Smart Power Limits:
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 may fail to curb demand, making shortages more common. We examine a power limit policy for residential electricity households that rations electricity consumption rather than setting it to zero, as in a traditional rolling blackout. We find that power limits can provide equivalent savings to large blackouts, even when generous. Additionally, due to selection, power limits reduce the number of households affected by a shortage event. We conclude by discussing the welfare consequences of power limits and their heterogeneous impact 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, the market may fail to clear. For example, high prices may not sufficiently curb demand during extreme events or unexpected shocks (Labandeira et al., 2017; Zhu et al., 2018; Romero-Jordán et al., 2014), particularly if consumers are unable or slow to adjust their consumption (Joskow and Tirole, 2007; Borenstein et al., 2023). In these cases, non-price interventions may be necessary to balance demand and supply, and shortages may occur. Indeed, rationing has been applied in a variety of scarcity situations for essential goods, such as limited gasoline access during the oil crisis in 1973 (Horowitz, 1982), reduced access to water during droughts (Renwick and Green, 2000; Ryan and Sudarshan, 2020; Abajian et al., 2024) or cutting off households' electricity supply during extreme weather events (Hunt. et al., 2018).

Climate change poses a growing threat to ensuring the provision of basic necessities, particularly during extreme events, and makes shortages potentially more frequent. 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] These conditions not only threaten the energy supply but also water provision for agricultural and residential users.[3] Due to the significant costs and distributional implications of shortages, regulators need to prepare for unexpected emergencies in which pricing alone may not be an effective tool to clear the market (Levin et al., 2022; Renwick and Green, 2000; Joskow and Tirole, 2007).[4] Improving shortage mechanisms has the potential to increase welfare 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 cap of \$9,000/MWh 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 ripple effects on retailer bankruptcies and household bills, highlighting the potential limitations of the price mechanism when dealing with essential goods during

[1] Pörtner et al. (2022) report 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 increasing. 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] For example, 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.

extreme events in otherwise well-functioning markets.[6]

In this paper, we focus on exploring alternative shortage mechanisms in the electricity residential segment. In most electricity markets, shortages cause households to lose access to electricity entirely, in the form of rolling blackouts. Rather than relying on blackouts to reduce demand, which is an extreme form of rationing, we study power limits using smart meters. The mechanism, also known as load limiting, uses the capabilities of smart meters to dynamically limit households' maximum consumption depending on the severity of the shortage, while still permitting some consumption. 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 power limits 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 by spreading the burden. Yet, we theoretically show that there exist general conditions under which power limits leave *fewer* households affected by the event, making the acceptability of power limits even more viable. The result works via *selection*. The distribution of electricity consumption is heavy-tailed, meaning that high-energy users are the ones contributing disproportionately to demand reductions. For the affected households, we highlight the risk reduction properties of the mechanism and show conditions under which power limits are an ex ante Pareto improvement to risk-averse households. These conditions depend on the preferences for risk under standard utility functions. We find that, under reasonable theoretical parameters, power limits may be a "no-brainer." This result applies to the rationing of goods whose distribution is heavy-tailed.

Empirically, using data from more than 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 power limits versus implementing 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 empirically examine 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. (2024) to assess first whether setting a uniform limit appears to be regressive, and second how it compares to setting a power limit proportional to the maximum contracted power that households pay for, which is highly correlated with income.[8] We find that high-consumption households, which tend to be higher-income in our data, are most affected by uniform limits. Thus, the approach could reduce 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). Secondly, electrical heating also plays a critical role for higher limits that heavily select these users, making the welfare considerations more nuanced when the targeting of high electricity users is more extreme. Finally, proportional limits affect more households than under a uniform limit, as high-income households contribute less on average towards electricity savings, disproportionately impacting lower income households.

[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 that already have this capability.

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

In summary, we highlight new shortage mechanisms enabled by smart meters. We provide a framework for assessing their benefits and costs. In many countries, these mechanisms could easily be implemented to improve blackout protocols. 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 better 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 We consider quantity mechanisms during extreme events. These mechanisms are often necessary during a shortage situation due to the need to ensure that quantity limits are enforced properly (Weitzman, 1974). 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). Additionally, while prices are often argued to be efficient, by allocating goods to those with the highest willingness to pay, they may not be equitable during an extreme event and lead to substantial utility losses (Weitzman, 1977).

For residential electricity 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 as a differentiated non-linear price schedule. This targeted approach 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 that may lead to rationing. 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, even when the price cap is allowed to be quite large.

Other studies have explored targeted blackouts as an improved response. 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 Germany using the production function approach and use these estimates 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 impacting fewer individuals tend to reduce damages more effectively, reinforcing our focus on the number of households as a key objective. Instead of focusing on how to improve rolling blackouts that apply to large areas, we explore power limits at the household level. However, these could be combined with other targeting strategies.

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

We focus on quantity-only mechanisms, but smart meters are already used in many countries in Europe as part of the pricing contract, to allocate fixed cost. In future work, we plan to explore emergency-contingent capacity contracts, similar to those used in industrial settings, such as interruptible contracts, and formally studied in the priority service literature (Chao and Wilson, 1987). Although the burden on low-income households may be socially unacceptable and the price response may be too uncertain during extreme events, these contracts may be attractive to increase demand response in the presence of renewable intermittent sources (Chao et al., 2022).

Our analysis abstracts away from potential investments that households can make to protect themselves from blackouts (Brown and Muehlenbachs, 2024), which are likely to be adopted by higher income households (Brehm et al., 2024). Although these dynamic considerations are beyond the scope of the paper, power limits tend to put a larger burden on high-income households and might encourage useful investments by the most able households.

In summary, this study contributes to the existing literature in two 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.

2 A Framework for Power Limits

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 power limit that sets a maximum amount $\kappa \in [0, \overline{\kappa}]$ 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. Intermediate values of κ may limit consumption to some users, but not all.

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* blackouts, 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 Uniform power limits

Smart meters allow for individual-specific power limits that are above zero and can be digitally adjusted during an extreme event that is known in advance, as during a planned blackout. This is in contrast to traditional meters, whose limit cannot be easily adjusted. Although limits can be flexibly set, rules might need to be simplified in practice due to informational 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 power limits in which households are randomly selected with some exogenous probability β and, conditional on being selected, they get their consumption limited to a common threshold $\kappa \in (0, \overline{\kappa})$. This simple rule can be easily conveyed to households. Because it does not entail targeting or customization, it is simple to implement. It is analogous to a rolling blackout, but selected households receive access to some electricity, rather than zero.

Under power limits 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^* and are selected with probability β^* so that total demand is equivalent to a share $(1-\alpha)$ of D.

This simple rule 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. While this is not modeled explicitly in the framework, it is likely to benefit all households.

Along the blackout-equivalent frontier, maximizing κ by setting $\beta = 1$ can be a natural benchmark under a declining marginal utility of consumption. 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 selected for a given power limit, and therefore the maximum equivalent blackout is achieved.

Definition 2. *The* ***maximum equivalent blackout*** *that can be achieved by a power limit policy with $\kappa > 0$ is*

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

This maximum blackout size can be useful to assess the extent to which power limits can mimic the demand-reduction impact of rolling blackouts, which is an empirical question.

2.3 Effectively selected 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 their consumption and it can create some practical inconveniences, which we discuss below in more detail. Therefore, it is useful to get a sense of the number of households impacted by the policy.

Definition 3. *Denote $\delta \equiv \beta/\alpha$, i.e., how many more households need to be selected under a limit to match blackout savings of α. Naturally, for any α-equivalent policy with $\kappa > 0$, $\delta \geq 1$.*

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 also those for whom the power limit is binding.

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

We find that the number of effectively selected households is not necessarily larger under a power limit than a blackout. More concretely, the number of households that are *effectively* selected 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 selected consumers ϕ under an α-equivalent policy are less than those selected by a blackout of size α as long as,*

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

Whether the power limiting event needs more 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 power limits and blackouts is the same in expectation. Therefore, **heavy-tailed distributions** lead to fewer consumers effectively selected than under a blackout.*[11]

Depending on the distribution of electricity consumption at a given point in time, there could be situations in which power 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 power limit mechanism 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.

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

2.4 Extensions

In the simulations, we consider two extensions: considering the impact of limits on households throughout an entire day and considering a power limit that is proportional to the maximum limit that households pay for in our sample.

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 selected during a subset of hours.

Mathematically, we can interpret this increased probability of being effectively selected as a function of the multi-dimensional distribution of electricity consumption during the day. A household is "effectively selected" 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 hourly probability.

The extent to which power limits will affect many households under these broader interpretation is an empirical question, and it will depend on the within- vs. across-household consumption variation. If electricity consumption is persistent within 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 to proportional power limits We also examine a second power limit that sets household-specific limits based on their 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 limits affect fewer households than rolling blackouts depends on the joint distribution $f(x_i, p_i)$ and the value of consumption x_i. A fat-tailed distribution of the ratio of $\frac{x_i}{p_i}$ does not necessarily imply that this power limit targets high consumers, as the ratio could be high for low consumers with low contracted power and high for consumers with high consumption and high contracted power.

2.5 Welfare considerations

Given the severity of blackouts, which provide a consumption of zero to households during the event, we may expect power limits to improve overall average welfare. In fact, this is true by construction, at least weakly, as a power limit equivalent to a rolling blackout remains in the feasible set.

A harder question is under which conditions a power limit can be a Pareto improvement. For households with consumption below the limit, it 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.

For households with $x_i > \kappa$, whether they are better off under a power limit scheme will depend on their consumption and risk tolerance. Households will be better off as long as,

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

Under the stylized case in which $U(0) \to -\infty$, all households prefer power limits. For example, with a constant relative risk aversion (CRRA) utility function, $U(c) = \frac{c^{1-\gamma}}{1-\gamma}$, power limits 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 still conclude that all households are better off due to the substantial decreasing marginal utility of electricity consumption.

For these two stylized utility functions, we derive conditions under which a power limit is a Pareto improvement.

Result 3. *Under CRRA utility function and $\gamma \geq 1$, all households are better off with power limits. 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]

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.

One can also consider the level of consumption that makes a household indifferent, holding the level of risk aversion constant. We calculate this in Result 4.

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.*

This limit is naturally above the actual power limit and increases with risk aversion, as households are more willing to be partially rationed if they are averse to a blackout. 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 and a function of the empirical distribution of demand.[14]

Although these are admittedly stylized representations of utility, they can provide an additional theoretical rationale for their welfare benefits with respect to a blackout.

3 Empirical assessment

We use smart meter data from nearly 1.3 million Spanish households to compare power limits to rolling blackouts. The data covers the period from January 1st, 2016, to April 30th, 2017 and it was provided by one of the largest Spanish utility companies. The geographic distribution of households is shown in the Appendix in Figure A.1.

Spain provides a good application as power limits are already available and part of the contracting environment. Smart meters let utilities set a maximum electricity consumption level per household, known as the "contracted power." This power limit does not reduce the flow of electricity but ensures that consumption stays within the specified limit. If a household's electricity consumption exceeds this limit systematically,

[13]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 $-\alpha = -\beta \exp^{-\rho\kappa}$.

[14]In our application, we find that, for low levels of risk aversion, the effect of κ dominates. Thus, more households consider the mechanism a Pareto improvement with higher κ, even restricting the attention to households that are always affected.

the circuit breaker trips.[15] To restore power without another disconnection, households must first reduce usage, such as by unplugging appliances, and reconnect (remotely or at home). If the household is empty during the power cut or unable to react, the disconnection may cause welfare losses (e.g. spoiled food).[16]

The data include hourly electricity consumption (kWh) at the household level, their contracted power, and their postal code. We combine these data with estimates of household-specific income and heating/cooling mode (HVAC) from Cahana et al. (2024). 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, electricity usage, and contracted power.

3.1 Simulating power limits

Our simulated power limits will consider the thought experiment in which the Spanish utility exceptionally adjusts the contracted power of households during an extreme event, which would be communicated in a similar fashion as a rolling blackout, but with consumption limits.[17] In our simulations, we calibrate the policy to achieve a 5% blackout.

For our simulations, we examine two sets of consumption limits: a *uniform limit*, in which all households face the same absolute cap on usage and a *proportional limit* where each household's cap is set as a share of its contracted power. For the uniform rule, conditional on being selected, we set the consumption of a household to

$$\hat{x}_{ih}^{U}(\kappa) = \min\{x_{ih}, \kappa\} \text{ for } \kappa \in \{0.25, 0.5, 0.75, 1, 1.5\},$$

in kWh per hour.[18] For the proportional rule, we set

$$\hat{x}_{ih}^{P}(\kappa) = \min\{x_{ih}, \kappa\overline{x}_i\} \text{ for } \kappa \in \{0.07, 0.15, 0.25, 0.35\},$$

where κ is interpreted here as the limit proportional to each household's individual contracted power, denoted by $\overline{x}_i$.

Note that our calculation imposes consumption limits in kWh, but power limits are enforced 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

[15] Voltage and amperage levels remain within standard operating ranges, preventing damage to electrical and electronic equipment.

[16] With minor changes to the electrical panels of households, utilities can automatically reconnect households at the end of the event. If many households are unaware or absent, the mechanism approaches a rolling blackout in the limit.

[17] Advance notifications could include guidance on which appliances could be used, depending on the limit. This approach could help address concerns about households' limited knowledge of their appliances' power consumption, leading to inefficient energy use and recurrent power cuts (Chen et al., 2015; Attari et al., 2010). In our empirical context, households are familiar with power limits, making these concerns less severe.

[18] Note that this provides a conservative amount on energy curtailed, as in practice most households would consume substantially less than κ after being tripped.

limit (kW), even if total hourly consumption (kWh) remains within bounds. We are limited by the hourly nature of our data, but the impact on our results is attenuated for the following reasons. First, short-lived fluctuations do not trigger power limits, as the smart meter will tolerate temporary overages. Secondly, as shown in Panel a) in Figure 2, our results are robust to excluding households with high-consuming cyclical appliances such as air-conditioning and heating.

3.2 Blackout-equivalent frontier

For each power limit, we compute how many households must be randomly selected to achieve the same energy reduction to that resulting from a household experiencing a blackout, denoted by δ (light bars in Figure 1). For the case of a uniform limit of $\kappa = 0.25$, we find that $\delta = 2$, meaning that for each household experiencing a blackout scenario, two households need to be selected under the scheme. One can see that δ grows more than linearly as a function of the limit.

Being selected does not mean all households are affected; it is only binding if their usage exceeds κ. As κ increases, more households need to be randomly selected, but fewer are effectively rationed (dark bars in Figure 1). For $\kappa = 1.5$, nine times more households need to be selected but much less than one is impacted by the event. As a result, the average consumption of rationed households rises, as savings are concentrated among a smaller, more heavily rationed group. We focus here on the uniform rule, but similar results can be found for the proportional rule (see Appendix Figure A.2).

Introducing daily events, in which households are selected for the entire day, increases the probability of being affected *at some point* during the day. For $\kappa = 0.25$, one and a half households are affected, but, on average, only 47% of hours in a day (yellow circles in Fig 1). This number goes further down as the limit increases. The number of households affected during a daily power limit tend to increase under mid-range power limits, as variance in consumption within a household will tip them over the limit at some point during the day and more households are selected. As the limit grows, when $\kappa = 1.5$, the number of households can even decrease at a daily level, even if many more households are potentially affected.

The red diamonds in Figure 1 show the maximum energy savings at each limit if all households are selected into the scheme. For $\kappa = 1.5$, the maximum blackout-equivalent reduction is about 13%, while still allowing significant power use.

3.3 Utility-based indifference frontier

Using the estimated outcomes from Figure 1, we estimate the risk-aversion consumption indifference frontier. Figure A.3a 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 power limits to be a Pareto improvement.

Figure A.3b 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 power limits, as their utility function is less concave. For households that are not risk averse, the frontier converges to κ: households prefer a lower probability of a blackout than being selected more often.

For the CARA utility, there exists a threshold ρ above which all households prefer power limits. As κ increases, this threshold decreases, meaning that households need to be less risk-averse in order to prefer limits over blackouts. This implies that high limits are a Pareto improvement for a larger set of households. Overall, these simulations highlight the value of power limits in mitigating extreme utility losses from blackouts.

3.4 Income and alternative limits

We calculate the probability of being affected by power limits along income quintiles. To make the rules comparable, we compute hourly β values required to achieve the same aggregate energy reduction as a 5% blackout, which we use to derive household-level expected probabilities of being affected. These probabilities are then aggregated by income quintile.

The probabilities vary significantly between income groups but all of them are below 5%. Uniform power limits are progressive while proportional limits are regressive (see Figure 2). Under uniform limits, higher-income households are more likely to be affected than lower-income households. This effect is particularly strong for households without heating or cooling appliances, as high-income households face an even greater likelihood of rationing (see Panel 3a in Figure 2). Due to the higher ownership of electric heating by low-income households, particularly in the Madrid region (Cahana et al., 2024), high limits can eventually be regressive due to the compositional mix in the HVAC mode (see Panel 2a in Figure A.4).

In contrast, proportional limits clearly disproportionately affect lower-income households. This is the result of the ratio of household consumption relative to contracted power: higher-income households tend to contract high power limits, paying for a buffer that protects them. 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. Because lower-income households tend to consume less electricity on average, proportional limits result in a greater number of households being affected to achieve the same overall energy savings as uniform limits.

The external validity of these results relies on the observed positive correlation between income, high electricity consumption, and contracted power. Although higher income is generally associated with greater electricity use (Kotsila and Polychronidou, 2021; Huang, 2015; Romero-Jordán et al., 2014), other factors such as household size, energy efficiency, appliance use, and insulation can play crucial roles in influencing consumption. As noted in Borenstein (2024), policies aimed at high electricity users may not necessarily target high-income households, as consumption patterns can vary regionally, change with the adoption of solar rooftops by wealthier households, and are influenced by other non-income factors. Therefore, the power limit scheme could be further refined with observable household attributes, such as household size, climate zones, 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 power limit mechanism, leveraging smart meter technology to limit household electricity consumption only during periods of potential shortages. Rather than implementing rolling blackouts, our mechanism ensures that households retain access to essential services like refrigeration and lighting by capping electricity usage with individualized limits. Through theoretical modeling and empirical analysis using data from more than a million Spanish households, we show that power limits affect fewer households than rolling blackouts. In addition, we find that under reasonable conditions, power limits can be a Pareto improvement for many households.

Our analysis opens several avenues for future research. How should more flexible blackout policies be implemented? Should the price mechanism be considered to manage scarcity conditions during extreme events? Should power 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.

References

Abajian, A., C. Cole, K. Jack, K. C. Meng, and M. Visser (2024). Dodging day zero: Drought, adaptation, and inequality in cape town. *Journal of the European Economic Association*. Revise and Resubmit.

Attari, S. Z., M. L. DeKay, C. I. Davidson, and W. B. de Bruin (2010). Public perceptions of energy consumption and savings. *Proceedings of the National Academy of Sciences 107*(37), 16054–16059.

Austin-Travis County (2021). Winter Storm Uri After-Action Report & Improvement Plan Technical Report. Technical report, City of Austin, Travis County. Accessed: October 21, 2024.

Becker, G. S. (1965, 09). A Theory of the Allocation of Time. *The Economic Journal 75*(299), 493–517.

Borenstein, S. (2024, January). Energy hogs and energy angels: What does residential electricity usage really tell us about profligate consumption? Working Paper 32023, National Bureau of Economic Research.

Borenstein, S., J. Bushnell, and E. Mansur (2023, December). The economics of electricity reliability. *Journal of Economic Perspectives 37*(4), 181–206.

Brehm, P. A., S. Johnston, and R. Milton (2024). Backup power: Public implications of private substitutes for electric grid reliability. *Journal of the Association of Environmental and Resource Economists 11*(6), 1419–1445.

Brown, D. P. and L. Muehlenbachs (2024). The value of electricity reliability: Evidence from battery adoption. *Journal of Public Economics 239*, 105216.

Byers, E. A., G. Coxen, J. Freer, and J. W. Hall (2020). Drought and climate change impacts on cooling water shortages and electricty prices in great britain. *Nature Communications 11*.

Cahana, M., N. Fabra, M. Reguant, and J. Wang (2024). The distributional impacts of real-time pricing. Technical report, CEPR Discussion Paper No. 17200. CEPR Press, Paris & London.

Chao, H.-P., S. Oren, and R. Wilson (2022, 9). Priority pricing for clean power under uncertainty. *Current Sustainable/Renewable Energy Reports 9*, 52–64.

Chao, H.-P. and R. Wilson (1987). Priority service: Pricing, investment, and market organization. *The American Economic Review 77*(5), 899–916.

Chen, V. L., M. A. Delmas, W. J. Kaiser, and S. L. Locke (2015). What can we learn from high-frequency appliance-level energy metering? results from a field experiment. *Energy Policy 77*, 164–175.

de Nooij, M., R. Lieshout, and C. Koopmans (2009). Optimal blackouts: Empirical results on reducing the social cost of electricity outages through efficient regional rationing. *Energy Economics 31*(3), 342–347.

Dludla, S. (2023). Eskom proposes r16bn smart-meter rollout to all households. Accessed: October 24, 2024.

Ganz, S. C., C. Duan, and C. Ji (2023, 10). Socioeconomic vulnerability and differential impact of severe weather-induced power outages. *PNAS Nexus 2*(10), pgad295.

Gerlagh, R., M. Liski, and I. Vehviläinen (2022). *Rational Rationing: A Price-Control Mechanism for a Persistent Supply Shock.* JSTOR.

Grafton, R. Q. and M. B. Ward (2008). Prices versus rationing: Marshallian surplus and mandatory water restrictions. *The Australian Economic Review 84*(1), S57–S65.

Haes Alhelou, H., M. E. Hamedani-Golshan, T. C. Njenda, and P. Siano (2019). A survey on power system blackout and cascading events: Research motivations and challenges. *Energies 12*(4).

He, G. and T. Tanaka (2023, 04). Energy saving may kill: Evidence from the fukushima nuclear accident. *American Economic Journal: Applied Economics 15*, 377–414.

Hellerstedt, J. (2021). February 2021 Winter Storm-Related Deaths - Texas. Technical report, Texas Department of State Health Services. Accessed: October 21, 2024.

Horowitz, J. (1982). Modeling traveler responses to alternative gasoline allocation plans. *Transportation Research Part A: General 16*(2), 117–133.

Huang, W.-H. (2015). The Determinants of Household Electricity Consumption in Taiwan: Evidence from Quantile Regression. *Energy 87*, 120–133.

Hunt., J. D., D. Stilpen, and M. A. V. de Freitas (2018). A review of the causes, impacts and solutions for electricity supply crises in brazil. *Renewable and Sustainable Energy Reviews 88*, 208–222.

Imelda and X. Guo (2024, Aug). Crime in the Dark: Role of Electricity Rationing. IHEID Working Papers 18-2024, Economics Section, The Graduate Institute of International Studies.

Jacobs, S. (2023). Eskom's plan to control electricity supply to every home in south africa. Accessed: October 24, 2024.

Joskow, P. and J. Tirole (2007). Reliability and competitive electricity markets. *The RAND Journal of Economics 38*(1), 60–84.

Kotsila, D. and P. Polychronidou (2021, 07). Determinants of household electricity consumption in greece: a statistical analysis. *Journal of Innovation and Entrepreneurship 10*.

Labandeira, X., J. M. Labeaga, and X. López-Otero (2017). A meta-analysis on the price elasticity of energy demand. *Energy Policy 102*, 549–568.

Lee, C.-C., M. Maron, and A. Mostafavi (2022, December). Community-scale big data reveals disparate impacts of the Texas winter storm of 2021 and its managed power outage. *Palgrave Communications 9*(1), 1–12.

Levin, T., A. Botterud, W. N. Mann, J. Kwon, and Z. Zhou (2022). Extreme weather and electricity markets: Key lessons from the february 2021 texas crisis. *Joule 6*(1), 1–7.

Nasr, J. and V. Eckert (2022). Germany girds for gas rationing, europe on edge in russian standoff. Accessed: October 21, 2024.

Peterson, S., S. Clark, M. Shelly, and S. Horn (2024, 03). Assessing the household burdens of infrastructure disruptions in texas during winter storm uri. *Natural Hazards 120*, 1–40.

Pörtner, H.-O., D. Roberts, M. Tignor, E. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, and B. Rama (Eds.) (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK and New York, NY, USA: Cambridge University Press. pp. 1470, 1963.

Renwick, M. E. and R. D. Green (2000). Do residential water demand side management policies measure up? an analysis of eight california water agencies. *Journal of Environmental Economics and Management 40*(1), 37–55.

Romero-Jordán, D., C. Peñasco, and P. del Río (2014). Analysing the determinants of household electricity demand in Spain. An econometric study. *International Journal of Electrical Power & Energy Systems 63*, 950–961.

Ryan, N. and A. Sudarshan (2020, July). Rationing the commons. Working Paper 27473, National Bureau of Economic Research.

Stone, B., E. Mallen, M. Rajput, C. Gronlund, A. Broadbent, E. Krayenhoff, G. Augenbroe, M. O'Neill, and M. Georgescu (2021, 04). Compound climate and infrastructure events: How electrical grid failure alters heat wave risk. *Environmental science & technology 55*.

Tokarski, F., S. D. Kominers, M. Akbarpour, and P. Dworczak (2023). A market-design response to the european energy crisis. Technical report, Technical Report, Stanford University, Jan 8.

Vliet, M. T. H., J. R. Yearsley, F. Ludwig, S. Vögele, P. Dennis, Lettenmaier, and P. Kabat (2012). Vulnerability of us and european electricity supply to climate change. *Nature Climate Change 2*, 676–681.

Weitzman, M. L. (1974, 10). Prices vs. quantities12. *The Review of Economic Studies 41*(4), 477–491.

Weitzman, M. L. (1977). Is the price system or rationing more effective in getting a commodity to those who need it most? *The Bell Journal of Economics 8*(2), 517–524.

Wolak, F. A. (2022). Long-term resource adequacy in wholesale electricity markets with significant intermittent renewables. *Environmental and Energy Policy and the Economy 3*, 155–220.

Wolf, A. and L. Wenzel (2015). Welfare implications of power rationing: An application to germany. *Energy 84*, 53–62.

Yalew, S., M. van Vliet, D. Gernaat, F. Ludwig, A. Miara, C. Park, E. Byers, E. De Cian, F. Piontek, G. Iyer, I. Mouratiadou, J. Glynn, M. Hejazi, O. Dessens, P. Rochedo, R. Pietzcker, R. Schaeffer, S. Fujimori, S. Dasgupta, and D. Vuuren (2020, 10). Impacts of climate change on energy systems in global and regional scenarios. *Nature Energy 5*.

Zhu, X., L. Li, K. Zhou, X. Zhang, and S. Yang (2018). A meta-analysis on the price elasticity and income elasticity of residential electricity demand. *Journal of Cleaner Production 201*, 169–177.

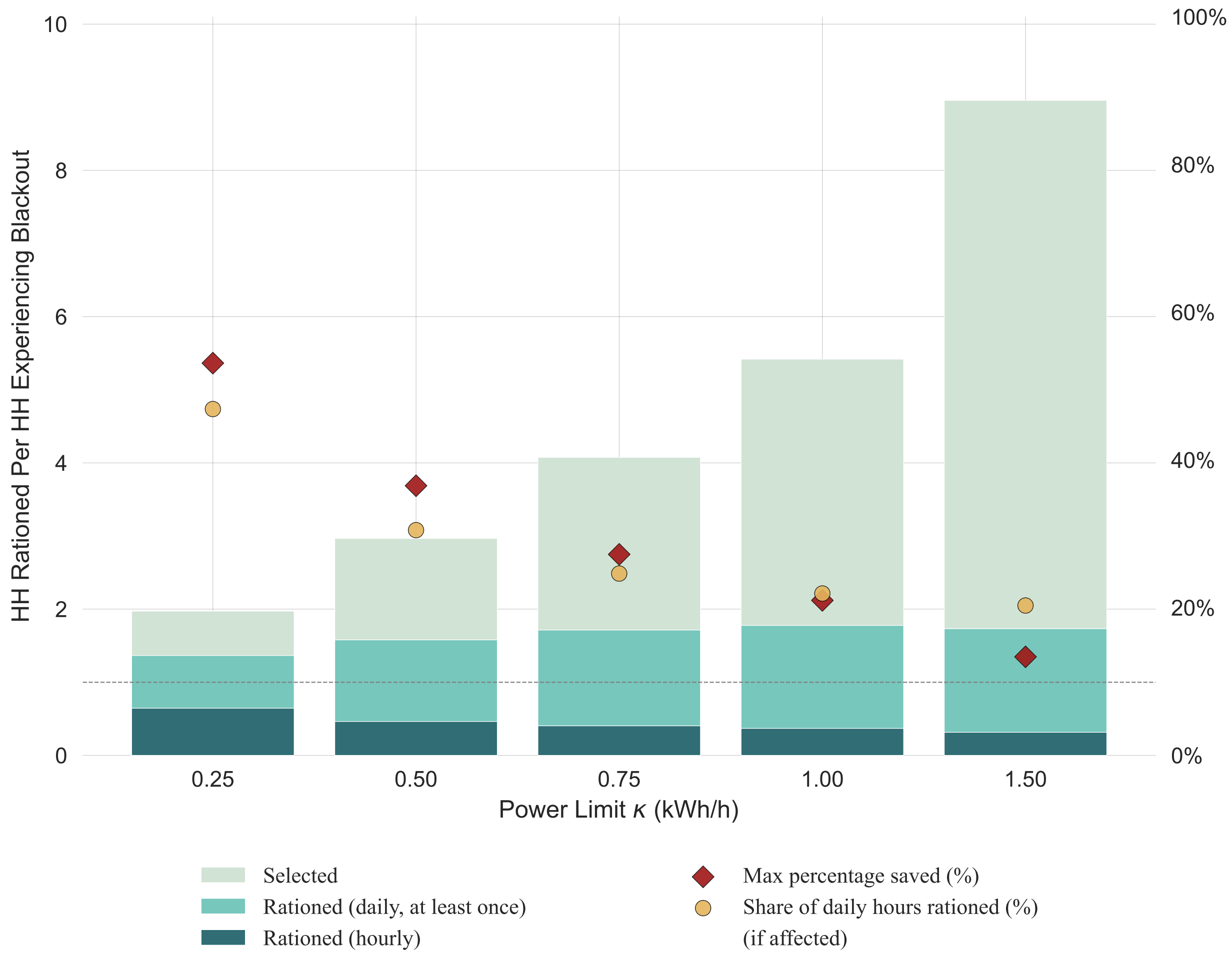
Tables and Figures

Table 1: Summary of Income Quintile

	$\overline{c}$	$\overline{\text{sd}}$	$\overline{c_{\max}}$	CP	θ_h	θ_c	N
Full sample	0.35	0.27	1.09	4.28	18.1	15.8	1,303,355
	(3.18)	(7.10)	(1.06)	(1.89)			
By HVAC							
No Heating or Cooling	0.25	0.19	0.80	4.03			909,102
	(3.77)	(8.47)	(0.63)	(1.75)			
Only Cooling	0.43	0.29	1.22	4.57			158,023
	(0.49)	(0.25)	(0.95)	(2.11)			
Only Heating	0.68	0.56	2.04	4.95			188,902
	(0.64)	(0.53)	(1.62)	(1.84)			
Heating and Cooling	0.79	0.29	2.29	5.48			47,328
	(0.66)	(0.53)	(1.68)	(2.38)			
By Income Quintile							
Q 1	0.33	0.26	0.99	3.47	27.5	18.0	254,204
	(0.11)	(0.16)	(0.37)	(1.45)			
Q 2	0.34	0.27	1.06	4.00	22.1	18.8	261,707
	(0.10)	(0.11)	(0.40)	(1.77)			
Q 3	0.35	0.27	1.09	4.32	19.6	20.3	263,117
	(0.11)	(0.12)	(0.42)	(1.91)			
Q 4	0.36	0.28	1.12	4.67	16.4	21.5	265,250
	(0.11)	(0.13)	(0.45)	(1.97)			
Q 5	0.37	0.29	1.17	4.91	14.4	21.5	259,077
	(0.12)	(0.15)	(0.47)	(1.95)			

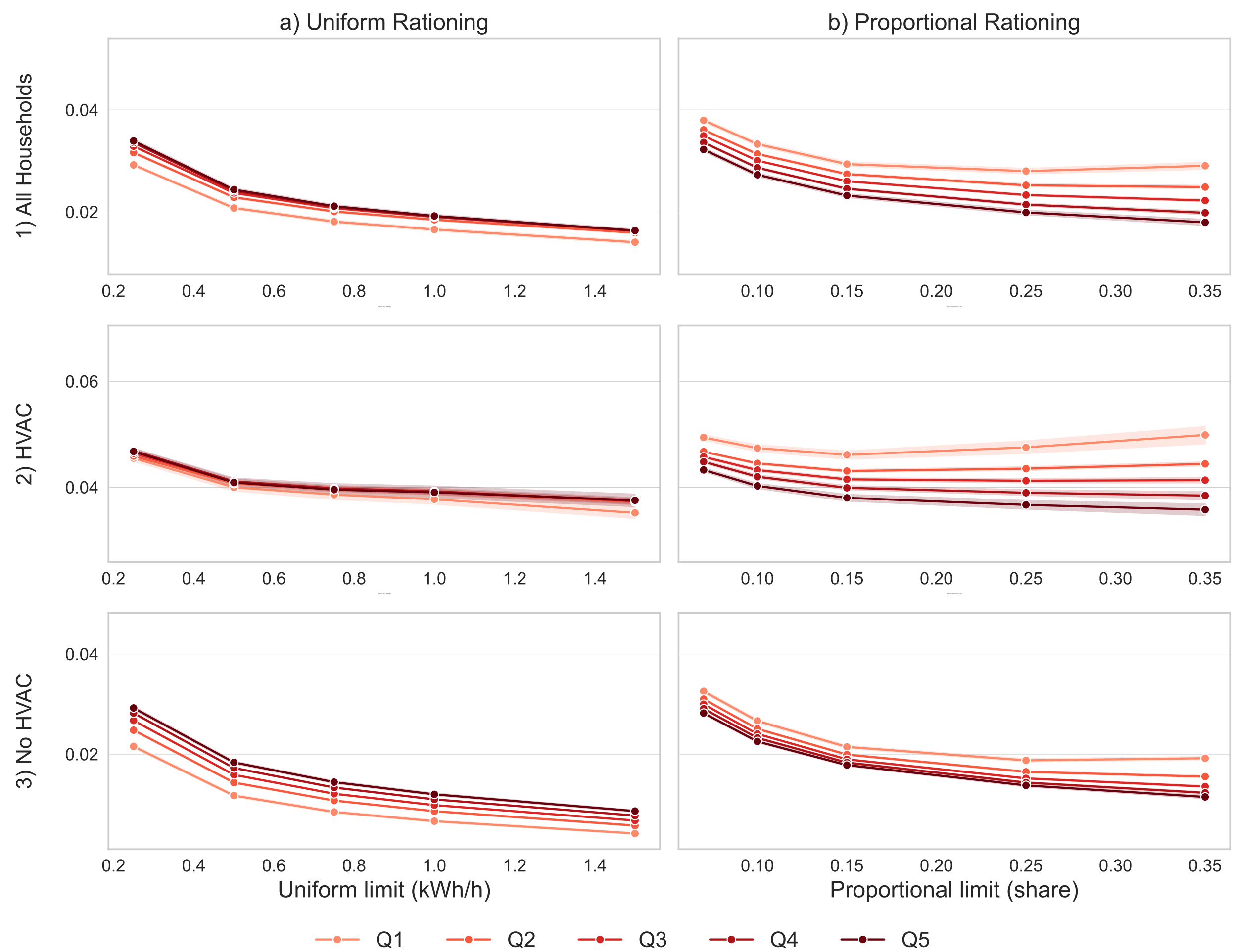
Notes: The unit of observation is a household (meter). $\overline{c}$ is the average hourly consumption, $\overline{sd}$ is the average daily standard deviation, and $\overline{c_{max}}$ is the average maximum daily (all in KWh). The contracted power represents the maximum power a household can contractually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

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



Notes: This figures shows power limits 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. The red diamonds show the maximum attainable size of a blackout that can be achieved with a limit κ. For $\kappa = 1.5$, the maximum blackout-equivalent reduction is about 13%, achieving substantial savings while still allowing significant power use. The yellow circles show the share of hours in a day in which households are affected, conditional on being affected at all.

Figure 2: Probability of affected 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 power limit mechanism along the income distribution (in quintiles) for uniform and proportional limits. Power limits for a) uniform power limits are defined in kW, power limits for b) proportional power limits are defined as % of contracted power. Panel 1) shows the outcome for the full sample, panel 2) for households with both heating and cooling, and panel 3) for households without electrical heating or cooling. The shaded area represents the variation in outcomes across different model specifications.

A Additional Online Material (non-essential)

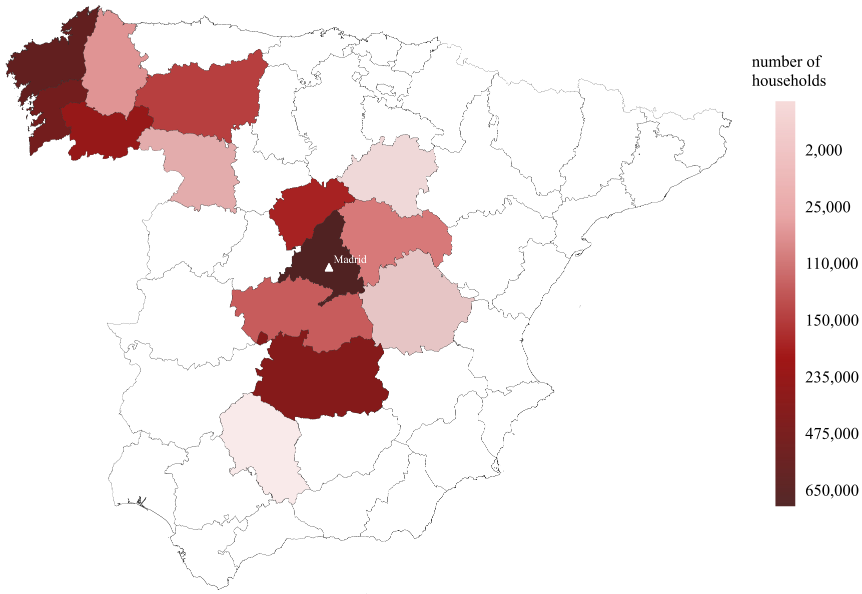
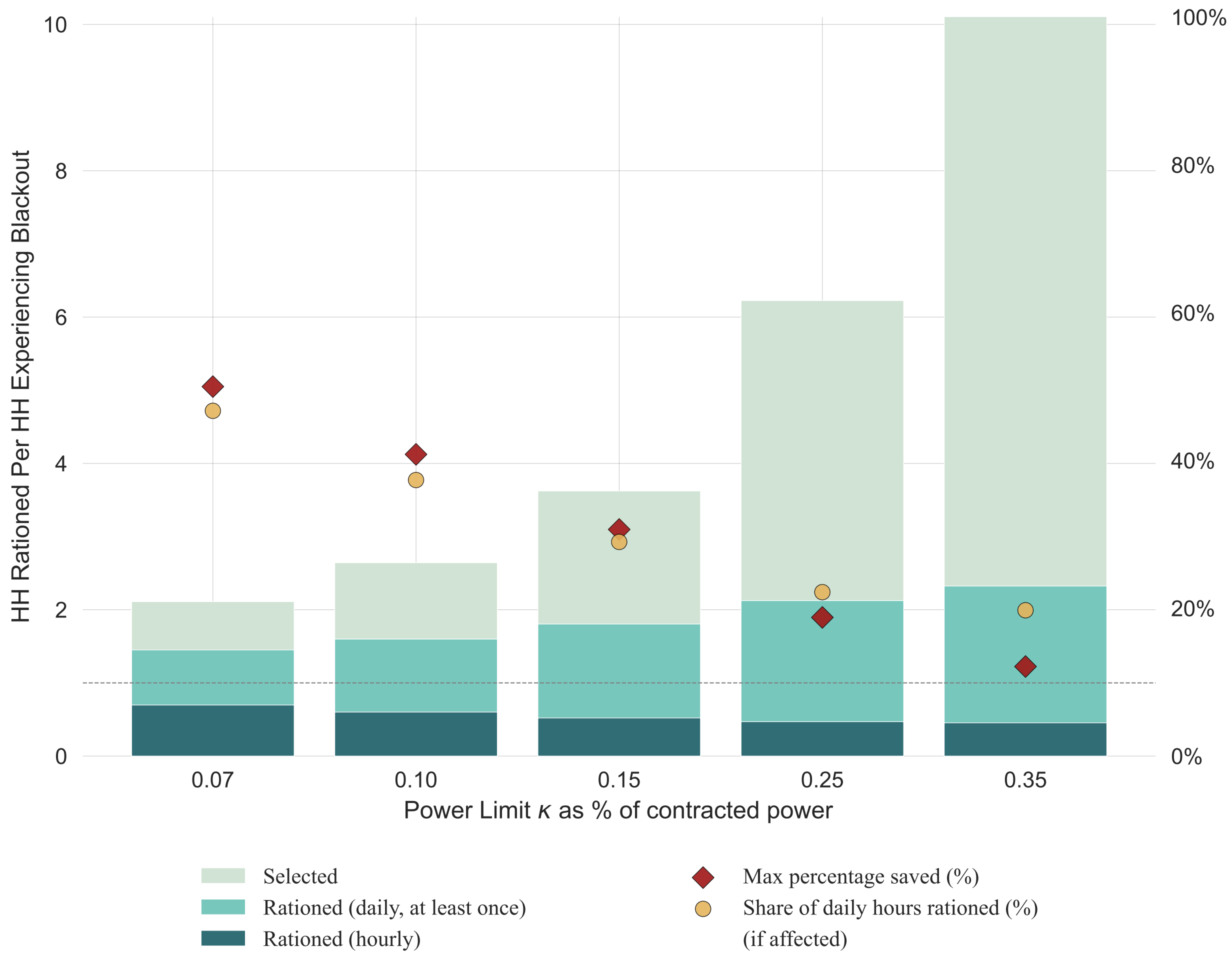


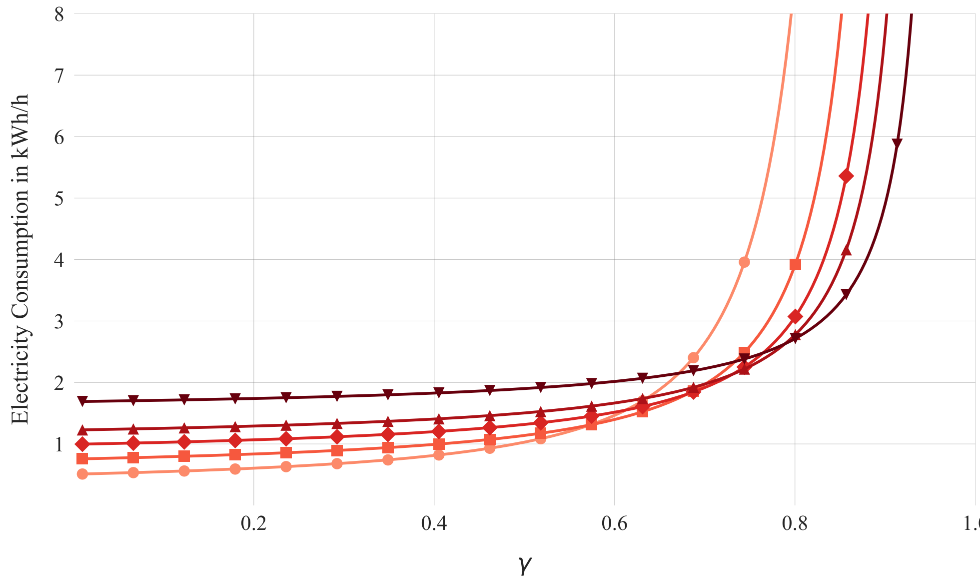
Figure A.1: Map of households in the distribution area

Figure A.2: Comparing the performance of blackouts vs. proportional power limits

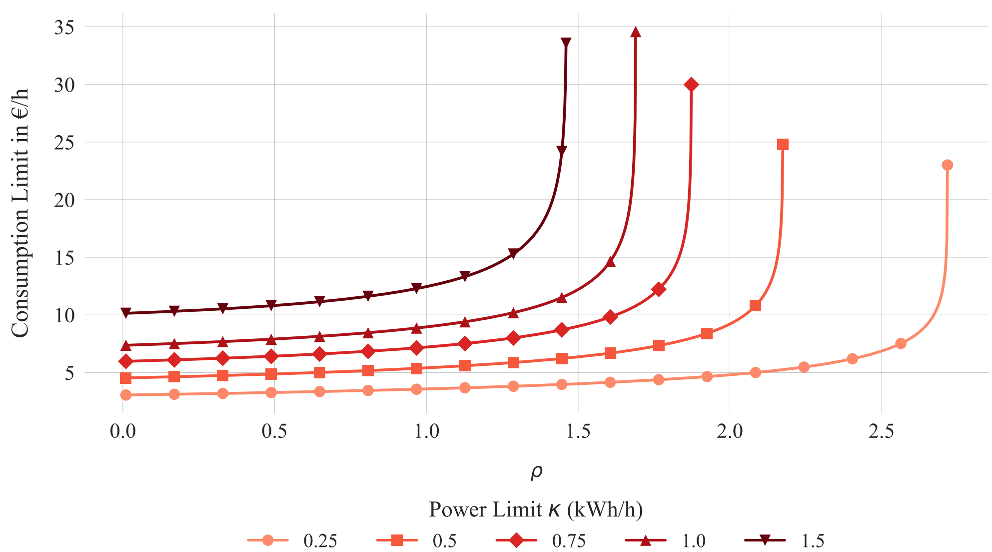


Notes: This figures shows power limits outcomes from hourly data of 1.28 million households. On the left-axis, one can see the rationed households vs. those experiencing a blackout, i.e., β/α. Selected households are displayed in light green, while rationed households for a given hour are displayed in dark green and households rationed at least one hour in a day are display in teal. The red diamonds show the maximum attainable size of a blackout that can be achieved with a proportional limit. The yellow circles show the share of hours in a day in which households are affected, conditional on being affected at all.

Figure A.3: Pareto-indifference curve between a blackout and power limits



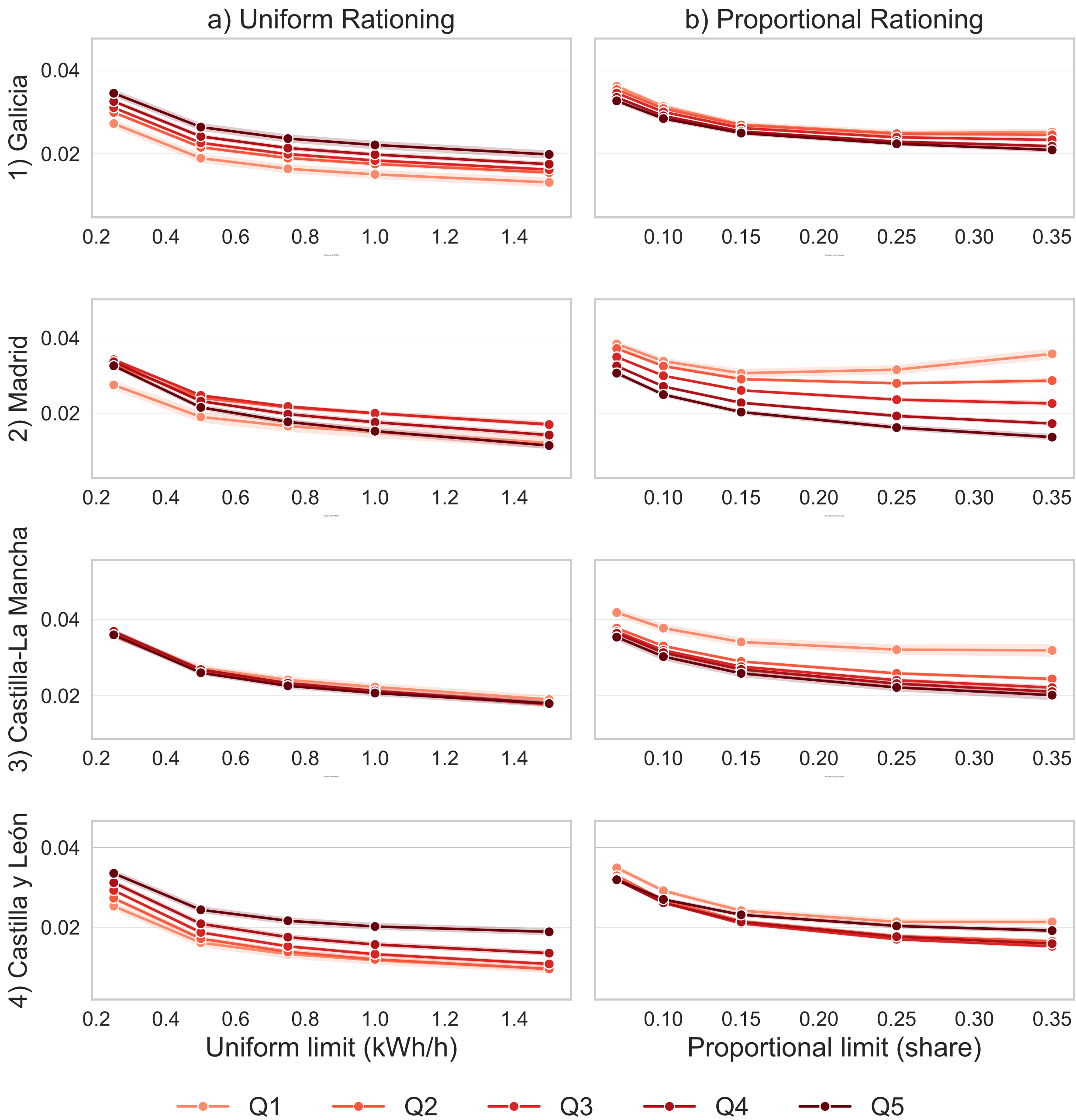
(a) CRRA Utility Frontier



(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 power limit 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.

Figure A.4: Probability of being affected by region



Notes: This figure shows the probability of a household getting rationed when it is selected under the power limit mechanism along the income distribution (in quintiles) for uniform and proportional limits. Power limits for a) uniform power limits are defined in kW, power limits for b) proportional power limits are defined as % of contracted power. The shaded area represents the variation in outcomes across different model specifications. The results are grouped by state, representing four distinct states in Spain.