Smart Rationing:
Designing Shortage Mechanisms for Extreme Events

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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.

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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 essential goods shortages, regulators need to prepare for unexpected emergencies where 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 use. Nowadays, shortages typically lead 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 dynamically limit households' consumption based on the severity of the shortage, with *rolling limits* serving as one example. 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 from Cahana et al. (2022) to assess first if setting a uniform limit appears to be regressive, and second how it compares to setting the partial limit as a proportional threshold of the households maximum contracted power [8]. We find that high-consumption households, which tend to be higher-income in our data, are most affected by uniform rationing. Thus, the approach could offer a more equitable method of rationing electricity, reducing the burden on lower-income households who consume less power and may be less equipped to handle complete outages (Peterson et al., 2024; Ganz et al., 2023). These findings remain

[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.

[8] In Spain, contracted power is the maximum amount of electricity a household can draw from the grid at any moment.

robust even when extending blackout periods over multiple hours. Secondly, while setting a proportional limit also affects fewer households compared to the blackout scenario, more households are needed compared to the uniform limit. Moreover, this approach disproportionately impacts lower-income households, as it is more restrictive for those with lower consumption.

In summary, we highlight 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.[9] 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 costs. Similarly, Wolf and Wenzel (2015) estimate the cost of short-run blackouts on the county level in

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

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, such as interruptible contracts, 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.[10] Intermediate values of κ may ration some consumers, but not all.

[10]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 $\phi > \alpha$.[11] 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.*[12]

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.[13]

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

[11] Under the uniform $U(a, b)$, $E[X \mid X > \kappa] - \kappa - \mu = \frac{b+\kappa}{2} - \kappa - \frac{b+a}{2} = -\frac{\kappa+a}{2} < 0$.
[12] Heavy-tailed distributions are those that are heavier-tailed than the exponential distribution.
[13] 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 may exceed power limits at certain hours, while consuming below the limit in others, being thus effectively rationed during a subset of hours.

Mathematically, 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 consumption variation. 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.

Extension proportional rationing We also examine a second rationing scheme that sets household-specific consumption limits based on contracted power. In this case, each household's consumption limit is determined by a fixed percentage of their contracted power. For example, if the proportional limit is set at 20%, a household with a contracted power of 4 kW would have a consumption limit of 0.8 kW. The probability of a household being rationed is an empirical question and depends on the ratio of their consumption (x_i) to their contracted power (p_i). Whether proportional rationing affects fewer households than rolling blackouts depends on the joint distribution $f(x_i, p_i)$ and the absolute value of households consumption x_i. A fat-tailed distribution of the ratio of $\frac{x_i}{p_i}$ does not necessarily imply that this rationing scheme targets high consumers, as the ratio can both be high for low consumers with low contracted power and high consumers with high contracted power.

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 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 rationing 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 $\overline{\rho} = \frac{\log(\delta)}{\kappa}$.*[14]

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.

2.5 Practical Considerations

When bringing this theoretical framework to the data, it is useful to consider some practical implementation aspects of power limits.

In Spain, smart meters let providers set a maximum electricity consumption level, known as the contracted power. This power limit does not reduce the flow of electricity but ensures that consumption stays within the specified limit. As a result, voltage and amperage levels remain within standard operating ranges, preventing damage to electrical and electronic equipment from low voltage or amperage. Thus, power limits can be implemented without the need of capital investments.

If a household electricity consumption exceeds this limit, the circuit breaker trips, requiring a manual reset at home or remotely through a website or app. To restore power without another disconnection,

[14]The result for the CARA utility function derives from noting that the utility limits to zero as consumption goes to infinity. therefore, the condition is satisfied when $\alpha U(0) = \beta U(\kappa)$, which leads to $-\alpha = -\beta \exp^{-\rho\kappa}$.

households must first reduce usage, such as by unplugging appliances. If the household is empty during the power cut, the disconnection may cause welfare losses (e.g. spoiled food). To reduce welfare losses, advance notifications could alert households of approaching limits, including guidance on which appliances could be used, depending on the limit. This approach could also help address issues arising from households' limited knowledge of their appliances' power consumption, which may lead to inefficient energy use and recurrent power cuts (Chen et al., 2015; Attari et al., 2010). However, in countries with power limits, households are typically accustomed to these constraints and have a clearer understanding of which appliances are likely to trigger a disconnection.

Our analysis imposes consumption limits in kWh, but power limits in the contracted power are set in kW. This raises concerns as some appliances with cyclical electricity and high startup surges (e.g. refrigerators, air-conditioner) cause short-term spikes in consumption, where a household temporarily exceeds the consumption limit (kW), even if total hourly consumption (kWh) remains within bounds. While this analysis may be improved with 5-minute level data, the impact on our results is likely minimal for the following reasons. First, short-lived fluctuations may not systematically affect households' ability to remain under the limit, as electricity provider tolerate brief overages. Secondly, as shown in A.4, our results are robust to excluding high-consuming cyclical appliances such as air-conditioning and heating.

3 Empirical assessment

We use smart meter data from nearly 1.3 million Spanish households to compare power limits to rolling blackouts [15]. The data include hourly electricity consumption (kWh) and contracted power for each household. We combine these with estimates of household-specific income and heating/cooling mode (HVAC) from Cahana et al. (2022). Income and HVAC estimates are derived by analyzing electricity consumption patterns and contracted power, which correlates with income due to its impact on electricity bills and appliance ownership. Additionally, a k-means clustering algorithm groups households based on 198 consumption-related variables, allowing for the estimation of income distributions at the household level. 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 electricity consumption across HVAC modes and income quintiles. Households with heating and cooling systems have the highest average and maximum daily consumption, while those without HVAC systems have the lowest. Both average consumption and contracted power rise from the lowest to the highest income quintile, indicating a positive correlation between income, energy usage, and contracted power.

3.1 Blackout-equivalent frontier

To study the effect of different rationing rules, we examine consumption limits, $\kappa \in \{0, 0.25, 0.5, 1, 2\}$, in kWh per hour, where, $\kappa = 0$ represents a blackout and values greater than 0 indicate partial rationing. Conditional on being selected for rationing at limit κ, we assume that household i's consumption at time t is given by $D^r_{it}(\kappa) = \min\{D_{it}, \kappa\}$, where D_{it} denotes the observed consumption.[16]

[15]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.

[16]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.

For each limit, we compute how many households must be selected for partial rationing to achieve the same energy reduction as a full blackout, denoted δ (light bars in Figure 1). By construction $\delta = 1$ 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 (dark bars in Figure 1). As κ increases, more households need to be selected for rationing, but fewer are effectively rationed. For $\kappa = 2$, for each twelve households selected, much less than one is actually impacted by rationing. As a result, the average consumption of rationed households rises, as savings are concentrated 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. However, not all hours in a day are affected by rationing. For $\kappa = 0.25$, only about 34 percent of all hours in a day are effectively rationed (red circles in Fig 1), 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.

For proportional rationing, we determine limits to achieve the same electricity savings as uniform rationing. Equivalent limits for 0.25, 0.5, 1, and 2 kW caps are 6.5%, 12.5%, 25%, and 46.5% of contracted power. While both schemes affect less households compared to blackouts, proportional rationing impacts more, especially at higher limits (hourly-proportional bar in Figure 1). At a 0.25 kW cap (6.5% limit), 9% more households are rationed, while at 2 kW (46.5%), 48% more are affected, shifting the burden toward smaller consumers.

3.2 Utility-based indifference frontier

Using the estimated rationing probabilities from Figure 1, we estimate the risk-aversion consumption frontier where households are indifferent between experiencing a blackout and being rationed at a given κ.

Figure A.2a depicts the consumption frontier for the CRRA utility function for values of risk aversion below one. The frontier follows a similar pattern across limits: when households are not risk-averse, the indifference point is close to the limit, but it grows exponentially as risk aversion approaches one. We find that the consumption frontier expands faster for lower consumption limits, 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. For higher limits, effectively rationed households require greater risk aversion for rationing to be a Pareto improvement.

Figure A.2b depicts the same frontier for the CARA utility function. Highly risk-averse households derive significant utility from guaranteed electricity access, even if 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 threshold ρ above which all households prefer being partially rationed. As κ increases, this threshold decreases, meaning that 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 ensuring minimum consumption, mitigates extreme utility losses from blackouts and benefits many households.

3.3 Income and alternative rationing rules

We calculate the probability of being rationed conditional on belonging to an income group for each income group along the distribution. Rationing probabilities vary significantly across income groups, with uniform rationing being progressive and proportional rationing being regressive (see Figure 2). Under uniform rationing, higher-income households are more likely to be rationed than lower-income households across all values of κ. This effect is particularly strong for households without heating or cooling appliances, where high-income households face an even greater likelihood of rationing (see Figure A.3).

In contrast, proportional rationing disproportionately affects lower-income households. This is the result of the ratio of household consumption relative to contracted power: higher-income households tend to contract to higher power limits, paying for a buffer that makes them less affected by proportional caps. In contrast, lower-income households, which contract power closer to their actual consumption to minimize costs, face a higher likelihood of being rationed due to more restrictive consumption limits.

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 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 household attributes, such as household size or heating type, similar 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 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 higher consumers. 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 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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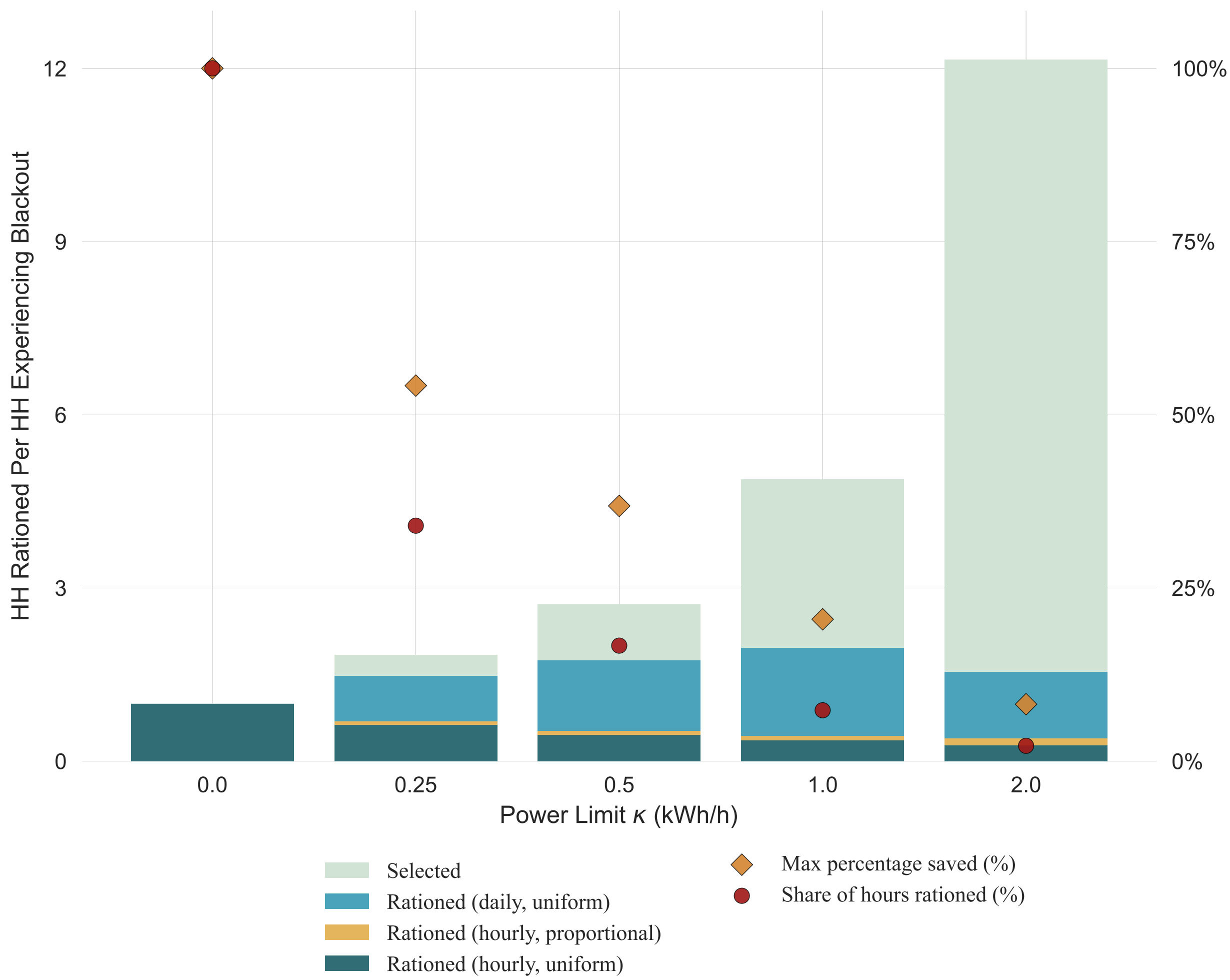
Tables and Figures

Table 1: Summary of Household Electricity Consumption

	$\overline{c}$	$\overline{\text{sd}}$	$\overline{c_{\text{max}}}$	Contracted Power	N
Full sample	0.34	0.26	1.06	4.12	1,277,633
	(0.38)	(0.30)	(0.98)	(1.51)	
By HVAC					
No Heating or Cooling	0.24	0.18	0.79	3.89	891,654
	(0.21)	(0.15)	(0.57)	(1.39)	
Cooling	0.40	0.27	1.16	4.39	156,219
	(0.39)	(0.21)	(0.78)	(1.73)	
Heating	0.66	0.55	1.99	4.75	182,959
	(0.61)	(0.51)	(1.52)	(1.41)	
Heating and Cooling	0.75	0.27	2.20	5.13	46,801
	(0.61)	(0.49)	(1.55)	(1.80)	
By Income Quintile					
Q 1	0.32	0.24	0.96	3.36	249,319
	(0.09)	(0.10)	(0.36)	(1.23)	
Q 2	0.34	0.26	1.05	3.88	256,657
	(0.10)	(0.11)	(0.40)	(1.46)	
Q 3	0.34	0.26	1.06	4.16	258,014
	(0.10)	(0.11)	(0.41)	(1.50)	
Q 4	0.34	0.27	1.09	4.45	259,981
	(0.10)	(0.11)	(0.43)	(1.50)	
Q 5	0.36	0.28	1.14	4.72	253,661
	(0.11)	(0.12)	(0.46)	(1.45)	

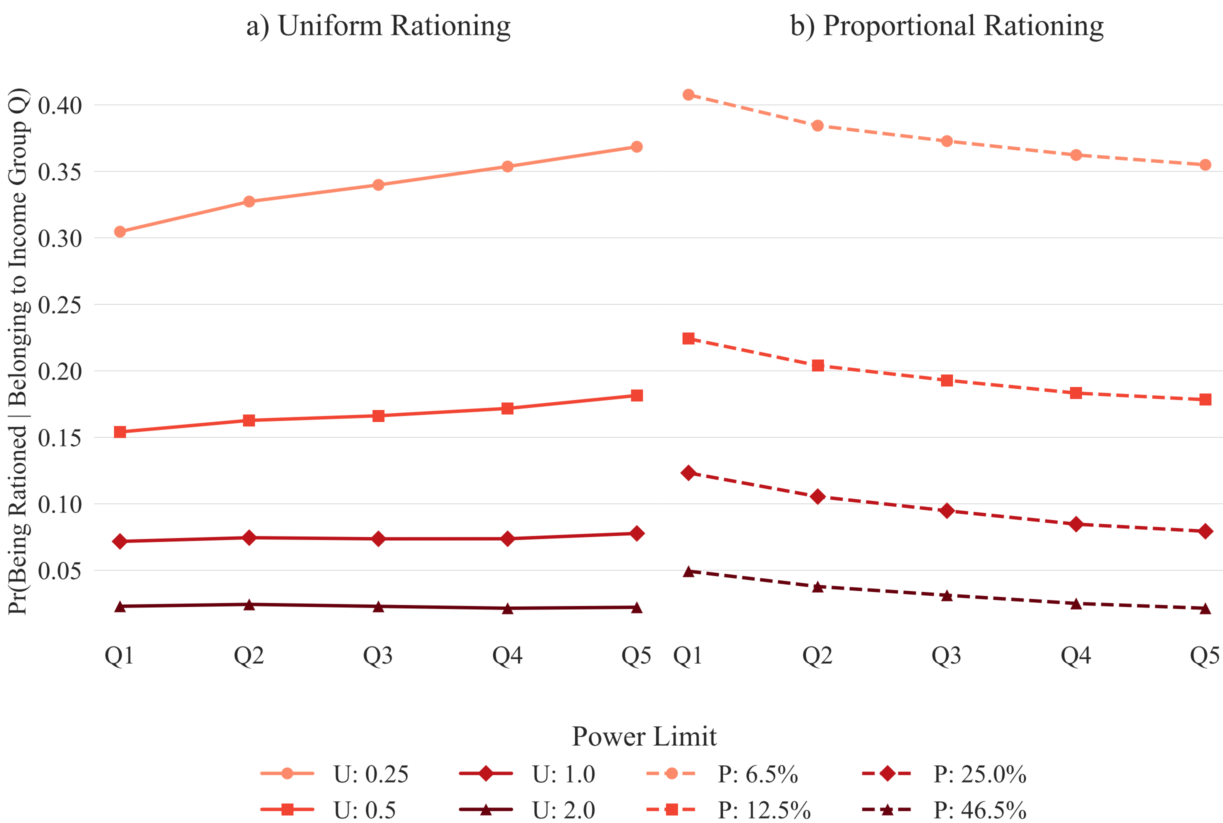
Notes: The unit of observation is a household (meter). $\overline{c}$ is the average hourly consumption, $\overline{sd}$ is the average daily standard deviation, and $\overline{c_{max}}$ is the average maximum daily (all in kWh). The contracted power represents the maximum power a household can contractually 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 1.28 million households. On the left-axis, one can see the rationed households vs. those experiencing a blackout, 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 (orange diamonds). For $\kappa = 2$, the maximum blackout-equivalent reduction is about 8%, achieving substantial savings while still allowing significant power use.

Figure 2: Probability of rationing as a function of income



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) for a) uniform rationing and b) proportional rationing. Rationing limits for uniform rationing (U) are defined in kW, rationing limits for proportional rationing (P) are defined as % of contracted power.

A Additional Online Material (non-essential)

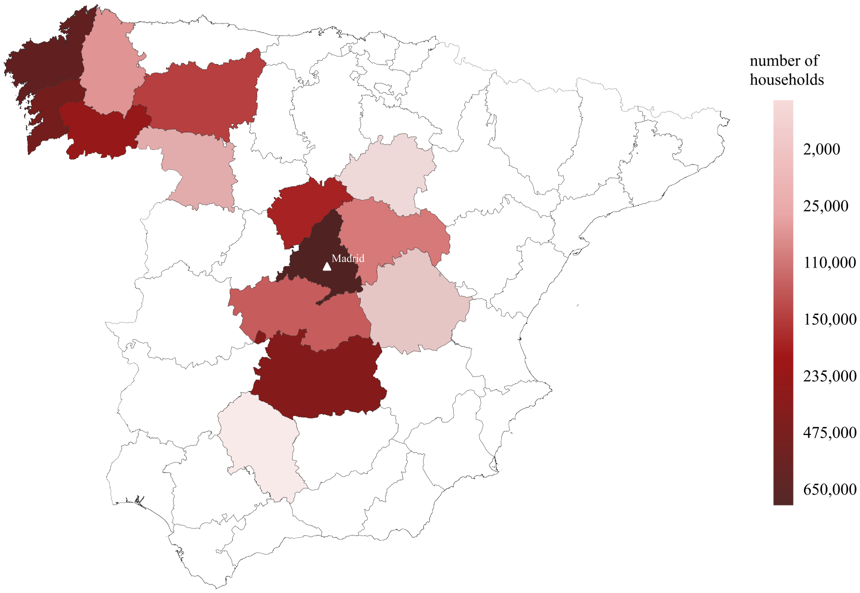
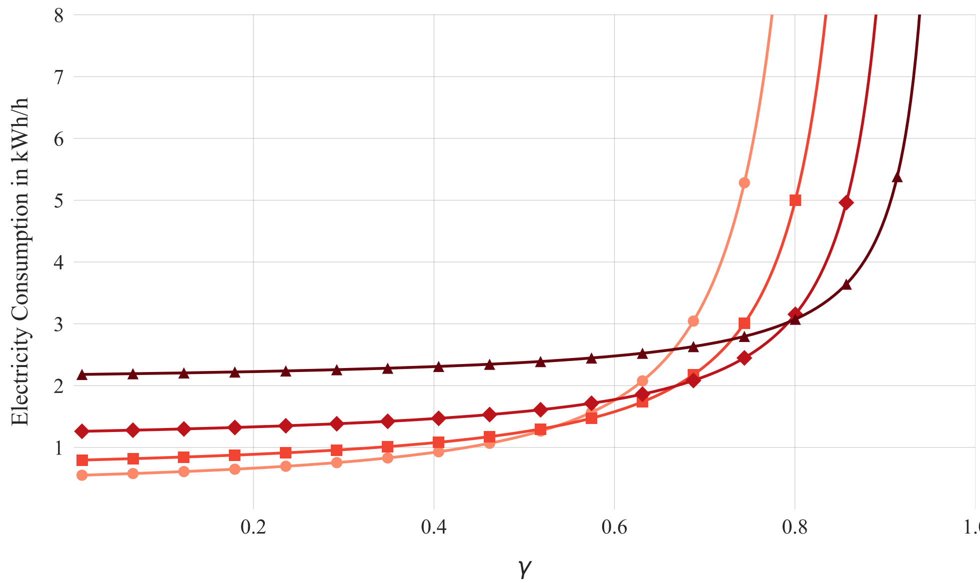
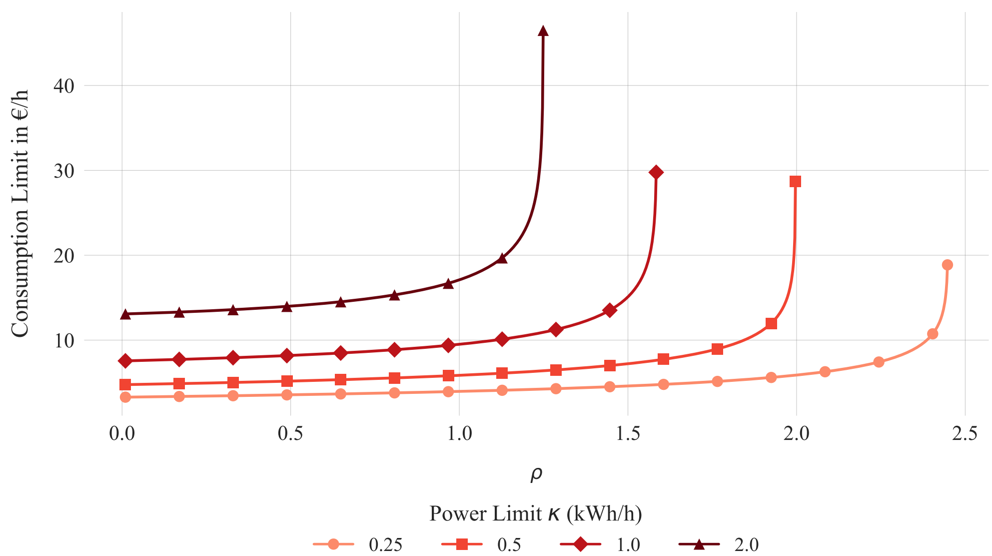


Figure A.1: Map of households in the distribution area

Figure A.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 interpreted as an hourly bargain in EUR.

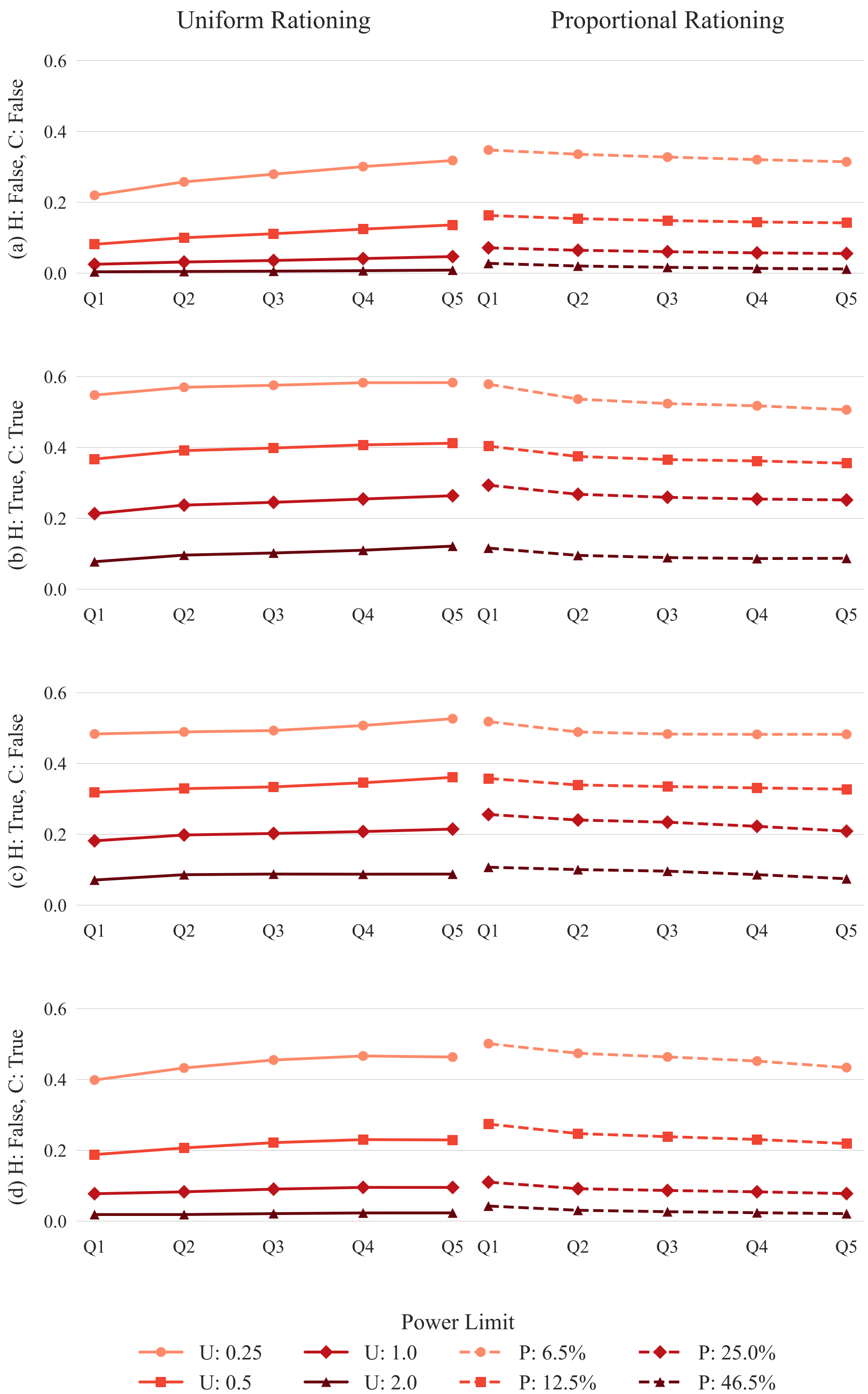
A.1 Role of HVAC

We calculate the probability of being rationed along the income distribution and different HVAC modes. As Figure A.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.4). This outcome may reflect that, in the absence of HVAC systems, higher-income households can display less energy-efficient behaviors than lower-income households.[17]

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 A.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).

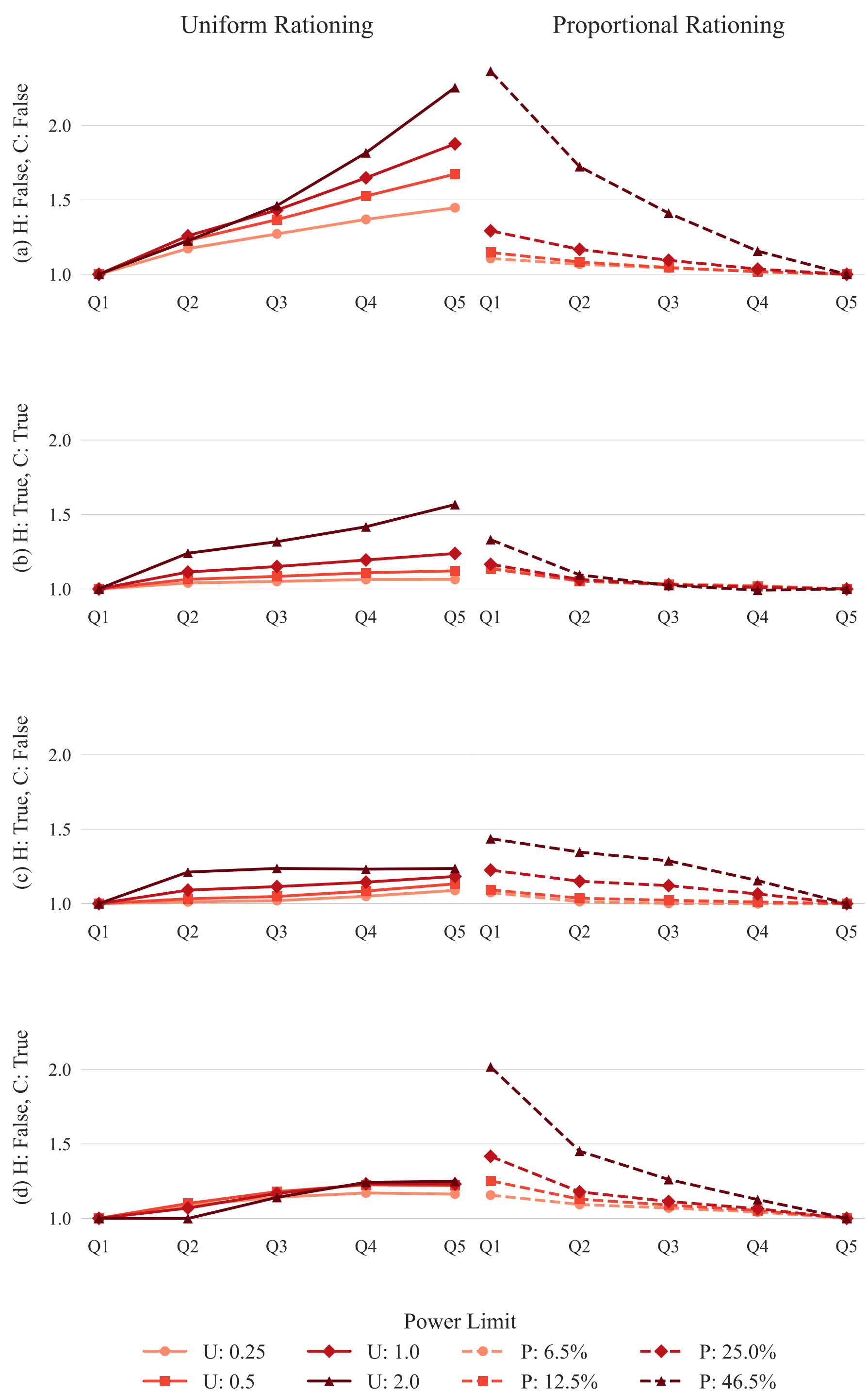
[17] Additional research might also consider other potential contributing factors, such as ownership of other electrical appliances, household size, or lifestyle.

Figure A.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) for both uniform and proportional rationing. 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 electric cooling. Rationing limits for uniform rationing (U) are defined in kW, rationing limits for proportional rationing (P) are defined as % of contracted power.

Figure A.4: Relative probability of rationing as a function of income for uniform and proportional rationing



Notes: This figure compares the relative probability of rationing for uniform rationing (left-hand side) and proportional rationing (right-hand side). For uniform rationing (proportional rationing), the figure shows the probability of a household getting rationed relative to the conditional probability of the lowest (highest) income quintile, Q1 (Q5). 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 electric cooling.