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# The flexibility gap: socioeconomic and geographical factors driving residential flexibility

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**Abstract**

Residential consumers are moving to the center of electricity systems and their flexibility is seen as a key resource to integrate renewable energy sources and support the grid. However, residential flexibility capacities are not homogeneous, as they depend on household appliances, comfort patterns, occupancy, and climate conditions. Here, we calculate the technical flexibility capacities of 45 consumer types in mainland Spain, organised according to income and regional criteria. We show that flexibility gaps exist at both regional and socioeconomic (income) levels with flexibility differences of up to 10 times more capacity between the household groups from the lowest to the highest capacities. These geographical and socioeconomic gaps in flexibility can lead to distortions in national markets and have the potential to exclude citizens from the provision of flexibility services. Our results show in quantitative terms that a consumer-centered approach without considering correcting measures nor these gaps in drafting energy policies may lead to increasing inequality levels in the residential sector. Under an economic competitive paradigm, households with lower income levels or located in regions with lower flexibility potential may be excluded from the provision of flexibility to the detriment of households with larger potential, raising justice concerns in a flexibility-based energy transition.

*Keywords:*
Residential flexibility, Energy inequality, Energy transition, Spain

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## 1. Introduction

If we aim to stay under a 1.5°C above pre-industrial levels climate scenario, Renewable Energy Sources (RES) will supply over 85% of electricity by 2050 (IPCC, 2018). This means a dramatic increase in the penetration of RES not only at the transmission and sub-transmission level (wind, hydro and large PV units) but also in the form of distributed generation, connected into the distribution grids, such as small scale PV combined with storage technologies (Rodriguez-Garcia et al., 2019). This massive integration of intermittent generation that will substitute fossil generation requires an increase in new flexible resources to maintain the stability and security of power systems at reasonable costs (Huber et al., 2014). Currently, this flexibility is mostly provided by centralised dispatchable generation (e.g. gas and hydro turbines) but, shortly, new forms of decentralised flexibility are expected from the demand side (Lund et al., 2015). These resources can bring enormous benefits to the system, including loss reductions (Bradley et al., 2013), increases in competition due to reductions in market power (Ribó-Pérez et al., 2019), as well as investments deferral and operational savings (Siano and Sarno, 2016).

From a technical perspective, demand side management and demand response are forms of providing additional ancillary services to the grid, either through direct or indirect incentives given to consumers (O'Connell et al., 2014). These resources have promising impacts on markets and system operations as well as introducing new opportunities for business models such as aggregators, energy communities, and energy services companies (Burger and Luke, 2017). These flexible services from demand resources are necessary for the system to ensure the security of supply and the reliability of the grid. From a policy perspective, the challenge is to unleash these flexible resources and create practical conditions for the massification of the flexibility services. After opening some ancillary services markets to large industrial consumers, the priority is now to extend these services to medium and small consumers, such as the residential sector, which represent between 30-40% of the final electricity consumption (IEA, 2017). To achieve this, several initiatives have been created to introduce the figure of the aggregator, allowing economies of scale in market participation (Burger and Luke, 2017), as well as to promote flexibility markets (Rodriguez-Garcia et al., 2019), and energy communities (Roby and Dibb, 2019).

At the level of the European Commission, these legal instruments and new business models have been introduced by recent directives (European Commission, 2019) with the aim of placing consumers in the center of the energy system, acting as rational and participatory agents in the market that provide flexibility services. The EU looks for consumers that generate their own electricity, choose better supply opportunities and deliver flexibility to the system in response to economic payments and incentives. Nevertheless, rational self-interest incentives are not the only driver of households' energy consumption or situation (Sánchez-Guevara Sánchez et al., 2020). The heterogeneity of the residential sector may lead to different levels of engagement and potential flexibility across consumers (White and Sintov, 2020). For example, the capacity to provide flexibility at the residential level is strongly linked with socioeconomic factors (such as income) as well as meteorological characteristics determined by the place where consumers are located. These factors are regionally determined and create regional gaps between the flexibility capacities of residential households. Thus, a significant portion of the electric flexibility is not determined by the consumers' behavior, but by their geographical and socioeconomic conditions. Unfavourable geographic and socioeconomic conditions may lead to inflexible consumption patterns, less ability to choose, and even exclusion from participating in new flexibility services. This exclusion may endanger the social objectives of the energy transition, especially in the context of the existing energy inequities already identified in both quantitative and qualitative terms (Carley and Konisky, 2020). Thus, as consumers' flexibility is brought to the center of electricity systems, the socioeconomic and geographic heterogeneity of the residential sector becomes a key aspect of policy definition and should be carefully studied to understand the differences and gaps in this capacity (Fell, 2020).

This paper contributes to the debate around the justice and distributional implications of energy transition by quantifying nationwide flexibility gaps in the residential sector across different levels of income and geographical locations in Spain. The analysis assumes clusters containing 1000 consumers. We build annual flexibility profiles of socioeconomic and regional clusters considering three income levels and fifteen regional locations. Then we obtain control groups at national, regional, and income levels by combining clusters according to their statistical representation in the population of the group. Finally, we create two simple indices to compare the clusters: 1) regional and seasonal flexibility gaps are described as a percentage difference in relation to the national average; 2) Socioeconomic flexibility gaps are described based on the ratio between AMI and LI groups. We find that citizens with economic conditions Above the Median Income (AMI), i.e. mid and high income groups, present 50 % more flexibility capacity than the Low Income (LI) group and regional gaps add up to 4 times more capacity. When combining geographic and socioeconomic gaps, it is possible to find capacity differences in a magnitude of 10 between LI groups in regions with lower flexibility and AMI groups in regions with higher flexibility. We believe that there is a need to point to and understand these gaps to address distributional issues in energy policies that will focus on untapped residential flexibility potential and at the same time, ensuring energy justice.

The rest of the paper is organised as follows. Section 2 presents the methodology background and the demand flexibility model of residential appliances. Section 3 provides information about the data and assumptions used in the study. The results and discussion arise in section 4, where the different flexibility gaps are presented. Section 5 concludes and draws the policy implications of this study.

## 2. Methodology

### *2.1. Background*

Unlike the flexibility of dispatchable generators, which can be directly derived from the technical limits and ramping characteristics of the generators, the quantification of demand flexibility is difficult to standardise, as it depends on a larger set of parameters including subjective factors such as comfort or consumption patterns. The definition of demand-side flexibility might change with the type of application, but it can be summarised as the availability of loads to respond with energy and power variations of consumption to an external signal sent by the system (Huber et al., 2014). Electricity consumption can be postponed or advanced thanks to thermal inertia or the possibility to defer certain loads without affecting comfort. In this sense, consumers can offer increases or reductions in the power demand with a time availability that relates to the energy that they can use but they do not.

In literature, several authors have modelled and quantified flexibility either from the perspective of the potential services or based on the nature of the consumption. The first approach quantifies flexibility considering the economic value of the demand participation in a specific service or market, including large-scale reserve and ancillary services (Ehrlich et al., 2015, Hao et al., 2015, Rodríguez-García et al., 2020) or local markets at the distribution grid level (Siano and Sarno, 2016). The second is agnostic to the flexibility valuation and focuses on the theoretical energy and power capacity potentials of demand change per consumer segments, either divided by continental regions (Gils, 2014) and individual countries (Aryandoust and Lilliestam, 2017) or by sectors of activity, such as residential (Reynders et al., 2017), office buildings (Chen et al., 2019), and industries (Rodríguez-García et al., 2020). The methodology used in this paper belongs to the latter category. We extend the existing literature by looking at the demand potential within the residential sector, considering both socioeconomic and geographical factors. The objective is to evaluate the fundamental differences in flexibility quantities, understood as the technical capacity that different clusters of residential households can offer the system fulfilling all comfort patterns, before assuming any particular flexibility service or value.

Two types of flexible loads in residential buildings are considered in this study: Shiftable Loads (SL) and Thermostatically Controlled Loads (TCL). The first group comprises household appliances that can be shifted in time, such as Dishwashers (DW), through behavioural changes or automatic control, whose flexibility is defined by an energy invariant time window (Fridgen et al., 2018). These demands are characterised by a determined consumption during consecutive time periods. They can be moved as a block from one time slot to another inside a range of hours established by household consumption patterns. The second group, TCLs, relates to loads that operate within a temperature band, such as Electric Heaters (EH) or Air-Conditioners (AC), acting as an energy reservoir that allows control without affecting consumers' comfort (Mathieu, 2012, Reynders et al., 2017). The thermal comfort is a characteristic embedded in the control of these loads (Callaway, 2009), while the energy needs and the flexibility are derived as a result of the consumers' comfort patterns and settings (Mathieu et al., 2013a). Our analysis is focused on the current individual household appliances that include Dish Washers (DW) and Washing Machines (WM) as SL and Electric Heaters (EH), Air Conditioners (AC), and Heat Pumps (HP) as TCLs with variable temperatures and Fridges and Freezers as base TCLs appliances. Other sources of flexibility in the future, namely the electric vehicles and household electrochemical storage, are out of the scope of our study.

TCLs are bounded to a dead band to fulfill their thermal comfort loads as presented by (Alvarez et al., 2004, Callaway, 2009, Ihara and Schweppe, 1981). These physical models are commonly used to characterise residential demand flexibility (Conejo et al., 2010, Heleno et al., 2015). Mathieu et al. (2013a) linearised this method into a time varying battery model to become computationally optimal by separating the control and optimisation of TCLs. The method considers the physical characteristics of TCLs by keeping track of their associated battery values, energy, power up, and power down capacities, which are time-varying by the nature of the resource, therefore not simplifying TCLs behaviour into a battery with constant parameters. We use the time varying batteries framework (Mathieu et al., 2015, Mathieu et al., 2013a) to quantify the flexibility of TCLs and extend it to include SLs, achieving a complete household flexibility model. Thus, we represent the flexibility of each residential cluster by an equivalent battery with time-varying characteristics described in three dimensions: energy capacity, power up capacity, and power down capacity. These three dimensions of the flexibility vary hourly with several geographical and socioeconomic factors, such as the existence of flexible loads in the building, consumption and comfort patterns, occupancy of the household, and climatic characteristics.

By adding these individual household flexibilities, and taking into account the presence of appliances across different socioeconomic and geographic groups, we are able to construct time varying battery profiles, each one representing the aggregated flexibility of 1000 residential consumers in a group. We aggregate different consumer clusters representing multiple regions and income levels to compare these three dimensions of the flexibility and produce annual, seasonal, and hourly analysis. The resulting aggregated profiles are affected by consumption patterns, climate conditions, and household occupancy of the different socioeconomic and regional groups that compose these aggregated groups.

### *2.2. Occupancy*

The occupancy characterisation in the proposed methodology follows previous work done by (Torriti and Santiago, 2016), which analyses the interplay between occupancy, simultaneity, and electricity consumption in households. We built the household occupancy profiles across the different socioeconomic and regional groups based on the time spent at home by each group compared with the average hourly profile $Oc_t$ since specific socioeconomic and regional information is only available as a daily sum $DT_i$. We generate hourly occupancy factors for each type of consumer, $oc_{t,i}$, by scaling up or down the national daily occupancy curve to ensure that the sum of the hourly occupancy matches with the time spent at home during a day. We minimise the scaling factor $\alpha_i$ that increases or reduces the hourly occupancy during daytime hours and in night hours (from midnight to 7 am), we assume the same occupancy for every type of consumer, which is the available hourly data $Oc_t$. Thus, the total hours spent at home $DT_i$ for each type of consumer are equal to the sum of the hourly occupancy during a day, the occupancy of each consumer group is equal to the average occupancy during night hours and proportional to an element $\alpha_i$ but never larger than 1 during the day. To obtain this household occupancy factor we apply a Mixed Integer Linear Programming algorithm, which is solved with the big M formulation of the problem to provide differences in usage by time period and type of consumers.

$$min \quad \alpha_i \tag{1}$$

Subject to the following restrictions.

$$\sum_{t}^{T} oc_{t,i} = DT_i \qquad \forall i \tag{2}$$

$$oc_{t,i} = \begin{cases} Oc_t, & if\, t \in N \\ \alpha_i \cdot Oc_t, & \text{if } \alpha_i \cdot Oc_t \leq 1 \quad \& \quad t \notin N \\ 1, & \text{if } \alpha_i \cdot Oc_t > 1 \quad \& \quad t \notin N \end{cases} \tag{3}$$

### 2.3. *Time varying batteries*

The flexibility of individual appliances is subjected to the fulfilment of certain constraints such as physical proprieties, comfort, current and previous usage, etc. This flexibility can be viewed as a battery, though with time-dependent energy and power capacities to meet the temporal characteristics of those constraints (Mathieu et al., 2013a). This is to say that a group of consumers, for flexibility representation purposes, can be modelled as a battery, with energy capacity, power up and power down parameters that vary in time in according to the availability given by their loads and their comfort patterns. We model the flexibility of a cluster of consumers, $i$, with a number and type of appliances, $z$, based on this analogy, and determine the corresponding battery power and energy capacities in each time, $t$, according to (4)-(9).

$$\sum_{z=1}^{Z} P_{i,z,t}^{min} \leq \sum_{z=1}^{Z} oc_{t,i} \cdot p_{i,z,t}^{BL} + p_{i,t}^{f} \leq \sum_{z=1}^{Z} P_{i,z,t}^{max} \qquad \forall i \in \mathscr{I}, t \in \mathscr{T} \tag{4}$$

where $P_{i,z,d}^{min}$ and $P_{i,z,t}^{max}$ show the maximum and minimum power limits of each appliance $z$. $p_{i,t}^{BL}$ and $p_{i,t}^{f}$ represent the power base load of each appliance of each class and the power used for flexibility purposes. In a similar pattern, the available energy stored at certain period of time also depends on the previous demand. The timely varying energy limits per appliance are included as $S_{i,z,t}^{min}$ and $S_{i,z,t}^{max}$. The demand resource of each group $i$ of components vary over the time and its limits are presented by:

$$\sum_{z=1}^{Z} S_{i,z,t}^{min} \leq s_{i,t} \leq \sum_{z=1}^{Z} S_{i,z,t}^{max} \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{5}$$

where $s_{i,t}$ is the state of demand of the battery associated to the customers class, which can be understood as the state of charge of a battery and evolves as:

$$S_{i,t+1} = S_{i,t} + (p_{i,t}^{f} + oc_{t,i} \cdot p_{i,t}^{BL})\Delta t + \sum_{z=1}^{Z} S_{i,z+1,t}^{In} + \sum_{z=1}^{Z} S_{i,z+1,t}^{Out} \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{6}$$

where $S_{i,z,t+1}^{In}$ and $S_{i,z,t+1}^{Out}$ represent new energy resources that are included or ejected from the battery availability. This capacity that goes in or out evolves with the availability of the demand resources and its expected baseline evolution. Both power and capacity come from two main types of loads, TCLs and SLs.

Finally, to assess the capacity of the aggregated batteries, we assume three main parameters, Energy Up, Power Up and Power Down capacities that represent the battery capacity to provide flexibility and are defined as follow:

$$S_{i,t} = \sum_{z=1}^{Z} S_{i,z,t}^{max} - \sum_{z=1}^{Z} S_{i,z,t}^{min} \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{7}$$

$$PUp_{i,t} = \sum_{z=1}^{Z} P_{i,z,t}^{max} - \sum_{z=1}^{Z} oc_{t,i} \cdot p_{i,z,t}^{BL} \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{8}$$

$$PDn_{i,t} = \sum_{z=1}^{Z} oc_{t,i} \cdot p_{i,z,t}^{BL} \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{9}$$

#### *2.3.1. Thermostatically Controlled Loads flexibility model*

TCLs such as ACs, HPs or EH work maintaining temperatures within temperature bands. This implies that, as long as these loads operate inside the bands, they can be modified without disrupting the comfort of the consumer (Mathieu et al., 2013a). A modelling framework for these types of loads is presented in (Callaway, 2009), adapted to the flexibility context in (Mathieu et al., 2015), and used to map the aggregated flexibility of TCLs into time varying batteries in (Koch et al., 2011, Mathieu et al., 2013a,b). Within this framework, the thermal characteristic of a cooling load is given by:

$$\theta_{z+1,i} = a_i \theta_{z,i} + (1 - a_i)(\theta_{z,i}^{a} - \tau_{z,i} \theta_{j}^{g}) \tag{10}$$

where $\theta_{z,i}$ is the temperature at the TCL space $i$ at time step $z$, $\theta^a_{z,i}$ is the outdoor ambient temperature and $\theta^g_i$ is the temperature gain of the TCL, equal to $R_z \cdot COP_z \cdot P_z$, thermal resistance of the cooled room, Coefficient Of Performance (COP) of the TCL and power applied respectively. $a_i$ is a dimensionless parameter defined as $\exp^{-h/C_iR_i}$, where h is the time control that we set in 15 minutes. Following the criterion adopted in (Mathieu et al., 2013b), $P_i$ is positive for cooling TCLs. Finally, $\tau_{t,i}$ represents a binary variable that is equal to 1 when the TCL is on and 0 when it is off, where we assume that TCLs are not available when temperatures are above or below their working bands. For cooling, TCLs availability in the model evolves:

$$\tau_{z,i} = \begin{cases} 0, & \theta_{z,i} < \theta^{min}_{i,z} \\ 1, & \theta_{z,i} > \theta^{max}_{i,z} + \theta^g_i \\ 0-1, & \text{otherwise} \end{cases} \tag{11}$$

The TCL works with $\theta^{min}_i$ and $\theta^{max}_i$ representing the minimum and maximum temperatures between where a user is comfortable. These two are defined by a set temperature ($\theta^{Set}_i$) and a comfort band ($\zeta_i$), which is chosen by the residential consumer, $\theta^{min}_i = \theta^{Set}_i - \zeta_i/2$ and $\theta^{max}_i = \theta^{Set}_i + \zeta_i/2$. These parameters set the temperature band within the TCLs can be flexible. To derive the different time varying batteries' parameters, the model assumes dependence of the internal temperature over a finite ambient temperatures and defines the duty cycles.

$$\Delta_{i,z} = \frac{h^{ON}_{i,z}}{h^{ON}_{i,z} + h^{OFF}_{i,z}} \tag{12}$$

$h^{ON}_{i,z}$ and $h^{OFF}_{i,z}$ are the times that TCL $i$ takes to travel from one limit of the temperature band to the other in the on and off states. Both parameters are defined as follows:

$$h^{ON}_{i,z,t} = -C_{z,i}R_i \ln \frac{\theta^{min}_i - \theta^a_{t,i} + \theta^g_i}{\theta^{max}_i - \theta^a_{t,i} + \theta^g_i} \tag{13}$$

$$h^{OFF}_{z,i} = -C_{z,i}R_i \ln \frac{\theta^{max}_i - \theta^a_{t,i}}{\theta^{min}_i - \theta^a_{t,i}} \tag{14}$$

Only positive numbers are used to compute $\Delta_{z,i}$. When $h^{OFF}_{z,i}$ is negative or non positive, the TCL is not available, $\Delta_{z,i} = 0$, while negative or non positive $h^{ON}_{z,i}$ force the $\Delta_{z,i} = 1$. With these auxiliary parameters the baseline power $P^{BL}_{z,i}$ and maximum power can be obtained as:

$$P^{BL}_{z,i} = \begin{cases} P_{z,i}\Delta_{z,i}, & \text{if available} \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

$$P_{z,i}^{max} = \begin{cases} P_{z,i}, & \text{if available} \\ 0, & \text{otherwise} \end{cases} \tag{16}$$

The maximum capacity is estimated as follows:

$$S_{z,i}^{max} = \begin{cases} P_{z,i} h_{t,i}^{ON} (1 - \Delta_i), & \text{if available} \\ 0, & \text{otherwise} \end{cases} \tag{17}$$

And the expected $S_{t,z}^{In}$ is correlated with the expected baseline power:

$$S_{z,i}^{In} = P_{z,i}^{BL} \Delta z \tag{18}$$

Finally, following the convention in Mathieu et al. (2013b) $S_{t,i}^{min}$ and $S_{t,i}^{Out}$ are all equal to zero.

*2.3.2. Shiftable loads flexibility model*

SLs such as DWs and WMs, are characterised by fixed load parameters and their consumption can be moved throughout the day according to starting and finishing times defined by consumers. In this work, we extended the concept of Time Varying Batteries from TCLs to SLs, following a similar modelling strategy adopted in (Mohsenian-Rad, 2015). Considering specific load parameters such as $P_{t,z}$, power of the appliance, $D_z$, duration of the process, $T_z^{av}$, time availability, $T_z^{st}$, starting time and $E_z$, energy consumed per period by the appliance once started, the time-varying battery model is given by (19)-(21).

$$P_{z,t}^{max} = \begin{cases} P_{t,z}, & i => T_z^{st} \ \& \ t < T_z^{st} + T_z^{av} \\ 0, & \text{otherwise} \end{cases} \tag{19}$$

$$S_{z,t}^{max} = \begin{cases} S_{z,t-1}^{max} + E_z, & t > T_z^{st} \ \& \ t <= T_z^{st} + D_z \\ S_{z,t-1}^{max}, & t > T_z^{st} + D_z \ \& \ t < T_z^{st} + T_z^{av} \\ 0, & \text{otherwise} \end{cases} \tag{20}$$

$$S_{z,t}^{min} = \begin{cases} S_{z,t-1}^{min} + E_z, & t => T_z^{st} + T_z^{av} - D_z \ \& \ t < T_z^{st} + T_z^{av} \\ 0, & \text{otherwise} \end{cases} \tag{21}$$

Whenever the $S_j^{max}$ gets back to 0 after its use, $S_j^{out} = S_j^{max}$ and the appliance stops providing flexibility.

### 2.4. *Measuring flexibility gaps*

The flexibility ratios reflect differences among the considered groups. National, regional and income groups are determined by the weighted addition of each of the 45 clusters of consumers and compared among themselves. The income gap is defined with an Above the Median Income/Low Income ratio (ratio AAI/LI) that determines how much more flexibility capacity an AMI group has compared with a LI group. The regional and seasonal ratio compares the flexibility potential of the regions as a percentage above or below the average yearly national flexibility potential.

$$ratio\ \ AMI/LI = \frac{S_r^{\bar{AMI}}}{S_r^{\bar{LI}}} \tag{22}$$

$$RS = \frac{\bar{S_r} - \bar{S_N^y}}{\bar{S_N^y}} \tag{23}$$

Where $\bar{S_r}$ represent the mean energy capacity of a region, $\bar{S_N}$ the national mean energy capacity and $S_r^{\bar{HI}}$ and $S_r^{\bar{LI}}$ the Above the Median Income and Low Income energy capacities of a particular region. These ratios are also used for power up and down capacities.

## 3. Data and Assumptions

We take as an example one of the most diverse countries in Europe, Spain, where we map these flexibility gaps introduced by household income levels and regional characteristics associated with electricity consumption. Indeed, Spain provides a good case to assess the impact of both parameters as the residential consumption accounts for 31.5 % of the total electricity consumption (IDAE, 2020), and it presents diversity in both income factors and geographical conditions. To assess the national flexibility of the residential sector in Spain, we aggregated consumers' baseline profiles based on the geographical location and household consumption patterns. We build annual flexibility profiles of 45 clusters considering 3 income levels - Above Median Income (AMI), Median Income (MI), and Low Income (LI) - in 15 administrative regions of mainland Spain.

We determine the hourly flexibility during 2018, taking into account demographic and socioeconomic information from three different surveys conducted by the National Statistics Institute (INE, initials in Spanish) (INE, 2010, 2011, 2018). Additionally, we use statistical data characterisation reports from the Institute for Energy Diversification and Savings (IDAE) (IDAE, 2011, 2016, 2019a,b), which provide information regarding residential occupancy, electricity bills as well as the presence and type of household appliances.

Based on this information we build 45 groups of representative consumers. In terms of meteorological conditions, the regions are represented by their main city or capital, and their temperatures are taken from COPERNICUS database ERA5 (Copernicus (C3S), 2019). Socioeconomic groups are formed according to the monthly household income, divided into three categories as presented in INE reports: less than 1000 € /month, assumed as LI; between 1000-1999 € /month, assumed as MI; and more than 2000 € /month assumed as AMI.

We build the household occupancy profiles across the 45 different socioeconomic and regional groups based on the occupancy time data presented in the INE survey (INE, 2011). We assume that the occupancy time is composed of the sum of three activities declared in the survey: personal care, household/family, and media. Hourly data of these three items are only available for the aggregated Spanish profile $Oc_t$, while specific socioeconomic and regional information is only available as a daily sum $DT_i$.

The statistical surveys characterise electric appliances and usage patterns across regions and socioeconomic groups. For example, the report (INE, 2010) collects information regarding appliances per income group and location in a separate manner. To combine this information we assume that the regional distribution of appliances across income groups follows the national trends. Therefore, the percentage of citizens per cluster with a determined number of appliances can be obtained by the percentage of citizens by income group in the region (INE, 2010) and the national average per income groups (INE, 2018).

Since the thermal parameters of TCLs are not provided in any survey, we generalise these characteristics by generating a random set of resistances, R, between 1.5 and 2.5 (ºC/kW), and thermal capacities, C, between 1.5, and 2.5 (kWh/ºC) associated with space heating/cooling devices (AC, HP, and EH). We set the nominal power from AC, HP and EH as a normal distribution from 2.5 to 5 kW and COP at 2.65, 3.65 and 1 respectively according to (IDAE, 2016, 2019b). We assume 2 devices for consumer groups declaring the presence in more than one room, and 4 devices for consumers declaring devices in all rooms (INE, 2010). Temperature set points for these appliances are assumed homogeneous across income and regions based on (INE, 2010), with a comfort band between $\delta$ between 0.5 and 2ºC. Analogously, for refrigeration systems, we estimate a thermal resistance between 80 and 105 (ºC/kW), a thermal capacitance C between 0.4 and 0.8 (kWh/ºC) and an external temperature of 20ºC. We also assume a nominal power within [0.2, 0.5 kW], a COP within [1.5 and 2.5] and set point temperatures in the ranges of [1.5, 4ºC] and [-6,-3ºC] for refrigerators and freezers, respectively (Mathieu et al., 2015).

We assume random starting times for SLs within the actual hourly ranges declared in (IDAE and Eurostat, 2011). DW nominal powers are obtained via a normal distribution within [0.5, 1.5kW], a 4 to 5 hours shiftable time is assumed and the starting time is considered within the slots: 14-15:30 and 20:30-21:30. Similarly, WM nominal power is generated within [0.75, 1.75 kW], shiftable time is assumed to be 3 to 4 hours and the starting time within the following slots: 10-11:30, 15-16 and 18:30-20. The duration of these appliances operation is assumed to be between 1 and 2 hours.

## 4. Results and discussion

In this section, we present the results and compare them, considering three flexibility capacity parameters: energy, power up, and power down of residential households. As discussed in section 2, we measure geographical and seasonal gaps comparing the regional flexibility capacities with the national average represented by the weighted addition of the 45 clusters analysed. Then we present this gap as a percentage variation over the national yearly average. We measure the socioeconomic gap as the number of times that AMI groups have more flexibility capacity over the flexibility that LI groups have.

### *4.1. National flexibility: the seasonal gap*

Figure 1 shows the average flexibility of a residential consumer in Spain considering the three dimensions: energy capacity, power up and power down, as well as the seasonal flexibility gaps, measured as a percentage deviation of the annual national average. Power up and down represent the capacity of a household to increase and decrease its consumption while the energy capacity represents the amount of energy that appliances can consume in excess or defer without affecting comfort patterns.

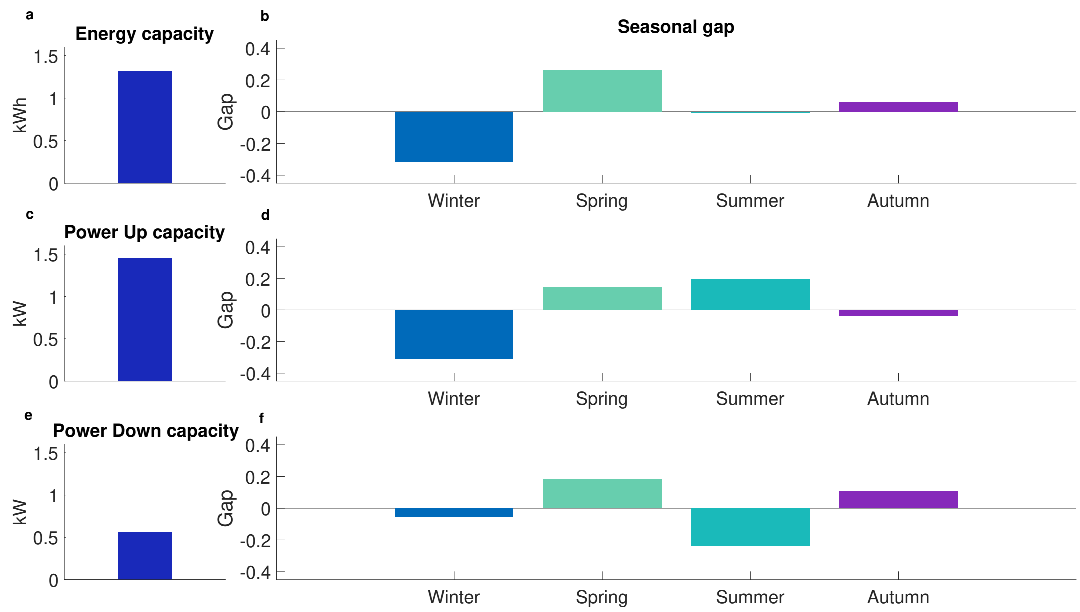


**Figure 1: National flexibility parameters and seasonal gaps.** a, c and e show the year average of the flexibility parameters. b, d and f present the percentage seasonal gaps compared with the year average, each colour represents the seasonal gaps of the three capacities. Winter presents the least flexibility while Spring shows the most except in the Power Up capacity presented in Summer.

The flexibility from residential loads has time scale variations based on intra-day and seasonal factors (Mathieu et al., 2015, Mathieu et al., 2013a). Seasonal differences are related to residential TCLs, which vary with ambient temperature and heating/cooling needs (Mathieu et al., 2012), while the consumption patterns associated with SLs were assumed constant throughout the year. In this sense, SLs result in a constant flexible capacity during the whole year with a stable hourly pattern. Thus, the main differences associated with SLs appliances are the amount of them in households. WM present a constant distribution between regions and incomes and DW are homogeneous between regions but present a wide divergence between income groups. The behavior of TCLs explains the relatively low flexibility values in the winter seen in Figure 1 as well as its increase during the mild temperature seasons (spring and autumn). Among these two seasons, spring has the largest energy capacity, as it combines months of relatively low heating and cooling requirements with a better flexibility performance of EH.

It is interesting to observe that, during the summer, residential consumers offer high power up flexibility together with low energy and power down capacities. This can be explained by the hourly distribution of the cooling needs, which increase during the day when the majority of consumers are not at home. Therefore, as ACs are not operating, the energy and the power down flexibilities are insignificant, but this large population of devices can be switched on if power up capacity is needed.

To better understand the variation of TCLs' flexibility with temperature and thus its implication in the seasonal gaps, Figure 2 presents how the TCLs' flexibility of the national average cluster of households vary with ambient temperature.

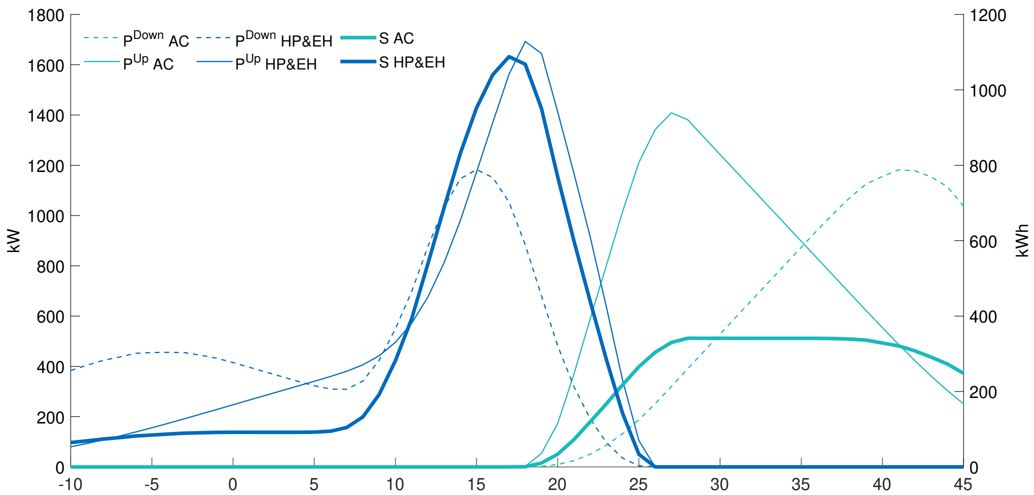


**Figure 2: Variation of the TCLs' flexibility capacity with temperature.**

The TCLs' flexibility varies depending on the ambient temperature, mid temperatures allow TCLs to have a more flexible operation than extreme temperatures when TCLs must be on to guarantee comfort patterns (Mathieu et al., 2013a). For example, heating TCLs (EHs and HPs) provide more flexibility capacity when working in mild temperatures, i.e. with lower heating needs, which allow them to be switched on and off for longer periods without affecting consumers' comfort. In contrast, when the ambient temperature falls below certain levels, the heating TCLs must operate at their rated capacity, limiting the flexibility (Mathieu, 2012).

### *4.2. The regional flexibility gap*

Figure 3 shows the regional flexibility gap per season, comparing the energy capacity of individual regions with the national average.

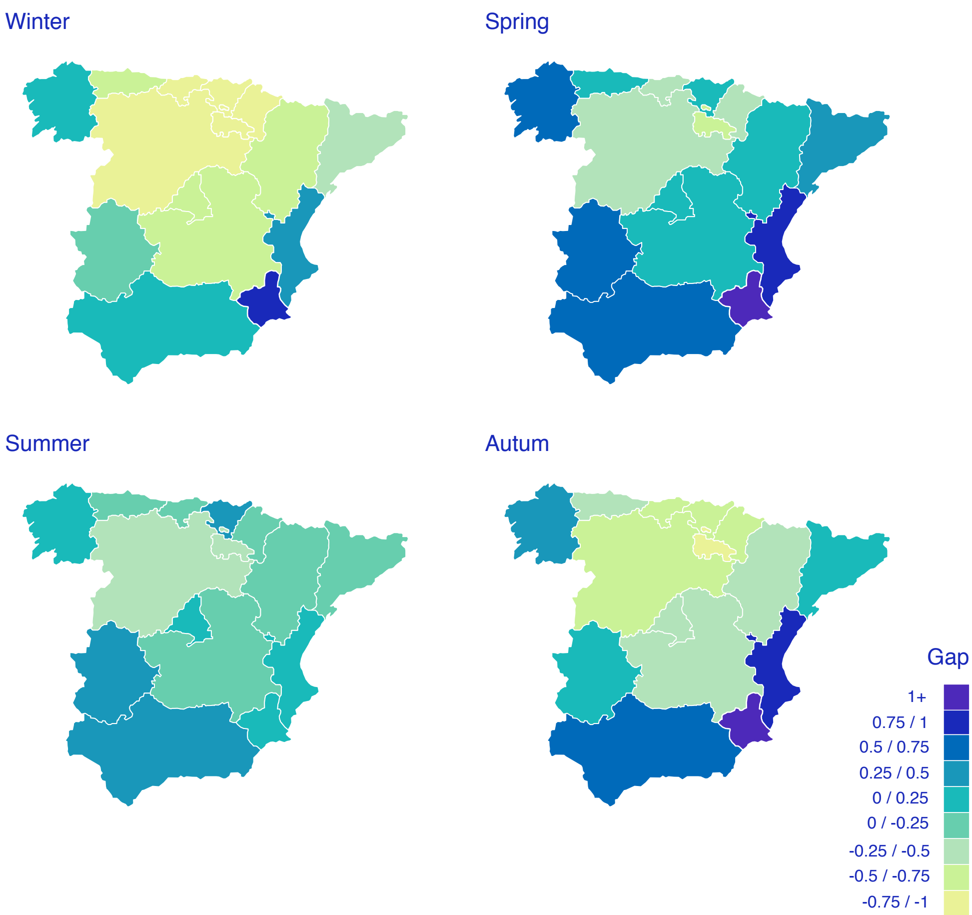


**Figure 3: Seasonal flexibility gap by regions.** Each map represents the seasonal difference of each region with the national yearly average. Lighter colours show negative gaps with the national mean while darker colours represent positive gaps.

Maximum flexibility potentials concentrate in the southern and eastern Mediterranean areas, where the energy capacity can be 100% higher than the national average during the mild temperature seasons, i.e. spring and autumn. In contrast, minimum flexibility potentials (75% lower than the average) occur in the central and northern regions during winter. This can be explained by two factors. First, in central and northern locations, households still rely on other heating sources, mostly gas, and flexible electric devices, such as HPs, are present in less than 1% of the buildings as presented in Table 1, which shows the TCL penetrations by region. Second, the few EH installations in the region need to operate at nominal levels during the winter due to the low temperatures, which excludes them from flexibility provision. In comparison, the regions of the south, besides the lower heating needs, rely more on EHs and HPs that translates into more flexibility capacity in the winter. When summer arrives, all households rely on electric ACs, and not on other energy sources, to cool their houses. This reduces the regional gaps in flexibility capacities in summer compared to winter, and a more homogeneous flexibility potential can be seen across the country.

**Table 1:** Distribution of TCL penetration by region (INE, 2010)

| **Region** | **HP** | **EH** | **AC** |
|---|---|---|---|
| Andalucía (And) | 3.8 | 23.5 | 57.4 |
| Aragón (Ar) | 2.7 | 13.2 | 37.4 |
| Asturias (As) | - | 17.5 | 0.4 |
| Cantabria (Can) | 1.2 | 13.1 | 0.7 |
| Castilla y León (CyL) | 0.4 | 8.6 | 3.3 |
| Castilla La (CLM) | 2.0 | 15.3 | 36.2 |
| Cataluña (Cat) | 7.1 | 15.4 | 36.1 |
| Comunitat Valenciana (CV) | 20.8 | 23.9 | 54.5 |
| Extremadura(Ext) | 14.4 | 28.3 | 58.0 |
| Galicia (Ga) | 1.3 | 14.8 | 1.0 |
| Madrid (Mad) | 2.3 | 15.6 | 43.5 |
| Murcia (Mur) | 28.1 | 40.6 | 63.9 |
| Navarra (Na) | 0.9 | 10.2 | 11.4 |
| País Vasco (PV) | 0.8 | 22.0 | 1.7 |
| La Rioja (LR) | 0.4 | 7.8 | 13.3 |

The role of TCLs in the overall flexibility capacity is crucial. Figure 4 shows how the flexibility capacity varies with the penetration of TCLs in the flexible load, defined as the ratio between the installed power of TCLs appliances over the installed power of flexible loads. The results of the 45 clusters show how as TCL penetration increases, so too does the energy flexibility capacity. Nevertheless, this increase is not linear as the behaviour of each type of TCL and ambient temperatures are also key in determining the overall TCL flexibility capacity as shown in Figure 2. For instance, fridges and freezers provide a stable energy capacity and their use is not dependent on the external temperature but with more limited power up and down capacities than heating and cooling TCLs.

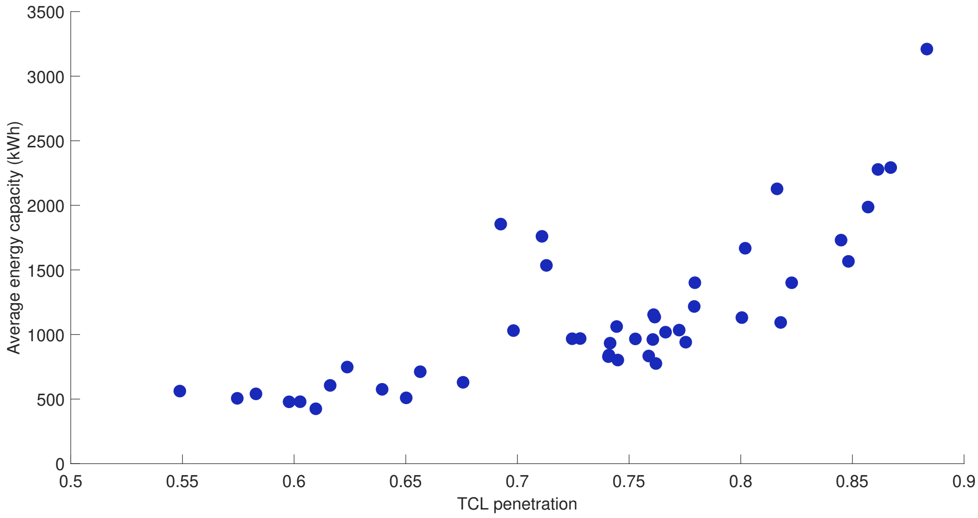


**Figure 4: Variation of energy flexibility capacity with TCL penetration in the flexible load.**

#### *4.3. The socioeconomic gap of flexibility resources*

Figure 5 presents the annual and monthly gaps between residential consumers with different levels of income. As described in section 3, the temperature and comfort patterns are assumed to be homogeneous between socioeconomic groups. Therefore, the only thing that differentiates flexibility between socioeconomic clusters is related to the appliances that people have at home and occupation patterns. The higher socioeconomic gaps occur in the power up component of flexibility, which reflects the capacity of the consumers to increase their load momentarily. Higher income consumers tend to have better equipped houses, both in terms of SLs and TCLs, and to spend less time at home, resulting in more availability to increase consumption when such services are requested. If power up flexibility is required, AMI households can switch on their TCL loads to preheat or precool their houses prior to arriving at their houses. In contrast, lower income households that spend more time at home, are already using the appliances and cannot provide that power up capacity. In particular, LI groups spend, on average, 2 additional hours per day at home (INE, 2011), leading to a limited power up capacity. Regarding the type of appliances, LI consumers have 50% fewer DWs, ACs, and EH than AMI consumers (INE, 2010), which represents a structural barrier to the provision of potential flexibility services. Due to this inequality in household equipment, the flexibility gaps across different socioeconomic groups are aggravated by the extreme temperatures, as seen in the bottom part of Figure 5.

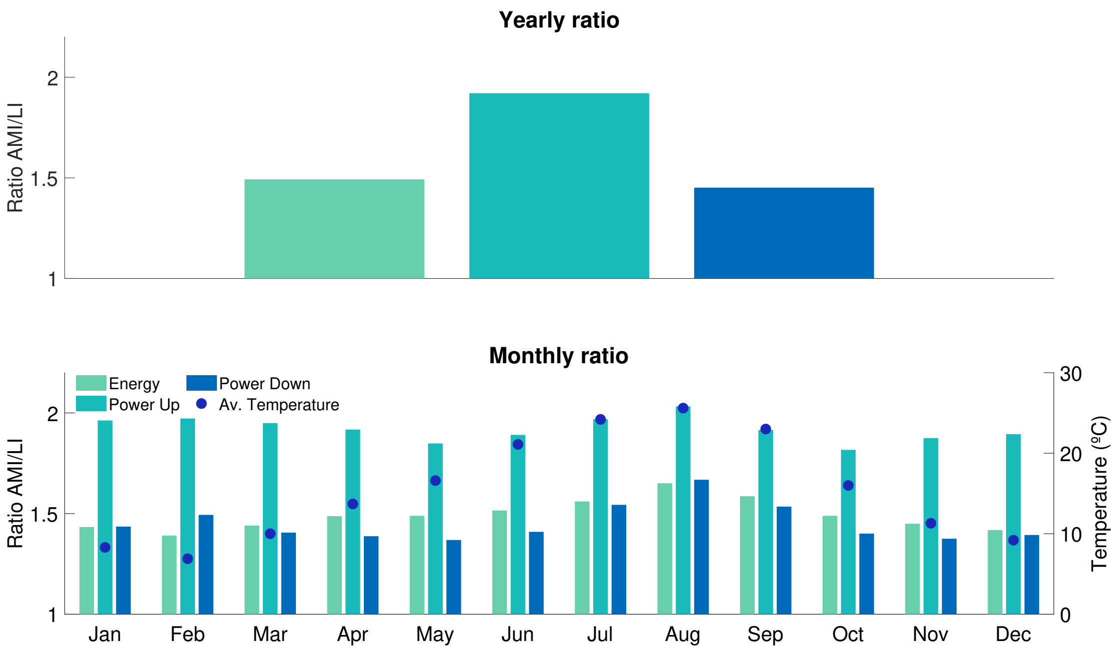


**Figure 5: Income flexibility gaps.** The ratios are obtained by comparison of a national control group of AMI and LI. a shows the yearly mean differences of the three flexibility parameters. b shows the monthly differences and Spanish mean temperature of the month.

Regarding the income gap among citizens of the same region, Figure 6 plots the AMI/LI ratio versus the energy capacity ratio of the 15 regions analysed. As seen in Table 1 we observe two types of regions: 1) the ones where flexibility income gaps grow with the overall flexibility of the region; 2) the ones where the gaps are relatively stable and do not depend on the flexibility capacity. Regions in the center, south, and Mediterranean area represent the first type. These regions have warmer climates and larger penetration of EH and AC, which are always above 15 % and 35 % respectively (INE, 2010). The second group contains northern regions, characterised by colder climates with milder summers where the penetration of electric TCLs is relatively low (e.g. AC devices only exist in 15% of the residential buildings).

Thus, the difference between these groups in terms of the penetration of TCLs shows an important conclusion: the electrification of heating and cooling needs can aggravate the flexibility gaps associated with socioeconomic conditions. In other words, the more thermal-related flexibility in a region, the higher inequalities in the potential provision flexibility services across socioeconomic groups. Again, this can be explained by the fact that not all consumers are able to equip their houses with electric TCLs, which has the potential to exclude a significant part of the population from the participation in flexibility services.

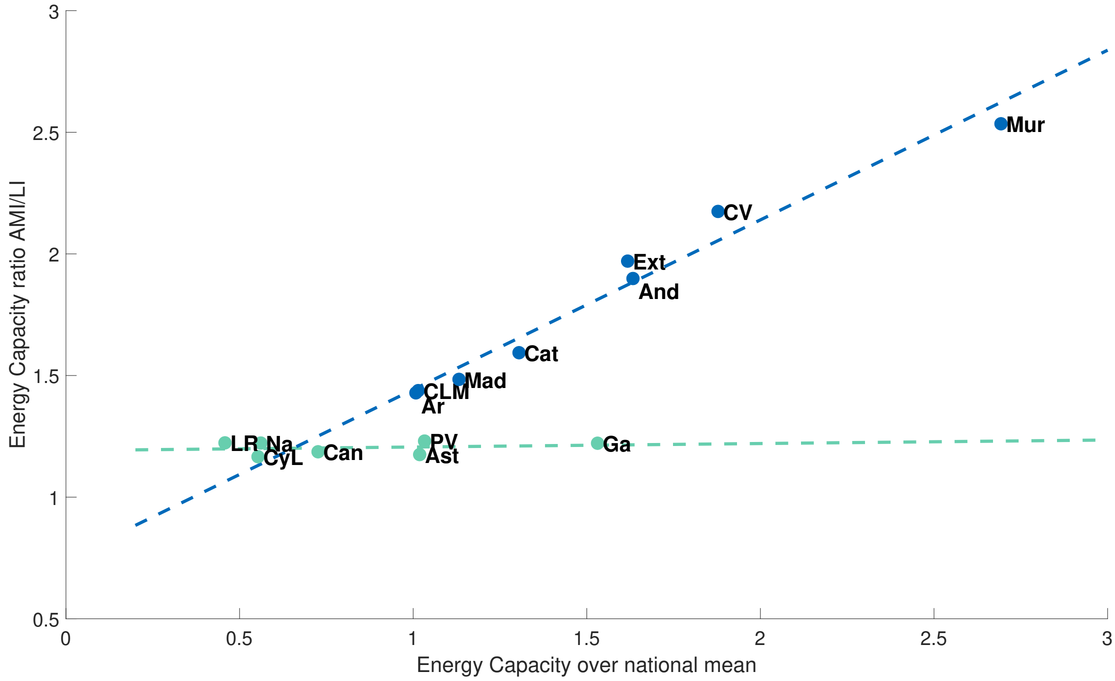


**Figure 6: Flexibility income gap versus region flexibility.** Lighter dots represent regions from the north of Spain while darker dots represent regions from the Mediterranean area, center and south of Spain. The linear correlation of the first groups is $y = 1.19 + 0.014x$ (adjusted $R^2 = 0.0419$) and the second group has a linear correlation $y = 0.74 + 0.70x$ (adjusted $R^2 = 0.97$). Each region is represented by the acronym shown in Table 1

*4.4. Overall flexibility gap*

Figure 7 plots the power up and energy capacities of the 45 groups analysed in this paper, showing the total residential flexibility gaps in a heterogeneous country like Spain. The colors and shapes associated with each group reveal, respectively, the geographical and socioeconomic flexibility gaps in the country. Consumer clusters from northern regions concentrate in the 50% of the population with the lowest energy and power flexibility capacities, due to the colder winters in the region combined with a strong dependence on non-electric heating sources. In contrast, southeastern regions have more potential flexibility caused by lower heating needs and larger penetrations of TCLs. These regions are in the upper quartile of the measured flexibility parameters, with a potential flexibility four times higher than the northern part of the country. Socioeconomic gaps are also seen in the graph, with two thirds of the LI consumers located in the lower quartile of flexibility and, regardless of the region, no presence among the 25% higher flexibility groups. This combination of geographical and income differences results in a significant flexibility gap: households with higher income in Mediterranean regions have 10 times more flexibility than lower income groups located in the North. At the same time, regions with higher flexibility capacities have proportionally larger gaps associated with socioeconomic conditions. In sum, existing socioeconomic and regional flexibility gaps are large, not homogeneous between regions, and therefore a significant part of the population can become excluded from participation in flexibility mechanisms.

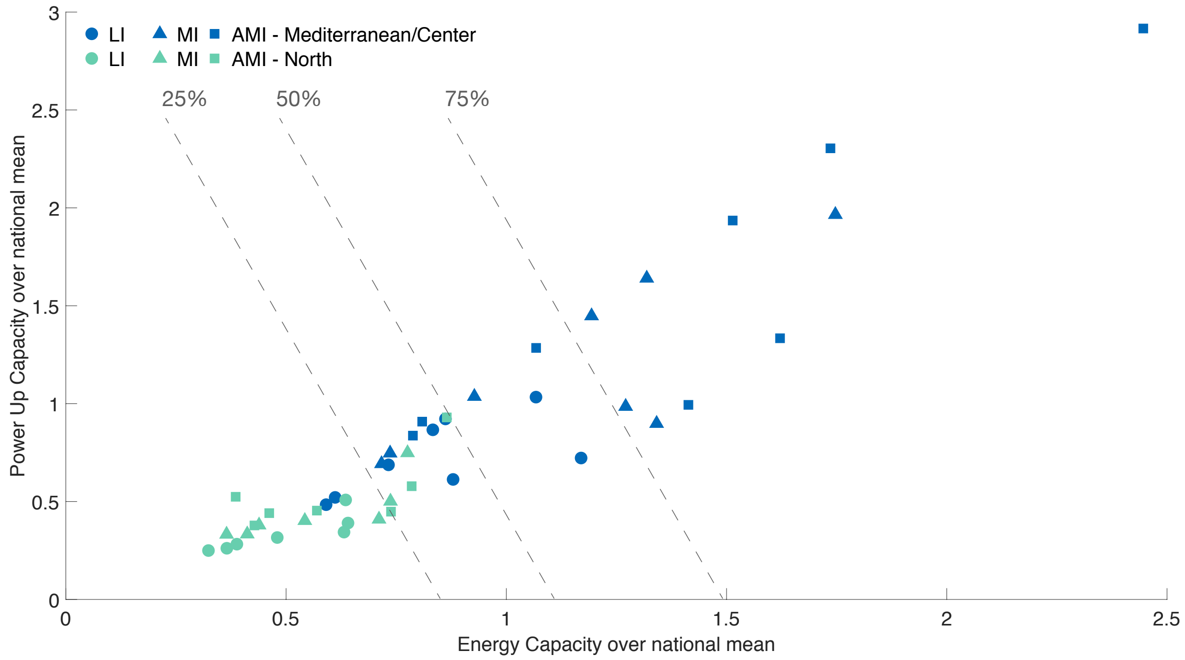


**Figure 7:** Overview of flexibility capacities of the 45 control groups. Lighter dots represent regions from the north of Spain while darker dots represent regions from the Mediterranean area, center and south of Spain, circles represent LI groups, triangles MI groups and squares AMI groups. Power up and energy capacity have a positive correlation.

## 5. Conclusions and policy implications

Significant geographical and seasonal variations exist in the flexibility of residential consumers in Spain. In this paper, we measured and analysed these gaps, and concluded that they are tied to meteorological and socioeconomic conditions, which indicates that similar gaps can be found in other countries and regions. Potential implications of these gaps in the development of policies to promote residential flexibility are threefold.

First, these gaps pose important challenges when conceiving national and continental services (e.g. reserves) supported by residential flexibility. In fact, centralised services benefit from the homogeneity of the flexible resources across the territory, providing better commitment and dispatch options for system operators. However, we showed that residential flexibility is a volatile and heterogeneous resource that may introduce seasonal and geographical distortions in national flexibility markets, making it less attractive for centralised system services. Additionally, when integrating this flexibility in a market context, an important aspect is the price-elasticity of the flexible resource, i.e., how can consumers change their behaviour to provide more flexibility in the system in relation to prices. Our analysis shows that while some residential flexibility can come from changes in comfort patterns, which comprises a behavioural nature, a large portion of the flexibility is dependent on pre-existing household equipment and meteorological conditions. This means that, in most cases, increasing flexibility is not an option for residential consumers. Thus, in the design of future residential flexibility markets, it is important to note that residential flexibility is very inelastic, geographically heterogeneous, and very dependent on meteorological and socioeconomic factors.

Second, some of these geographical and seasonal gaps can be corrected by energy policy measures. For example, as discussed above, the low winter flexibility in the north of Spain can be explained by the reliance on non-electric sources to supply heating needs. In this case, the electrification of space heating systems would increase the flexibility resources in the region during the winter, mitigating a seasonal and geographical gap. Alternatively, policies that increase the overall flexibility of the sector may attenuate geographical differences. For instance, policies that incentivise the adoption of electric vehicles would introduce a new flexible resource, with the advantage of being independent of the meteorological conditions and making the residential flexibility more homogeneous across seasons.

Third, policies exclusively focusing on the energy systems are not enough to address all the flexibility gaps. When analysing the impact of household living conditions on the potential flexibility, we conclude that poorly equipped houses and longer occupancy times impose severe limitations to the flexibility on low income consumers. More importantly, we observe that the flexibility gap between high and low income groups grows with the average flexibility of the region. This means that increasing the overall flexible resources does not necessarily correct the flexibility gaps, as they reflect the asymmetries in socioeconomic conditions. Without correcting these asymmetries, energy policies aimed at homogenising flexibility profiles will be limited. Going back to the example of the electric vehicle, and assuming that the adoption of private cars is significantly lower among low income consumers, it is clear that the EVs would increase the overall flexibility of the residential sector, but they would aggravate the flexibility gaps between income groups.

At the time where governments are putting consumers in the centre of the energy systems, and demand-side flexibility services gain relevance in energy transition policies, socioeconomic flexibility gaps become a serious challenge. In fact, in the process of extending flexibility services to the residential sector, the risk of exclusion of a significant segment of the population cannot be neglected. In that scenario, the massification of flexibility services has the potential to become a factor in exacerbation of economic inequalities. If flexibility markets or flexibility payments are established without aiming to include all kinds of residential consumers, most of these economic incentives will end up in the households with the most flexibility capacity, high income households, leading to an unjust energy transition model. Thus, important decisions around flexibility remuneration, market design, legal requirements for aggregators, tariff allocation of system flexibility costs, etc., should consider these socioeconomic gaps to guarantee equity standards in access and provision of flexibility services.

### CRediT authorship contribution statement

David Ribó-Pérez: Conceptualization, Methodology, Software, Data Curation, Writing - original draft, Writing - review & editing. Miguel Heleno: Conceptualization, Methodology, Writing - review & editing, Supervision. Carlos Álvarez-Bel Writing - review & editing, Supervision.

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