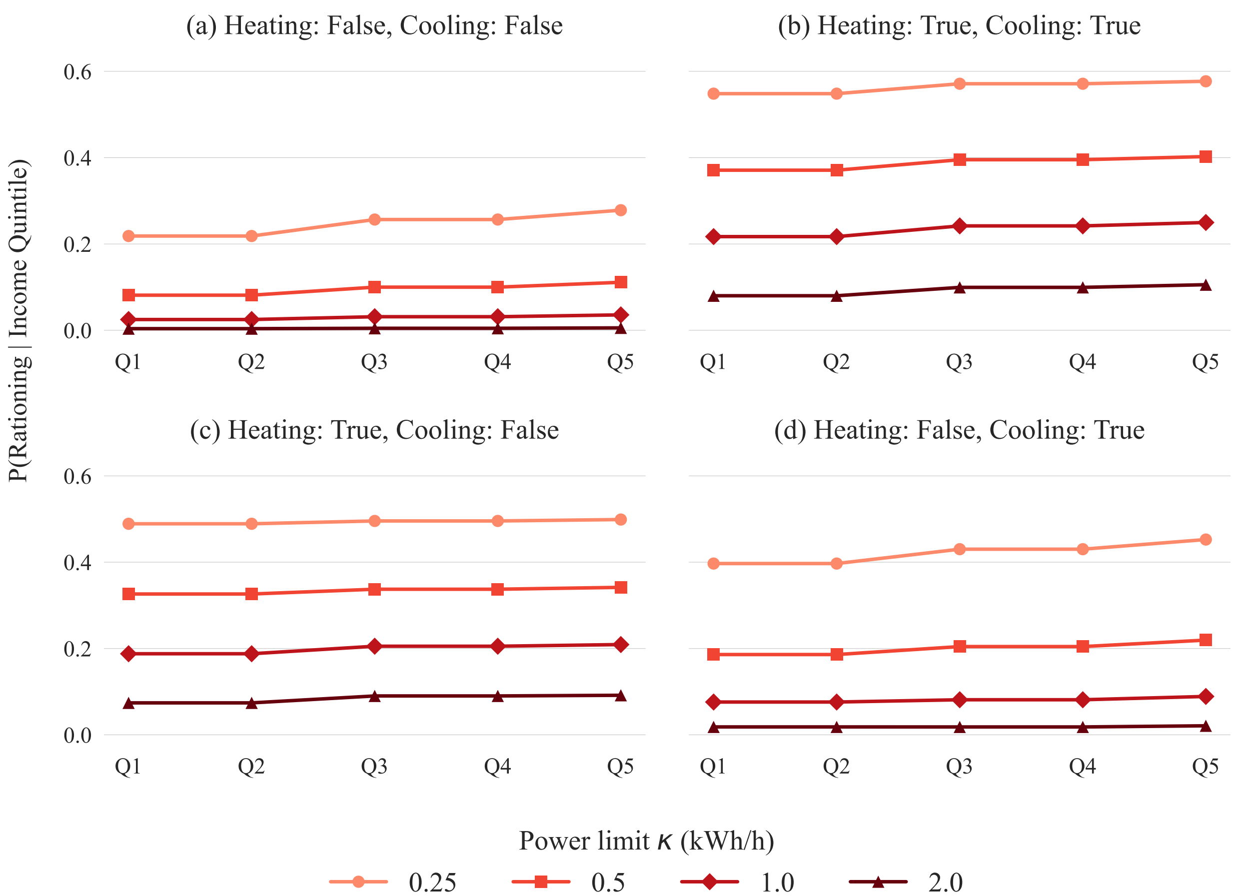
(a) CRRA Utility Frontier



(b) CARA Utility Frontier

Notes: The results plot the consumption indifference point for varying values of γ between a probability of blackout of five percent ($\alpha = 0.05$) and an α-equivalent partial rationing mechanism with limit κ. For the CARA utility, we use a conversion between KWh to Euros using a value of lost load (VOLL) of 6 EUR/KWh so that the lottery can be interepreted as an hourly bargain in EUR.

Figure 3: Probability of rationing as a function of income and HVAC use



Notes: This figure shows the probability of a household getting rationed when it is selected under the partial rationing mechanism along the income distribution (in quintiles). Heating:TRUE is an indicator of whether a household is estimated to have electric heating. Cooling:TRUE is an indicator of whether a household is estimated to have air conditioning.

A Additional Online Material (non-essential)

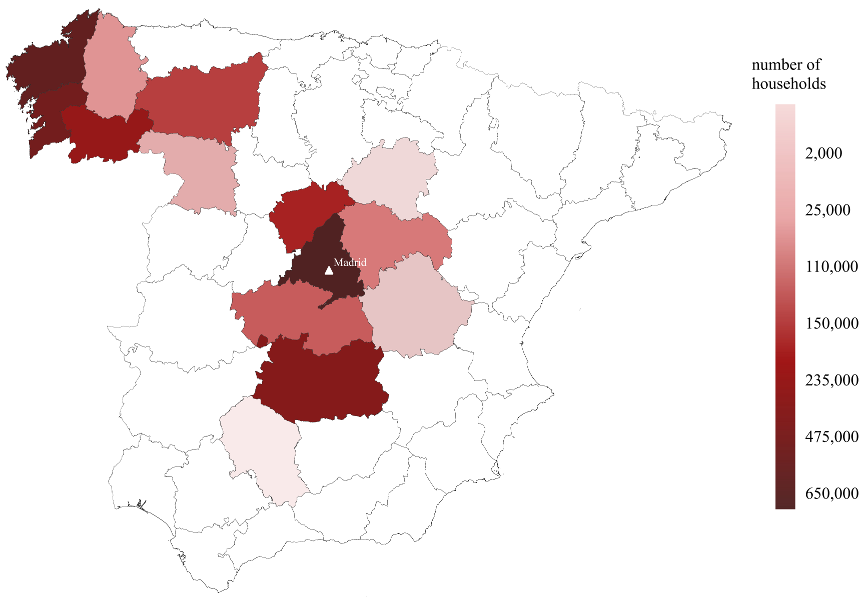
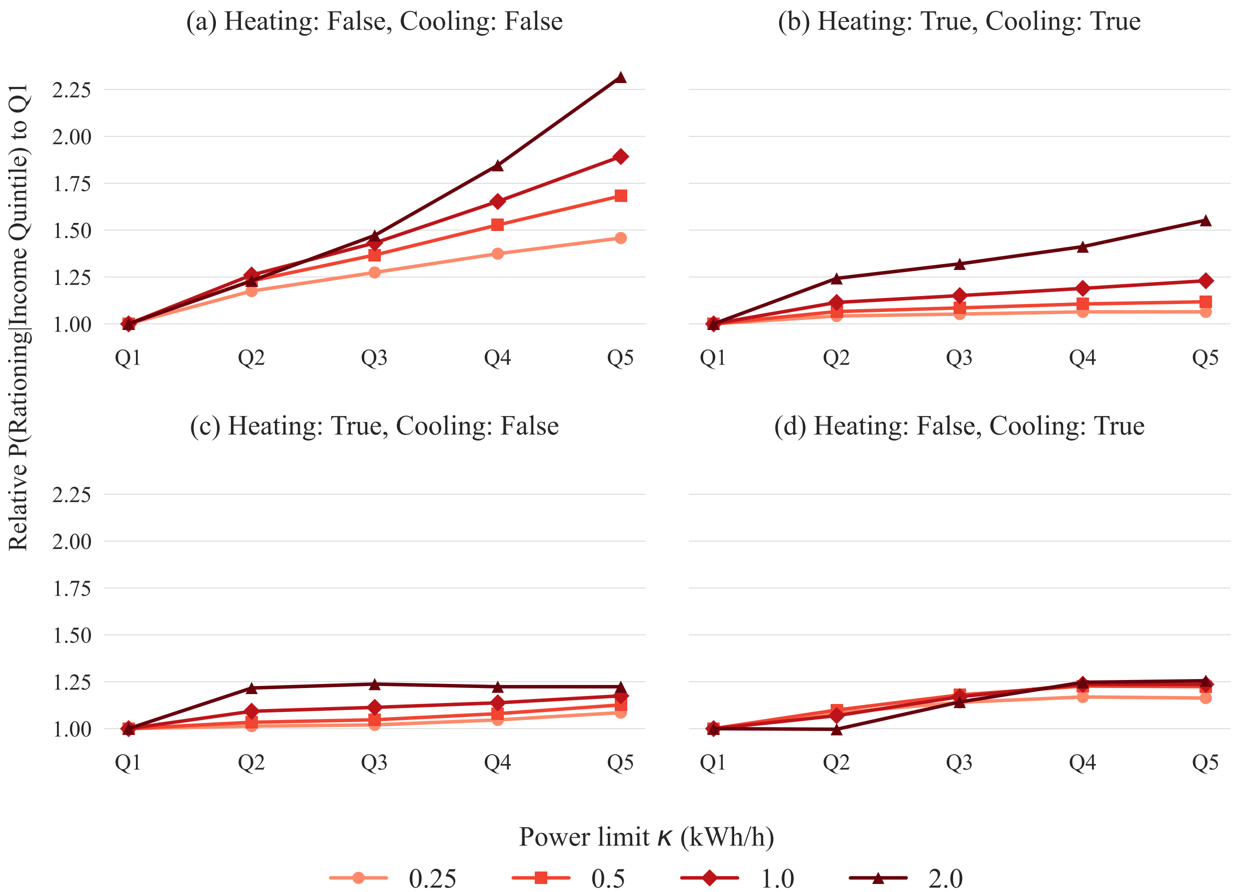


Figure A.1: Map of households in the distribution area

Figure A.2: Relative probability of rationing as a function of income



Notes: This figure shows the probability of a household getting rationed relative to the conditional probability of the lowest income quintile (Q1). Heating:TRUE is an indicator of whether a household is estimated to have electric heating. Cooling:TRUE is an indicator of whether a household is estimated to have air conditioning.