Affordable, sustainable and inclusive housing for marginalised communities


# D4.2 Smart meter data for measurement and identification of energy poverty

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Web: http://houseinc.eu

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## About

The objective of HouseInc is to apply innovative methodology to deeply analyse interlinked dimensions of housing inequalities in the context of marginalised communities.

HouseInc will empirically examine economic, social and ecological drivers and assess impacts of various indicators on housing inequality to derive policy recommendations that foster the adoption of effective measures addressing housing inequality across Europe. With a transdisciplinary dialogue, the project develops innovative social, financial and digital solutions that can be up scaled and thus, contribute to a better socio-economic and sustainable integration of vulnerable groups in European societies.

HouseInc takes a systemic view and assesses interlinkages of housing inequalities - emphasising energy and mobility poverty, digital dimensions, employment opportunities, family and socio-demographic conditions, energy-efficiency, and health - on a micro-, meso- and macro-level. The interdisciplinary HouseInc consortium - consisting of research institutes and universities, policy think tanks, NGOs, and practitioners on the ground - involves case studies to engage directly with members of four marginalised communities in or from Eastern Europe.

Besides a mix-method approach, including modelling and a GIS-based analysis depicting geographical and future housing inequality, we implement a multinational survey to better understand housing inequality in light of recent events such as COVID-19 and Russia's invasion in the Ukraine. The research results will be assessed, mapped, and scaled up using Living Labs and various stakeholder engagement activities to provide innovative solutions addressing housing inequalities and translating them into valid local, regional, national and EU policy recommendations impacting EU and national funding programs and providing a comprehensive overview and guidance for policymakers to mitigate housing inequalities.

## Project partners

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## Abbreviations

| | |
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| **FEP** | Feeling Energy Poor |
| **AEEP** | Actual Expenditure Energy Poverty |
| **SERL** | Smart Energy Research Lab |
| **UCL** | University College London |
| **REEP** | Required Expenditure Energy Poverty |
| **EBSS** | Energy Bill Support Scheme |
| **EPG** | Energy Price Guarantee |
| **DSO** | Distribution System Operators |
| **MIS** | Minimum Income Standard |
| **RRRSTI** | Remote Rural, Remote Small Town and Island areas |
| **HBS** | Household Budget Survey |
| **ECO** | Energy Company Obligation |
| **EPC** | Energy Performance Certificate or Energy Price Cap |
| **LILEE** | Low Income Low Energy Efficiency |
| **LIHC** | Low Income High Cost |
| **TPR** | True Positive Rate |
| **AUC** | Area Under the Curve |
| **ROC** | Receiver Operating Characteristic |
| **EPAH** | Energy Poverty Advisory Hub |
| **SMETER** | Smart Meter Enabled Thermal Efficiency Ratings |
| **ONS** | Office for National Statistics |
| **SAP** | Standard Assessment Procedure |
| **GDPR** | General Data Protection Regulation |

# 1. EXECUTIVE SUMMARY

Energy poverty severely impacts the physical and mental health of individuals, with cold homes leading to excess winter deaths, and increased burdens on national health services.

## 1.1. CHALLENGES IN MEASURING AND IDENTIFYING ENERGY POVERTY

The collection of detailed data on household energy use, energy expenditure, living conditions and energy poverty metrics is essential for understanding the scale and nature of energy poverty, designing targeted interventions to ensure that support is provided to those most in need and evaluating the effectiveness of various programs to maximize the impact of scarce resources.

Household surveys are the common method of collecting data on energy poverty indicators and these can be costly to administer, slow to produce data, subject to recall bias and are not commonly longitudinal in nature, all of which results in barriers to effective monitoring of energy poverty and design of solutions. Furthermore, existing methods for identifying households in or at risk of energy poverty are either expensive or inaccurate (failing to correctly identify households who are energy poor), leading to wasted resources, misallocation of funding and reduced societal benefit. There are substantial problems therefore with energy poverty measurement and identification.

## 1.2. OPPORTUNITIES PRESENTED BY SMART METER DATA

The roll-outs of smart meters present an opportunity to improve the quality and quantity of data collected for these purposes, and as a result this report investigates the use of smart meter data to improve measurement and identification of energy poverty by conducting a detailed case study using a dataset of 13,000 households in Great Britain equipped with smart meters and with linked socio-technical contextual data: the SERL Observatory dataset.

The results of the case-study show that smart meter data can improve the quality and quantity of data on energy prices, energy use, energy expenditure and energy expenditure-based indicators of energy poverty, as well as enabling household-level analyses relevant to energy poverty such as the relationship between changes in energy prices and energy demand, building thermal efficiency and under-heating.

## 1.3. NEW INSIGHTS INTO EXPENDITURE-BASED ENERGY POVERTY

While the calculation of energy poverty based on an actual expenditure-based indicator is not novel, what makes this novel is its derivation based on highly accurate smart meter energy use and energy tariff data, and therefore not subject to the same recall biases and errors associated with self-reported energy expenditure. This means that, given the use of smart meter data, energy poverty estimates can be derived at higher temporal resolution, longitudinally, with lower participant burden and lower instrumentation costs than those based solely on surveys.

With the large-scale deployment of smart meters throughout the EU and UK, opportunities are emerging to fill some of the data gaps related to energy poverty, improve how energy poverty is measured, and ultimately help tackle this pressing societal problem.

Given this opportunity, we compare the Actual Expenditure Energy Poverty (AEEP) indicator enabled by smart meter data with other commonly used indicators in particular the subjective Feeling Energy Poor (FEP) indicator (or "inability to keep warm during winter"), using data for the SERL Observatory participants where available. The report focuses on the objective AEEP and subjective FEP indicators because these are directly measurable using the SERL Observatory data, and are well-established in the energy poverty literature.

Compared to the Feeling Energy Poor indicator, the AEEP indicator has a false positive rate of around 24% (or a specificity of 76%) and a false negative rate of 54% (or a recall rate of 46%). So approximately 1 in 4 households who are not energy poor according to the FEP indicator will be falsely identified as energy poor using the AEEP indicator. And about 1 in 2 households who are actually energy poor according to FEP indicator are not identified using the AEEP indicator. The AEEP indicator has a precision of 30% compared to the FEP indicator, indicating that approximately 1 in 3 households identified as energy poor using the AEEP indicator were actually Feeling Energy Poor.

Reducing false negatives is particularly important for an energy poverty indicator and we show how reducing the threshold for the AEEP indicator from 10% to 9% improves the performance compared to the FEP indicator: increasing the recall rate from 46% to 54%, albeit with a drop in specificity from 76% to 71%.

Overall, these results show that the AEEP and FEP indicators are largely identifying *different* groups of households and that as a result AEEP should be viewed as a complementary indicator to FEP rather than a replacement. Indeed, we discuss the potential for merging these two indicators together to make a hybrid indicator that could be a proxy for the objective Required Expenditure Energy Poverty (REEP) indicator, defined as more than 10% of household disposable income before housing costs spent on energy bills, which was formerly used by Government in England and still in use in Wales and Northern Ireland. In this report we provide some speculative assessments of the performance of the AEEP indicator versus the REEP indicator and recommended further research to analyse their relationship and applicability in identifying energy poverty.

## 1.4. EVALUATING THE IMPACT OF ENERGY POLICIES ON ENERGY POVERTY

The AEEP indicator is important because, where smart meter data are available, it is easier to implement than other expenditure-based energy poverty indicators, and this opens more opportunities for improving the understanding of energy poverty and tackling it effectively. By way of example, we evaluate the impact on energy poverty levels using the AEEP indicator of key energy policies implemented by the UK Government to reduce the impact of steep energy price rises: the Energy Price Cap, Energy Price Guarantee (EPG), and Energy Bill Support Scheme (EBSS). The results show the substantial impact these policies had on reducing energy poverty levels. Without the EPG and EBSS, 48% of households in the SERL Observatory would have been in energy poverty according to the AEEP 10% indicator, as opposed to 28%, a decrease in absolute terms of 20%.

## 1.5. REVEALING DIFFERENCES IN ENERGY USE BETWEEN ENERGY POOR AND NON-ENERGY POOR

The report then investigates the potential to use smart meter data and machine learning to improve methods for identifying households in energy poverty. The development of a smart meter data-based machine learning model is based on the fundamental assumption that there are significant differences in patterns in the input data (smart meter data) between the different groups to be identified (energy poor vs non-energy poor). If there are no differences in smart meter data between the energy poor and the non-energy poor, then it is not reasonable to assume that a machine learning model can be trained to identify the groups based on smart meter data. This report therefore conducts exploratory data analysis to investigate the presence or lack of differences in smart meter data between energy poor and other households in the SERL Observatory. The more there are apparent differences then the greater motivation and justification for developing a machine learning classification model that uses smart meter data as an input to predict energy poverty status. The results are supportive of the hypothesis that energy poor households use less energy than non-energy poor households, *when energy poverty is measured using the Feeling Energy Poor indicator*. When using the AEEP indicator, however, the results refute this hypothesis as the (AEEP) energy poor actually use significantly more gas (though not electricity) than the non-energy poor. This finding holds when comparing average annual energy use as well as energy use during particularly cold weather periods (in this case considering the period December 2022 which was particularly cold in GB).

Smart meter data record energy consumption at high-resolution, 30-minutes in the case of the SERL Observatory data. In addition to overall levels of energy usage, therefore, half-hourly gas and electricity demand profiles were compared between energy poor and non-energy poor households. The results of the demand profile analysis reveal substantial and significant differences in patterns of gas usage by time-of-day between energy poor and non-energy poor households. Feeling Energy Poor households use less gas than non-energy poor households throughout the day, while AEEP households tend to use more than non-energy poor households, particularly during the daytime.

We also investigated whether there were any differences in irregularity of energy use between energy poor and non-energy poor households by comparing statistics of dispersion of the household-level half-hourly energy use data and determining if any differences between the two groups were statistically significant. The statistics examined were: standard deviation, coefficient of variation, skew, and kurtosis. The results show that households who are Feeling Energy Poor, on average and compared to non-energy poor households, have energy use that is more variable, more skewed, and more likely to have extreme (high and low) values. By contrast, households who are Actual Expenditure Energy Poor, on average and compared to non-energy poor have energy use that is less variable, less skewed, and less likely to have extreme (high and low) values.

The results therefore show the presence of significant differences in energy use distributions and patterns between energy poor and non-energy poor households. Moreover, the results show that the differences between energy poor and non-energy poor are *different for the two different energy poverty indicators* (Feeling Energy Poor vs Actual Expenditure Energy Poor).

To the extent that there are substantial and significant differences in patterns of energy use, and more specifically smart meter data, between energy poor and non-energy poor households, the results give evidence that supports the development of machine learning models to predict the energy poverty status of households that are trained on and use smart meter data as an input. The results emphasise the greater importance of using gas smart meter data as an input than electricity, at least where gas use is driven by heating behaviour, as well as the importance of contextual data as input such as weather data, and calendar and time data.

## 1.6. RECOMMENDATIONS FOR POLICY AND RESEARCH

The results demonstrate that the roll-out of smart meters is an opportunity to improve the quality and quantity of data relating to one particular energy poverty indicator (Actual Expenditure Energy Poverty), and the related indicators like energy price/tariff, energy use and energy expenditure. We are not advocating the use of the AEEP indicator over other energy poverty indicators, however, we do argue that, while AEEP is just one more "tool in the box" when it comes to tackling energy poverty, with the smart meter roll-outs it is a tool that is becoming increasingly useful for measuring energy poverty. AEEP serves as a valuable complementary tool, particularly alongside subjective indicators such as FEP. Together, these indicators offer a more comprehensive understanding of energy poverty, enabling policymakers to address both the objective and subjective aspects of the issue. Where smart meters are widely deployed, we recommend Governments, regulators and stakeholders make better use of smart meter data for energy poverty monitoring, and particularly for program evaluation.

The results are an encouraging first step in the journey towards the goal of developing a machine learning model of energy poverty identification that uses smart meter data as input. Smart meter data is already being collected by utilities, entities that are often interested in or obligated to help the energy poor. We therefore strongly encourage further research to develop and test these models.

This research would not have been possible but for the SERL Observatory dataset. We also therefore strongly encourage the development of further similar Energy Demand Observatories for other EU member states, given their potential for enabling previously impossible research and development of the kind that is needed for tackling energy poverty and achieving a clean energy future.

# 2. INTRODUCTION

## 2.1. WHAT IS ENERGY POVERTY?

The Energy Poverty Advisory Hub (EPAH) of the European Commission define energy poverty as "the inability of a household to ensure their energy needs" (EPAH, 2022). This refers to a condition where a household is unable to access or afford essential energy services, such as adequate heating, cooling, and lighting, due to a combination of low income, high energy costs and inefficient energy infrastructure.

In this report we focus specifically on energy poverty related to heating, and winter heating in particular. Heating demand dominates energy poverty concerns in the UK and much of the EU due to the climate and serious health risks associated with cold homes. For our working definition of the term, we will adopt the official definition of fuel poverty used in England and Wales which regards "a person in a fuel-poor household as someone on a low income, that cannot keep their home warm at a reasonable cost" (Committee on Fuel Poverty, 2024). For the purposes of this report, we will treat the terms energy poverty and fuel poverty as identical and interchangeable.

## 2.2. WHY IS ENERGY POVERTY AN IMPORTANT PROBLEM TO SOLVE?

Energy poverty is a significant and pressing issue affecting the health and well-being of individuals and societal equity. Safety and shelter are basic human needs, and access to safe, comfortable and affordable housing, should be considered a fundamental human right in a modern, enlightened society. Energy poverty undermines this right, leading to serious negative impacts on quality of life, health and safety.

Energy poverty can severely impact individuals' physical and mental health. Cold homes contribute to respiratory and cardiovascular problems, which are particularly dangerous for vulnerable groups such as children and the elderly. Lack of warmth worsens existing health conditions, increases the risk of hypothermia and leads to higher mortality rates during colder months. Excess winter deaths have been estimated to be three times higher in the coldest quarter of homes than in the warmest, attributable to cardio-vascular and respiratory diseases, and children living in cold homes are more than twice as likely to have respiratory problems than those living in warm homes (Dear & McMichael, 2011). Feelings of lower wellbeing were found to be more common in households likely to be energy poor (those finding it difficult to keep comfortably warm in the home and struggling with meeting heating costs), providing evidence of a link between energy poverty and negative mental health outcomes (Huebner et al., 2023). These negative health impacts can place a significant burden on national health services, increasing costs and stretching resources.

Globally, energy poverty affects a large number and proportion of people. The World Bank has estimated that, in 2020, 733 million people globally did not have access to electricity, but that the number could be even higher at 1.18 billion according to analysis of satellite imagery data (Min et al., 2024). In these contexts, energy poverty can mean a lack of basic lighting after dark or the inability to use life-saving medical equipment at home. In the EU, 40% of the population qualify as energy poor according to at least one energy poverty indicator (Maier & Dreoni, 2024). In England, energy poverty affected between 13.0% and 36.4% of all households in 2023, depending on which indicator is used to measure energy poverty (DESNZ, 2024), representing between 3.17 million and 8.91 million homes likely to be struggling to afford their energy bills and maintain a warm, healthy home.

While energy poverty is a problem that has preceded the cost-of-living crisis, the sharp rises in energy prices after the Covid-19 pandemic and driven by Russia's war in Ukraine, has made it considerably worse, significantly increasing the scale and depth of the problem, and made energy poverty a pressing matter for governments, institutions and individuals to address.

## 2.3. HOW CAN ENERGY POVERTY BE SOLVED?

Solutions to the problem of energy poverty can be focussed on its three main causal drivers: inefficient buildings, high energy prices and low incomes.

1. Improving building energy efficiency: one of the most effective ways of reducing energy poverty is by upgrading the energy efficiency of buildings as this leads to reduced energy usage for heating, lower energy bills and improved thermal comfort of occupants. Efficient buildings are also a key part of achieving a clean energy transition, reducing the overall size of electricity grids and generation capacity required to meet demand, and significantly reducing the investment costs of the transition (NESO, 2024). Governments have, as a result, made improvements to building energy efficiency a key part of strategies to reduce energy poverty (BEIS, 2021b).
2. Subsidising energy costs: direct financial assistance to energy poor households is another important solution. This can involve subsidised energy tariffs or payments to reduce household energy bills. These solutions can ensure that households are more likely to be able to afford to heat their home and are less likely to sacrifice basic needs.
3. Addressing structural poverty: energy poverty is linked to the broader issue of income inequality and structural poverty. Policies to improve income levels, particularly for low-income households, are essential for addressing the root cause of energy poverty.

The design, implementation, and evaluation of effective solutions to energy poverty has a cross-cutting need for systematic data collection and monitoring (EPAH, 2023). Collecting detailed data on household energy use, energy expenditures, and living conditions as energy poverty metrics are essential for understanding the scale and nature of energy poverty. They also allow for targeted interventions, ensuring that support is provided to those most in need. Effective data analysis helps in evaluating the effectiveness of various programs and refining approaches to maximize impact.

As a result, the aims of this report are:

1 To improve how energy poverty is measured for the purposes of monitoring and program evaluation,
2 and to improve how households in or at risk of energy poverty are identified.

## 2.4. THE PROBLEMS WITH ENERGY POVERTY MEASUREMENT AND IDENTIFICATION

To effectively design, implement, monitor and evaluate solutions to energy poverty requires the measurement of energy poverty (EPAH, 2023). Measurement refers to the process of quantifying or calculating the extent of energy poverty based on specific indicators. It involves using data (e.g., energy expenditure, income, household conditions) to determine whether households meet the criteria for energy poverty. This requires choosing one or more indicators, which should be specific, measurable and observable, and which essentially simplify the complex nature of energy poverty into a single variable or set of variables. Given the complex multi-faceted nature of energy poverty, there are many indicators. For instance, the EU Energy Poverty Advisory Hub publishes national data on 28 indicators relevant to energy poverty (Gouveia et al., 2022). One of the benefits of having many indicators to choose from is that there is flexibility in choosing those that are most suitable for the local context. However, a potential drawback is that it can make it more difficult for harmonising and comparing efforts across diverse situations. For example, the Committee on Fuel Poverty has stated as a problem the fact that "*there is no consensus as to how we capture the full scope and reality of fuel poverty across the UK*" (Committee on Fuel Poverty, 2024).

A challenge affecting nearly all indicators is the collection of data at scale. The household-level indicators of energy poverty that are commonly used typically require household surveys, such as the subjective indicator "inability to keep the home adequately warm" or the objective indicator "households spending more than a specific percentage of their incomes on energy services". While surveys are a powerful tool for collecting data directly from households, they can be costly to administer, slow to produce data, the data can be subject to recall bias and they are rarely longitudinal in nature, which limits the ability to track changes over time and identify causal relationships between variables. The challenges of data collection for measurement of energy poverty produce barriers to effective monitoring of energy poverty and design of solutions. The challenges are however particularly acute relating to the evaluation of energy poverty reduction programs due to the constraints on time and resources that are common in such situations.

Energy poverty identification refers to the process of *predicting* a household's energy poverty status according to a given indicator if insufficient data is available to directly calculate the indicator. For example, predicting a household is energy poor according to England's LILEE (Low Income Low Energy Efficiency) indicator solely based on knowledge of a building's EPC rating. The reason for doing this is that programs and resources to reduce energy poverty can be effectively targeted to households that are most in need.

However, another consequence of the general challenge relating to collection of household-level data relevant to energy poverty is that existing methods for identifying households in or at risk of energy poverty are either expensive or inaccurate. Identification refers to predicting or detecting which specific households are in energy poverty. It often involves using data-driven methods or models to predict individual households that meet the criteria for energy poverty when complete data is not available. This has led to a situation where much of the resources being allocated by governments to specifically help the energy poor end up being received by households who are not energy poor (Committee on Fuel Poverty, 2020; Deloitte LLP, 2020), leading to wasted resources, misallocation of funding and reduced societal benefit.

In summary, there are substantial problems with energy poverty measurement and identification and there is a need to solve or reduce these problems with more accurate, cost-effective methods such as data-driven approaches leveraging accessible high-resolution data (e.g., smart meter data), to more effectively understand and reduce energy poverty.

## 2.5. THE POTENTIAL FOR SMART METER DATA TO IMPROVE ENERGY POVERTY MEASUREMENT AND IDENTIFICATION

Smart meters are being rolled out in large numbers across EU countries. 95% of all Distribution System Operators (DSO) in member states have started to implement a smart meter roll-out program, 30 DSOs have achieved over 70% penetration level, and 25 have completed their roll-out programs (De Paola et al., 2023). Smart meters collect and store detailed household energy data, typically 30-minute resolution gas or electricity use data and, depending on the exact technical specification, additional contextual data such as tariff or power quality information like voltage. These data collected by smart meters provide opportunities for innovation and cost reduction such as: reducing costs associated with manual meter reading, reducing energy theft or fraud, providing increased information to consumers (via in-home displays, or apps) to improve energy awareness and energy efficiency behaviour, and enabling greater participation of consumers with energy markets to improve the security and sustainability of electricity grids.

In capturing detailed information about household energy usage, and potentially energy prices, smart meter data are also highly relevant to energy poverty, and as a result the smart meter roll-out provides an opportunity for improving data collection relating to energy poverty measurement and identification. The advantages of smart meter data are:

- Accessibility – smart meter data can be accessed remotely, easily, quickly and with low latency, this enables much more rapid and responsive, agile, research and analysis.
- Low cost – once smart meters are installed, as well as the communications infrastructure in place necessary to collecting their data, the cost of data collection is negligible. Moreover, the costs of data collection are equal for all households provided they have a smart meter. This means data collection is equitable and representative, and certain groups of households are not disproportionally advantaged or disadvantaged.
- Universality – a limitation of traditional surveys is that there are often "hard to reach" parts of the population, meaning it is difficult to gather data equally on a population. As smart meters are or are being rolled out universally, they do not have this issue, though we acknowledge that the roll-out itself may not progress equitably.
- Longitudinal - critically this enables insight into dynamic changes over time in a way that cross-sectional data cannot. Longitudinal data provide insight into how and why change occurs. For example, if energy use is reducing over time, longitudinal data enables the identification of which types of households are driving that reduction. By observing how variables change over time, provided that they follow a rigorous structural causal model (Pearl & Mackenzie, 2018) and that the appropriate variables are collected, longitudinal analysis can establish cause-effect relationships, rather than just correlations.

- Consistency – the same measurements are collected for every building / household using instruments with consistent technical specifications. Smart meter data have known and specified accuracy, are not subjective (i.e. do not depend on the individual's opinions, beliefs, etc.) do not depend on the household's demographics, and poor and rich households have the same type of instrument.
- High temporal resolution – the high resolution of smart meter data enables sophisticated analysis techniques that can reveal insights about the building's energy efficiency (Few et al., 2023), or household's energy usage behaviour, which are relevant to energy poverty.
- Geographically precise, uniquely identifiable – smart meter data will have meta-data that allow them to be precisely associated with a household or building's address or geographical location. This facilitates linking to useful contextual data such as local weather data, publicly available information about the building such as Energy Performance Certificate data.

## 2.6. CASE STUDY: REAL-WORLD APPLICATION OF SMART METER DATA FOR ENERGY POVERTY MONITORING AND IDENTIFICATION

Given the multiple beneficial features of smart meter data and their potential relevance to energy poverty measurement and identification, this report aims to investigate the use of smart meter data to improve measurement and identification of energy poverty by conducting a detailed case study using a dataset of 13,000 households equipped with smart meters and with linked socio-technical contextual data: the SERL Observatory dataset (Webborn et al., 2021). This dataset provides a rich source of information, enabling us to analyse household energy consumption and its changes over time in relation to changes in energy prices, and to explore how energy expenditure-based indicators of energy poverty can be produced from smart meter data with minimal participant burden. The following analysis demonstrates not only how smart meter data can enhance our understanding of energy poverty but also produce the actionable insights that can inform policy and program evaluation.

The contents of this report are as follows. First, we critically review different definitions and indicators used to measure energy poverty, methods for identifying energy poverty, and the use of smart meter data to improve these. Second, using a case-study of the SERL Observatory dataset, we investigate the use of smart meter data to improve measurement of energy poverty and compare how different definitions of energy poverty identify different groups of households. Thirdly, we investigate the potential to use smart meter data to identify households in energy poverty by analysing differences in patterns of energy use between energy poor and other households. Finally, we discuss our findings and draw conclusions.

# 3. LITERATURE REVIEW

The aim of this chapter is to critically review different definitions and indicators used to measure energy poverty, methods for identifying energy poverty, and the use of smart meter data to improve these. The goal is to set up and inform the following detailed case study analysis using a dataset of 13,000 households equipped with smart meters and with linked socio-technical contextual data. The literature review focusses on critically examining key studies and sources relevant to the measurement and identification of energy poverty in the EU and UK context, discussing their limitations, and the use of smart meter data as a potential solution to address these limitations.

## 3.1. MEASURING ENERGY POVERTY

The measurement of energy poverty is critical for monitoring of energy poverty. If energy poverty cannot be measured, then it cannot be monitored, and monitoring is an important part of solving energy poverty problem as it is necessary for understanding the scale and dynamics of the problem, its distribution, patterns, causes and effects. Energy poverty can affect different groups in different ways and for different reasons. Understanding these differences allows for more precise design of interventions and targeting of resources. Without a clear picture of the nature of the problem of energy poverty, responses and solutions risk being misaligned or ineffective. Monitoring, and measurement of energy poverty, are therefore critical for informing policy making, strategies and interventions.

Moreover, measurement and monitoring of energy poverty enables international comparison, such as the Energy Poverty Advisory Hub's National Indicator Observatory (Gouveia et al., 2022), and can inform international collaboration, the direction of funding, international alignment of goals, and encourage best practice.

Furthermore, measurement of energy poverty is important for the aim of evaluating the effectiveness of programs designed to reduce energy poverty. Evaluation is important for measuring impact and thus determining whether and how much programs or measures are making a positive difference (EPAH, 2024). Evaluations can measure how many households are benefiting, how much energy costs are reduced (Lartey et al., 2023), whether households have better access to energy services, assessing the direct impacts (e.g., numbers of households moved out of energy poverty, severity of energy poverty reduced) but also indirect impacts such as improved health outcomes (Telfar Barnard et al., 2011), and reduced carbon emissions. Without this it is difficult to know if programs are working as expected or require adjustments.

Evaluation is critical for developing effective strategies to reduce energy poverty, so that programs or measures that are most effective are identified, prioritised over ineffective ones, and scaled up, ultimately so that limited resources are spent to most effectively reduce human suffering associated with energy poverty.

### 3.1.1. CURRENT APPROACHES TO MEASURING ENERGY POVERTY

In the context of the measurement of energy poverty, an indicator is a measurable variable used to measure and track the level of energy poverty in a population or group. An indicator is quantifiable (based on data that can be measured), comparable (allowing comparisons over time or between groups) and simplified (it condenses a complex phenomenon like energy poverty into a single or small set of variables, making it easier to interpret or analyse the data).

The Energy Poverty Advisory Hub recommends 24 "most used" indicators, and lists 32 "additional" indicators, for use in designing, planning, implementing and evaluating energy poverty reduction programs (EPAH, 2023). Of the former, those relevant to household-level measurement of energy poverty in the context we use it in this report are:

- Low building energy efficiency (as indicated by low Energy Performance Certificate (EPC) rating)
- Energy consumption per capita
- Presence of water leakage, damp or rot in dwelling
- Connection to gas or electricity grids
- High expenditure relative to income
    - Spending more than a specific percentage of household income on energy services
    - Share of income spent on energy expenditure more than twice the national average ("2M").
- Vulnerable household (e.g., lone parents, low income, in receipt of social support, etc.)
- Arrears on utility bills
- Inability to keep the home adequately warm in winter (or cool in summer)

In the UK, the official indicators used by government are (DESNZ, 2024):

- England:
    - Low Income Low Energy Efficiency (LILEE) defined as a household that has a residual income below the poverty line (after accounting for required fuel costs) and lives in a home that has an energy efficiency rating of band D or below.
- Scotland:
    - A household is fuel poor if in order to maintain a satisfactory heating regime, total fuel costs necessary for the home are more than 10 per cent of the household's adjusted (after housing costs) net income; and
    - if after deducting fuel costs, benefits received for a care need or disability and childcare costs, the household's remaining adjusted net income is insufficient to maintain an acceptable standard of living. The remaining adjusted net income must be at least 90 per cent of the UK Minimum Income Standard (MIS) to be considered an acceptable standard of living, with an additional amount added for households in remote rural, remote small town and island areas (RRRSTI).
- Wales and Northern Ireland:
    - A "10 per cent indicator": a household is fuel poor if they are required to spend more than 10 per cent of their net income (before housing costs) on fuel costs.

Surveys are the typical approach to collecting data for these indicators. The EU statistics on income and living conditions (EU-SILC) are a harmonised annual cross-sectional survey delivered mostly in person or over telephone and implemented by each participating EU member state and that collects data that include the following indicators:

- Vulnerable household (e.g., lone parents, low income, in receipt of social support, etc.)
- Arrears on utility bills
- Inability to keep the home adequately warm in winter (or cool in summer)
- High expenditure relative to income
    - Spending more than a specific percentage of household income on energy services

  - Share of income spent on energy expenditure more than twice the national average ("2M").

The EU Household Budget Survey (HBS) is a harmonised survey focussed on household expenditure that is conducted every 5 years, administered via interview, and which collects household-level expenditure data on housing, water, electricity, gas and other fuels (Eurostat, 2003). This enables the calculation of the following indicators:

- High expenditure relative to income
  - Spending more than a specific percentage of household income on energy services
  - Share of income spent on energy expenditure more than twice the national average ("2M").

The English Housing Survey (MHCLG, 2020) is a combination of face-to-face participant survey of households and physical survey of buildings by expert building surveyors that enables the estimation of the "required" energy expenditure (based on the SAP building energy model and normative assumptions about occupancy and heating requirements to maintain adequate levels of thermal comfort), and thus calculation of the LILEE indicator, or indeed any of the UK indicators which are all based on "required" energy expenditure, as opposed to actual energy expenditure. The English Housing Survey also collects data to identify:

- Presence of water leakage, damp or rot in dwelling
- Connection to gas or electricity grids
- Vulnerable household (e.g., lone parents, low income, in receipt of social support, etc.)
- Inability to keep the home adequately warm in winter (or cool in summer)

Energy consumption per capita is calculated by European and national statistics organisations from national energy balance sheets and population estimates.

There are a number of limitations associated with these indicators and the current approaches to collecting data, which create barriers to the measurement of energy poverty and its effective monitoring and evaluation.

### 3.1.2. LIMITATIONS OF SURVEY-BASED ENERGY POVERTY INDICATORS

Indicators that are reliant on surveys have a set of associated limitations.

- Subjectivity in self-reported indicators – there are advantages to subjective indicators like the "inability to keep warm" indicator because they are simple and easy to administer. Essentially, they only identify there being a problem if people say they feel like there is a problem. An argument for using this indicator is that there is no advantage in trying to reduce a household's suffering if they do not feel like they are actually suffering. The inability to keep warm indicator is, as a result, very widely used. It is nonetheless a subjective indicator, and at risk of false negatives, e.g., older people may not feel like their homes are as cold as they are, or people may feel comfortable at low temperatures that are in fact a health risk to them (Hills, 2011).

- Recall bias – Recall bias refers to the systematic error that occurs when respondents inaccurately remember or report past events, leading to incorrect or imprecise data. Self-reported expenditure estimates in household budget surveys are known to be affected by recall bias, with length of the recall period and type of respondent affecting the quality of the response (Silberstein, 1989). Recall bias and error in energy expenditure estimates could be considerable due to the variation in the underlying variables (energy use and energy prices) due to weather, and irregular billing cycles, and lack of awareness. This raises an important need to validate these data and techniques for capturing energy expenditure information, something that should be possible to do with smart meter data to act as a ground truth to compare with self-reported expenditure estimates.
- Resource requirement – EU-SILC and household budget surveys are predominantly face-to-face or telephone interviews. There is therefore a requirement for skilled labour to administer the survey. This problem is even more acute for UK indicators which require a physical survey of the building by an expert surveyor, combined with a practitioner with knowledge and skills to use the collected data as input to a building energy model to produce the necessary required energy use estimates. These associated costs necessarily limit the scale, scope, frequency and speed of such surveys and the production of the energy poverty indicators they enable. This is particularly so for household budget surveys and the expenditure-based indicators which are (currently) reliant on them, e.g., the EU Household Budget Survey is conducted only every five years leading to conclusions that expenditure-based indicators are "not available in a timely and fully harmonised manner across all Member States" (Menyhert, 2023).
- Model error – indicators that rely on modelling of required energy use are dependent on the model's accuracy. This is a non-trivial requirement to achieve, and indeed there is evidence that the model that underpins the UK's energy poverty indicators shows considerable discrepancies when compared to actual energy use in buildings, even when occupant characteristics are controlled to match the assumptions made in the model (Few et al., 2023)...
- Participant burden – clearly surveys involve participant burden and while efforts can be made to compensate participants for their time, this increases the survey's overall costs. Furthermore, there is evidence of declining response rates to surveys over time (Czajka & Beyler, 2016) increasing search costs and the impact of non-response bias.

In summary, when it comes to indicators, there is a need for and value in improving the data collection process in particular:

- quality (improving the data accuracy, granularity)
- costs (reducing costs)
- speed (increasing speed of data access and publishing)
- reducing participant burden

Moreover, while current approaches to measuring energy poverty in the EU and UK provide valuable insights, they are constrained by several significant limitations that create barriers to the effective monitoring of energy poverty.

### 3.1.3. EVALUATING THE EFFECTIVENESS OF PROGRAMS

The problems associated with current methods for measuring energy poverty are especially clear when it comes to program evaluation. Evaluations often have time, budget and data privacy constraints which make impractical the time or resource intensive methods for measuring energy poverty.

For example, one of the aims of the UK's Green Homes Grant Voucher Scheme, which provided subsidies for the installation of energy efficiency measures such as solid wall insulation and heat pumps, was to reach energy poor households (Ipsos et al., 2023). The Government-commissioned independent evaluation of the scheme included the objectives of assessing how many households that applied for the scheme were likely to be energy poor and estimating the impact that the measures installed through the scheme had on reducing the number of households in energy poverty. The evaluation used England's official fuel poverty indicator LILEE (Low Income Low Energy Efficiency) which requires information about household income (after housing costs) and the Energy Performance Certification (EPC) energy efficiency rating of the dwelling, as calculated using the SAP building energy model. As stated in the final evaluation report (page 90):

*"To perform a true RdSAP (EPC) calculation, a lot of detailed information regarding the physical characteristics of the dwelling and energy efficiency measures is required. It is not feasible to acquire this level of information for dwellings being improved as part of GHGV scheme."*

As limited information was available regarding the physical characteristics of the buildings, a simplified model was used to estimate the EPC rating using imputed data. An exercise in validating the method for dwellings where EPC data were available revealed good agreement on average, but with substantial variance (a standard deviation of over 10 points on a 100-point scale, which is approximately equivalent to the range of a band, e.g., EPC rating C = 69-80 SAP points).

While this was undoubtably a practical method for estimating the energy poverty status of the applicants to the scheme, and the resulting change due to energy efficiency measures installed, nonetheless it reveals that the ability to evaluate the effectiveness of programs in reducing energy poverty in the UK is limited by the difficulty in collecting or accessing the data needed to accurately measure energy poverty before and after interventions, and that the resulting requirement to use modelling methods which are based on considerable assumptions results in a variance error which is likely to produce a significant number of false positives and false negatives.

While subjective self-reported energy poverty indicators such as the "inability to keep warm" indicator are easier to collect data for using surveys, compared to those such as LILEE which require detailed information about building physical characteristics collected by a trained surveyor, they nonetheless have an issue relating to the need to conduct the surveys during heating seasons before and after the intervention, the timing of which may not be practical for an time-constrained evaluation.

Current approaches to measuring energy poverty therefore have limitations which constrain and reduce the accuracy of identifying and measuring energy poverty as well as the evaluations of energy poverty programs, and which therefore detract from our ability to learn from and improve upon these programs in future.

## 3.2. IDENTIFYING HOUSEHOLDS IN OR AT RISK OF ENERGY POVERTY

Identifying households in or at risk of energy poverty is a critical step in the path to solving energy poverty. If households who most need help cannot be identified, then this creates a substantial barrier to getting them help. Unfortunately, there are substantial problems with current methods for identifying energy poverty. The UK's Committee on Fuel Poverty has "*highlighted, year after year, the need for more accurate targeting of resources, and energy efficiency programmes, directed to fuel poor households*" (Committee on Fuel Poverty, 2024).

There are limited resources available to reduce energy poverty. By identifying households most at risk, programs can direct resources where they will have greatest impact. This ensures that programs do not waste resources on households that are not in immediate need. In the UK, however, of the £2.5 billion per year budget for schemes designed to help energy poor, only 10-30% is estimated to be received by energy poor households (Committee on Fuel Poverty, 2020). This presents a substantial misallocation of resources that if allocated more accurately would help to reduce energy poverty.

While clearly the priority is allocating resources to those most severely affected by energy poverty, identifying households who are at risk of falling into energy poverty allows for preventative measures rather than reactive ones. Helping people avoid falling into energy poverty also prevents human suffering and should be included in the overarching goals of reducing energy poverty.

We described above how there are limitations to current approaches to measuring energy poverty directly, and these also create barriers to identification of energy poor households. In most situations where the goal is to proactively identify households in energy poverty to better target limited resources, it can be impractical or otherwise difficult to directly measure energy poverty in a population. In these situations, where there are not sufficient data to be able to directly measure energy poverty, then other methods are required to help identify households that are likely to be in energy poverty. In the following section, we review current methods for identification and describe their limitations.

### 3.2.1. CURRENT APPROACHES TO IDENTIFYING HOUSEHOLDS IN OR AT RISK OF ENERGY POVERTY

Current methods for identifying energy poor in GB are expensive or inaccurate. The Energy Company Obligation (ECO) is a government energy efficiency scheme in GB that is designed to reduce energy poverty and carbon emissions. It places obligations on energy suppliers to help energy poor households reduce their energy usage and costs through energy efficiency measures such as upgrading home insulation. Because of the specific focus on energy poverty, energy suppliers are required to target energy poor households, and current approaches have led to considerable "search costs" for energy poor households. In the 2018-2022 period, energy suppliers spent £257 million on search costs for fuel poor households, with up to £1000 per "lead" (Deloitte LLP, 2020). Another study reported that energy efficiency programs can spend 2% of capital expenditure budget on fees to agents for leads to identify energy poor households with conversion rates as low as 20% (Connected Places Catapult, 2021).

Given these considerable search costs, low-cost identification methods are clearly needed. The UK Government published guidance for identification methods that included an option to use the publicly available Energy Performance Certificate (EPC) database to identify households facing high energy costs as defined by the indicator EPC band D or below. The EPC data are free to access and therefore a good option for lowering search costs, however this comes at a cost in accuracy. EPCs are only available for 55-60% of the housing stock, and analysis has shown that only 51% of households identified in this way would be energy poor (BEIS, 2019). So, while low cost, this method is not accurate. Ideally, what is needed is a method for identifying energy poverty that is both accurate and low cost.

The EU-funded project EnergyMeasures had an overarching objective of engaging with and assisting energy poor households and highlighted that identification of energy poor households was a key element of the project. The project reviewed methods of identifying energy poor households and concluded that there was a gap between the macro- and meso-level analyses of energy poverty, which comprise the bulk of the literature, and the identification of individual or specific energy poor households, which is required for projects or initiatives that focus on targeting interventions to energy poor households (Dunphy, 2020). They found that the "vast bulk" of projects have focussed on methods other than data-oriented approaches such as seeking referrals from social workers, or organisations already working with the energy poor, highlighting that energy poverty identification has a barrier in the form of lack of data, and data-driven approaches such as machine learning modelling. However, data on actual energy consumption can make a significant contribution to better analysis and targeting of energy poverty, particularly in identifying those who are energy rationing and those in arrears in energy bills (Stavrakaki, 2023).

### 3.2.2. DATA-DRIVEN APPROACHES FOR ENERGY POVERTY IDENTIFICATION (INCLUDING MACHINE LEARNING)

The EU-funded project ENPOR aimed to make energy poverty in the private rental sector visible and quantifiable. To address this, the project developed and piloted tailored energy efficiency policies in seven EU countries. Among the project's most important challenges and barriers was "difficulty to identify energy poor households and engage them into the planned policies and measures" and among its conclusions were that policies could be improved by "*specific targeting of energy poor [Private Rental Sector] tenants and landlords to address energy poverty effectively within this* *(Vondung et al., 2023)*. A notable exception was the EU-funded project SocialWatt which investigated data-driven approaches to identifying energy poor households and concluded that energy suppliers have access to "very granular data on each customer… Data on actual energy consumption can make a significant contribution to better analysis and targeting of energy poverty, particularly in identifying those who are energy rationing and those in arrears in energy bills." Machine learning, as a statistical and data-driven approach, can learn from existing data to build predictive models. Therefore, the increasing availability of data such as energy consumption data or survey data, coupled with data-driven approaches such as machine learning prediction models, offers significant potential for predicting energy poverty.

The UK Committee on Fuel Poverty has also identified this as a promising area of research and development that should be prioritised, stating: *"we [have] identified that advanced statistics/machine learning [AI] has the potential to help improve the ability to identify fuel poor households"* (Committee on Fuel Poverty, 2020). Several studies (González Garibay et al., 2023; Hassani et al., 2019) propose that big data could improve the data collection quality and mechanism and provide insights into data-driven models for energy poverty forecasting.

In recent years, there has been a significant increase in research applying machine learning algorithms to existing data to develop models for predicting energy poverty (López-Vargas et al., 2022). These studies typically use survey-based factors as input data for training models, including variables such as construction type and dwelling characteristics (Hong & Park, 2021; van Hove et al., 2022; Wang et al., 2021), household energy efficiency and income (Al Kez et al., 2024), as well as occupant-related characteristics such as age of main person, and social benefits and education levels (Abbas et al., 2022; Ghorbany et al., 2024; Wang et al., 2021). Consequently, not only do the energy poverty indicators used as target variables in these studies, such as LILEE (Al Kez et al., 2024) and LIHC (Dalla Longa et al., 2021; van Hove et al., 2022), rely heavily on survey data, but the input data for model training are also predominantly survey-based. This reliance on survey data introduces limitations related to inefficiency, potential resource waste, and data collection challenges, as outlined in section 3.1.1.

Additionally, some machine learning models that aggregate data at the country level (Mukelabai et al., 2023) or rely on satellite remote sensing data (Al Kez et al., 2024) will lack the details required for accurate household-level predictions. Smart meter data, by contrast, offer a promising alternative by providing detailed, high-resolution information on household energy usage. Studies like those by (Darby, 2012) and (Sareen et al., 2020) have highlighted the potential of smart meter data to enhance energy poverty prediction. By incorporating smart meter data into machine learning models, it may be possible to improve the accuracy and efficiency of energy poverty identification at the household level, overcoming some of the limitations associated with traditional survey-based approaches.

On the other hand, in terms of machine learning model performance, some studies rely solely on accuracy as a performance metric. For example, one study reports a model achieving 78% accuracy (Ghorbany et al., 2024), but does not provide additional performance metrics. In situations where the classifications being predicted are imbalanced in the population, then accuracy can give a false sense of model performance. For example, if only 10% of the population is energy poor, then a superficial model that predicted *all* households were *not* energy poor would achieve an accuracy of 90%. Clearly relying only on accuracy can be misleading, as it may overlook other important aspects of model performance.

In contrast, some models use a more comprehensive set of metrics but still reveal limitations. Recall, also known as the "true positive rate" or "sensitivity", measures the proportion of actual energy poor households that the model correctly identifies. This is particularly important when the goal is to capture as many vulnerable households as possible. Precision measures the proportion of households identified as energy poor by the model that are actually energy poor. A high precision ensures that resources are directed to those truly in need, reducing the number of non-energy poor households incorrectly classified as energy poor. For instance, a model in one study achieved an AUC (Area Under the Curve), a metric derived from the ROC (Receiver Operating Characteristic) curve to evaluate the model's performance of 86% (Al Kez et al., 2024) but had lower scores in precision (65%), recall (57%) and F1, which is the harmonic mean of precision and recall (61%). AUC measures the machine learning model's ability to distinguish between energy poor and non-energy poor households but does not prioritize vulnerable households specifically.

Another model reached a high true positive rate (TPR) of 90% but only had an accuracy of 79% (Wang et al., 2021). Furthermore, certain studies, such as that by (Hong & Park, 2021) report extremely high performance (for all metrics) but lack transparency about whether these results apply to training or testing data. In machine learning, datasets are typically divided into two parts: a training set and a testing set. The model is trained using the training set, where it learns to recognize patterns from these data. Its performance is then evaluated using the testing set, which helps to ensure that the model can effectively apply what it has learned to new, unseen data. However, there is a risk when a model is trained on the training set with excessive complexity; it can "cause overfit" of the training data. Overfitting occurs when a model learns the training data too well, including their noise and outliers, to the extent that it performs poorly on new data. Essentially, the model memorizes the training data rather than learning to generalize from it. This issue of overfitting can lead the model to perform exceptionally well on the training data but poorly on the testing data. This is a classic beginner's error in machine learning as while the model can appear to be performing excellently, in fact the overfitting introduces error into the model predictions and worsens its performance when evaluated using test data. This is why it is critical to be sceptical about reported performance results where it is not clear if they are for the training or testing evaluation.

Additionally, only a few studies have employed data sampling techniques to manage imbalanced dataset, a common challenge in machine learning that can significantly skew model performance. Imbalanced data are where the data are categorised into groups, such as energy poor and non-energy poor, but the groups are imbalanced and one group significantly outnumbers the other. The larger group is called the majority class (non-energy poor in our example), and the smaller group called the minority class (i.e., energy poor households). For example, (Dalla Longa et al., 2021) applied down-sampling techniques to ensure that the machine learning model do not overfit to the majority class and neglect the minority class, which often represents the energy poor households.

Therefore, using a comprehensive set of evaluation metrics, not only the AUC or accuracy, but also precision, recall, and F1 score, and dealing with imbalanced datasets are essential for a thorough evaluation of energy poverty prediction models. Additionally, focusing on reducing false negatives, thereby enhancing recall, is crucial to ensure that vulnerable households are not overlooked in model predictions.

## 3.3. SMART METER DATA FOR MEASURING AND IDENTIFYING ENERGY POVERTY

The previous sections illustrated that there are substantial limitations associated with current methods for measuring and identifying energy poverty in EU and UK and this is leading to adverse outcomes such as misallocation of scare resources, and ineffective programs to reduce energy poverty. This section considers the potential role of smart meters and smart meter data to improve the current approaches to measuring and identifying energy poverty. We start by describing some of the variables or indicators that smart meter data could help produce, which are relevant to the measurement of energy poverty. We then discuss the potential of smart meter data for enhancing energy poverty identification, particularly when paired with machine learning techniques. We will address questions of how smart meter data have been applied in current studies and why they could contribute to improved identification of energy poverty. As a reminder, the difference between measurement and identification here is that with the former all the information that is needed to measure energy poverty is available, while with identification that is not the case, and the aim is to accurately predict or identify whether an individual household is energy poor based on other data.

### 3.3.1. ENERGY PRICES

Energy prices directly affect energy poverty and are a key driver of this problem. All else equal, higher energy prices cause higher levels of energy poverty. Energy prices are one of the energy poverty indicators recommended by the EU Energy Poverty Advisory Hub (EPAH)(Gouveia et al., 2022). Smart meters are capable of storing energy price (tariff) information, and all smart meters in GB do (DECC, 2013), and so smart meters are a potential source for these data.

Despite the centrality of energy prices to energy poverty, there is often only a limited picture of energy prices provided by national statistics. In GB, for example, the national debate regarding the recent cost of living crisis, with its associated sharp rises in energy prices has been generally restricted to conversations about the average or typical price of electricity and gas (Bolton, 2024). While understanding of the central tendency of the distribution of energy prices is important, it fails to give any information about the dispersion of energy prices in the population and whether energy prices are systematically different for different types of households, particular the energy poor or vulnerable. Moreover, as we necessarily progress into the clean energy transition, flat-rate electricity prices will need to increasingly give way to more complex time-of-use tariffs and the standard assumption that everyone pays the same price will be less valid.

As smart meter tariff data become increasingly available they can enable novel analyses and insights relevant to energy poverty such as:

- To what extent there is heterogeneity in tariffs in the market?
- To what extent is there uptake of new, innovative tariffs?
- To what extent households are paying more than they could be if they were on a more advantageous tariffs available on the market?
- Are energy poor households more likely to be on disadvantageous tariffs?

### 3.3.2. ENERGY USE

Energy use is a central component of energy poverty. The more energy households are required to use to fulfil their needs, the more likely they are to be in energy poverty. Energy use is one of the energy poverty indicators recommended by the Energy Poverty Advisory Hub and is a required variable for the calculation of several other expenditure-based energy poverty indicators. Smart meters measure and record high-resolution and accurate data on gas and electricity use and make these data available remotely to approved users for legitimate applications. Unlike traditional meters that require manual readings and provide limited aggregate information (e.g., monthly or quarterly consumption), smart meters automatically and frequently record consumption data by advanced devices installed in households, often at intervals as short as every 15 to 30 minutes. This high-resolution data offer a precise, time-stamped view of energy usage patterns over time, allowing for an in-depth understanding of when and how energy is used within households.

When combined with external temperature data, high-resolution gas and electricity usage data can enable the calculation of smart meter enabled thermal efficiency ratings (SMETER) which is an estimate of the Heat Transfer Coefficient of a building (Allinson, 2022). This means that smart meter data can be used to estimate the energy efficiency of the building. Smart meters can therefore directly enable the measurement of several energy poverty indicators.

Moreover, smart meter data enable analyses that are useful, or insightful for improving energy poverty identification, especially coupled with machine learning technologies. For example, smart meter data can be used to train machine learning models which can be used to predict counterfactual household energy use (Zapata-Webborn et al., 2024). When compared to actual energy use, this gives an estimate of whether there has been a change in energy use in a household, and this in turn could help to identify households with unusually low energy use and who are potentially under-heating.

Smart meter data can also be used to generate or characterise end-user load profiles (Buttitta & Finn, 2020; Gouveia & Seixas, 2016; Khan et al., 2019; Kipping & Trømborg, 2016; McLoughlin et al., 2015; Pullinger et al., 2024; Tang et al., 2022; Viegas et al., 2016). The end-user load profile can help to identify the household that has low energy use, or a change of energy use patterns, which enables us to predict the potential household that will be energy poor due to the changed behaviour. Gas smart meter data and machine learning technologies are used to detect who receive government assistance and therefore can infer which households are under energy poverty situation (Hurst et al., 2020). Smart meter data can also be used to detect appliance usage patterns through machine learning technologies, so can identify and predict unique characteristics of energy poor households based on appliance usage (Fergus & Chalmers, 2021).

### 3.3.3. ENERGY EXPENDITURE

The combination of energy and price data enables the calculation of energy expenditure, as well as investigation of the relationship between price and demand. Energy expenditure is a central component to energy poverty. Energy expenditure is a required input to measuring expenditure-based energy poverty indicators such as "Spending more than a specific percentage of household income on energy services". Smart meter data enable actual energy expenditure to be collected and measured, and therefore enable the measurement of expenditure-based energy poverty indicators (such as energy burden (Ghorbany et al., 2024), defined as the proportion of expenditure relative to income) that are based on actual energy expenditure, provided income data are also available.

Given the important role of energy expenditure in energy poverty, there is value in governments and regulators having a good understanding of the distribution, patterns, causes and effects of energy expenditure in the population, in order to have evidence-based answers to questions such as:

- How is energy expenditure changing, or expected to change, over time, e.g., in response to changes in energy prices, or extreme weather events?
- How does energy expenditure vary for different groups of households, and particularly for the energy poor or the vulnerable?
- Or counterfactual questions like "what would energy expenditure have been if circumstances had been different, e.g., in the absence of a government policy to reduce energy prices, or if households were on more favourable tariffs, or if weather conditions had been more mild or severe?"

Looking ahead, an important area of research is to accurately assess the distributional impacts of changes to energy prices due to the clean energy transition, e.g., transfer of green levies from electricity to gas prices, and the consequences of electricity prices decreasing and gas prices increasing over time. Who are the winners, who are the losers, and to what extent will low-income or vulnerable groups be disproportionately impacted (Sherriff et al., 2022)?

Questions such as these are of central importance to governments, regulators and energy consumer advocacy groups, yet answers to these types of questions are limited by lack of data. For example, in GB, the energy regulator Ofgem and the Government are necessarily restricted by lack of data to considering how changes in energy prices affect "typical" consumers (Bolton, 2024), and are therefore limited in their ability to consider anything beyond the mean / typical consumer. Because energy use and tariff data at the meter-level are not more widely available, analysis is limited to considering the central tendency of the population. This is an issue because while the mean of a distribution holds important information, it does not reveal the diversity of the distribution, and it is the households at the extremes of the distribution that can be most affected.

## 3.4. CHAPTER SUMMARY

This chapter has explored various dimensions of energy poverty, critically reviewing methodologies for its measurement and identification within the EU and UK contexts. It underscores the critical role of accurate measurement in monitoring, evaluating and ultimately mitigating energy poverty. Traditional approaches, while foundational, are often hampered by limitations such as data timeliness, accuracy and the high costs associated with surveys and physical inspections. The introduction of smart meters presents an opportunity to overcome these barriers.

When it comes to the measurement of energy poverty, smart meter data can improve the quality and quantity of data on energy prices, energy use, energy expenditure and energy expenditure-based indicators of energy poverty, as well as enabling household-level analyses relevant to energy poverty such as the relationship between changes in energy prices and energy demand, building thermal efficiency, and under-heating. With the large-scale deployment of smart meters throughout the EU and UK, opportunities are emerging to fill some of the data gaps related to energy poverty, improve how energy poverty is measured, and ultimately help tackle this pressing societal problem.

Moreover, the integration of machine learning techniques with smart meter data can enhance the prediction and identification of energy poverty. These data-driven approaches, equipped with a robust set of evaluation metrics enables more accurate, timely and targeted identification of energy poor households, helping to ensure that interventions are directed to those most in need and supporting the development of more effective, data-driven policies for addressing energy poverty.

Moving forward, enhancing the quality of smart meter data, and expanding the use of comprehensive evaluation metrics will be critical. Prioritizing metrics such as "recall" can help ensure that vulnerable households are not overlooked, supporting targeted and effective policy responses. In conclusion, while challenges remain, the potential for smart meters and machine learning to improve energy poverty identification is significant and deserves further exploration.

# 4. USING SMART METER DATA TO MEASURE ENERGY POVERTY INDICATORS: A CASE-STUDY USING THE SERL OBSERVATORY DATASET

The previous chapter argued that smart meter data, for a number of reasons including their growing availability, could be used to improve how energy poverty is measured, and thereby monitored and understood, and this chapter focusses on investigating this topic using the SERL Observatory dataset as a case-study.

Based on the literature review of the previous chapter, this chapter has the following objectives.

1. to demonstrate that smart meter data can be used to derive indicators that are relevant to energy poverty, in particular to calculate Actual Expenditure Energy Poverty (AEEP) for SERL Observatory participants (those with energy burden equal to or above 10%),
2. to analyse the energy expenditure data from smart meters and show how these compare to the conventional, limited information regarding residential energy expenditure that underpins the national debate, in particular its variation over time, and differences between individuals and groups, and
3. to analyse the relationship between the AEEP indicator and Feeling Energy Poor (FEP) indicator by comparing the households identified by the two, and discuss the relationship between AEEP and Required Expenditure Energy Poverty (REEP), which is the official indicator that was used in England prior to the Hills Review, and still in use in Wales.

## 4.1. METHOD

This case study is based on analysis of the SERL Observatory dataset. The dataset consists of household-level smart meter (electricity and gas where available) data with linked household socio-technical data including weather, building physical characteristics from the open Energy Performance Certificate database, and household and building characteristics collected via self-completion questionnaire of which there are several collected over a period of several years (Webborn et al., 2021). The households were selected from a stratified random sample of GB addresses with a smart meter and approximately 13,000 households were recruited in three waves in 2019 to 2020. The sample is broadly representative of GB households across several building and socio-demographic characteristics but notably under-represents flats / apartments, and private rental households due to non-response biases and relative lack of these in the early years of the GB smart meter roll-out. Nonetheless, the combination of high-resolution gas and electricity use data with rich socio-technical data for longitudinal panel is a unique data resource that enables innovative research into residential energy use. The SERL Observatory is accessible to Accredited Researchers working on approved projects (Elam et al., 2024). The analysis presented here was conducted by ONS Accredited Researchers and received research ethics approval from UCL, and approval from the independent SERL Data Governance Board.

The analysis presented here focussed on smart meter data covering the period October 2021 to March 2024 inclusive. This period was chosen to cover the winters before and after the "cost of living crisis" winter of 2022/2023, which in GB involved unprecedented energy price rises and government interventions to subsidise individual's energy costs (Bolton, 2024). Energy use in GB is winter dominated due to colder weather in winter and general requirement for space heating during the winter. Most households use gas boilers for space and water heating, and gas use is primarily driven by space and water heating end-uses, with cooking a secondary driver. Both gas and electricity use data are available from the SERL Observatory at a household-level.

To make it easier to interpret the gas and electricity use results, we have restricted analysis to households whom we have reason to believe use gas boilers as their primary heating source. We have determined this using the household's answers to the question: *"What type of central heating does your accommodation have?"* Households with electricity as their primary heating source are therefore not included in the analysis. The following table shows the resulting breakdown of primary fuel use for heating for the SERL Observatory, we only include households in the "Gas" or "Gas and electric" categories in the following analysis.

**Table 1 – Number of households in SERL Observatory based on primary fuel used for heating.**

| Primary fuel used for heating | Number of households in SERL Observatory |
|---|---:|
| Gas | 10560 |
| Other | 1211 |
| Electric | 719 |
| Unknown | 344 |
| Gas and electric | 308 |
| None | 151 |

The gas and electricity use data included in the SERL Observatory are available at half-hourly and daily resolution for each household. We aggregate these data over time into monthly summaries and over groups into group-level summaries (e.g., energy poor households, non-energy poor households) using the same method as used to produce the SERL annual statistical report, which includes a description of the method (Few et al., 2022). In addition to these aggregated energy use data, we also aggregate the energy tariff data that are available as part of the SERL Observatory dataset. The tariff data are collected from individual gas and electricity meters at approximately monthly frequency, though there are periods of missing tariff data of considerable duration, for example, during the winter of 2022/2023, due to technical issues with the SERL data collection infrastructure.

To deal with missing tariff data, tariffs were imputed based on using rules developed for a previous project (McKenna et al., 2023a, 2023b) which covered part of the time period analysed here, and extending these rules to the full time period covered. Essentially, the imputation rules relied on identifying the region and payment type of each household (direct debit, standard credit, pre-payment) and where data were missing assuming that households were on the prevailing "energy price cap", a government-set upper limit on the unit cost and standing charge, which applied to approximately nine in ten households in GB during this period (Bolton, 2023).

Once tariffs were imputed, these were then aggregated to monthly resolution tariff data for each household, and combined with the monthly resolution energy use data, to produce monthly resolution expenditure data for gas and electricity at the household level, and these then aggregated in the same manner as the energy use data. Given that 90% of households in GB were protected by the Energy Price Cap and Energy Price Guarantee in July 2023, the risks of imputation introducing substantial bias to the results are minimal.

Household income is needed to calculate energy burden (energy expenditure as a percentage of household disposable income) and energy poverty indicators that are based on energy burden, as well as to classify households as being "low income". The estimation of household income within the SERL dataset follows a structured approach, beginning with gross income and progressing to disposable income and equivalised income. Gross income includes all earnings from employment, benefits, investments, and other sources before housing cost (such as rent and mortgage interest payments) and is estimated based on the midpoint of self-reported income bands from the SERL Observatory follow-up survey, reflecting income for the period 2022-2023. Income of the household reference person (HRP) and any partner are included in this analysis.

To estimate disposable income, a calculation was made by deducting direct taxes (e.g., income tax, national insurance contributions, council tax, etc.) from gross income. This disposable income estimate relies on regression functions tailored to income quintiles, as derived from the ONS dataset (ONS, n.d.). This model enables an approximation of disposable income within each income quintiles band. Additionally, disposable income was adjusted by adding the Energy Bill Support Scheme (EBSS) for the year 2022-2023 (UK Government, 2024), a government grant of £400 per household, specifically for energy affordability assessments. The estimated disposable income result was used as "Household income" when calculating energy burden and expenditure-based energy poverty indicator.

To classify low-income group, disposable income was then equivalised following UK government guidelines of how to define "low income" households (UK Government, n.d.). Equivalisation adjusts income based on household composition (number of adults and children) to provide a standardized income measure. A household is classified as low income if its equivalised disposable income falls below 60% of the national median equivalised disposable income for that year, a threshold used to identify households experiencing relative low income. By employing this methodology, we can accurately classify of households within the dataset into low-income group and not low-income group, aligning with government standards and enabling targeted analysis of energy expenditure.

"Feeling energy poor" is the term we used for a subjective indicator of energy poverty. It is based on data from the SERL Observatory follow-up survey which was conducted in February 2023. Households are classified as Feeling Energy Poor (FEP) based on the method of Waddams Price et al. (2012) which is if, when asked "*During cold winter weather, can you normally keep comfortably warm in your living room?*", they answer "*No*" and then to the follow-up question "*Did you answer "No" to the previous questions for any of the following reasons?*" they answer "*You feel it is difficult to afford the fuel to heat your home*". In addition, households are classified as Feeling Energy Poor if they answer that it is "*Fairly difficult*" or "*Very difficult*" to the question "*How easy or difficult is it for you to meet your heating/fuel costs?*".

We calculate expenditure energy poverty based on the method of Waddams Price et al. (2012) which is that a household is defined as "Actual Expenditure Energy Poor" (AEEP)[1] if they actually spend 10% or more of their household disposable income on total (gas + electricity) energy expenditure. This is different from the '10 per cent indicator' used in Wales and Northern Ireland, and previously used in England, which is based on households *requiring* to spend 10% or more of their household disposable income[2] on energy expenditure. As stated in Waddams Price, AEEP provides a 'lower bound of true fuel poverty if all households who spend more than a tenth of their income need to do so' and so makes the AEEP a *conservative indicator* compared to the 10 per cent *required* energy expenditure indicator.

## 4.2. THE CONVENTIONAL VIEW ON GB RESIDENTIAL ENERGY EXPENDITURE

Before analysing the SERL Observatory data, we first show the conventional understanding of residential energy expenditure which underpins the national debate in GB, which is that of how energy bills for households vary over time and the effect of changes to energy prices due to Government policy. Note this focuses on the conventional view of energy expenditure in GB and not *energy poverty* which has official indicators such as Low Income Low Energy Efficiency, or the 10% indicator (more than 10% of household disposable income before or after housing costs required to be spent on fuel).

Figure 1 shows the variation in annual total (gas + electricity) bills for a typical GB consumer paying by direct debit assuming they were on the Government's key energy bills support policies during the cost-of-living crisis (the Energy Price Cap and Energy Price Guarantee). The figures in this section are based on publicly available information about the Energy Price Cap and Energy Price Guarantee, and are not based on SERL Observatory data. At the time the energy regulator Ofgem assumed a typical consumer used 12,000 kWh for gas and 2,900 kWh for electricity. The Energy Price Cap covers all customers on 'default' or standard variable tariffs, not those on fixed tariffs. It sets a cap on the unit costs and daily standing charges for all consumers in GB. Ofgem combines these with the typical consumption values to arrive at an average UK bill, and is responsible for publishing of this information. This information is the best available information about how changes in energy prices are affecting energy bills and therefore critically underpin the national debate, particularly by providing information to government ministers (Bolton & Stewart, 2023).

[1] Waddams Price used the term 'Expenditure Fuel Poverty'

[2] In Wales and NI this is 'before housing costs' while in England this was 'after housing costs'.

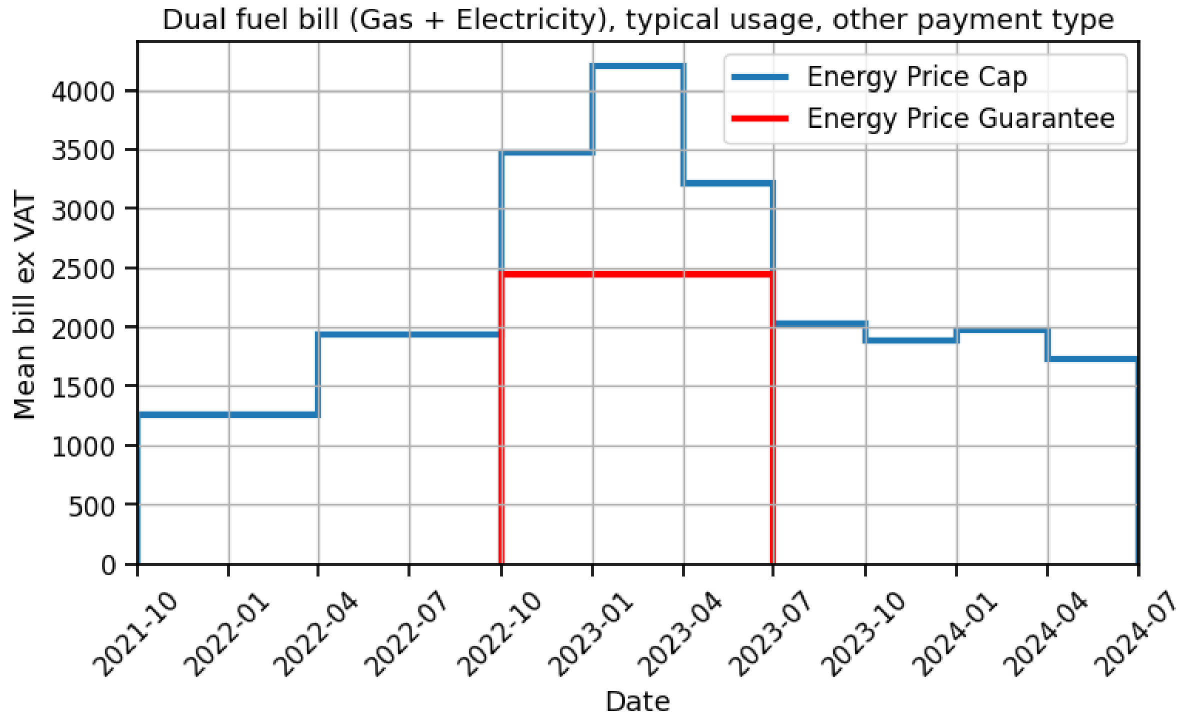


**Figure 1 – Variation in annual energy bills (gas + electricity) for a 'typical' consumer under the Government's Energy Price Cap and Energy Price Guarantee schemes over the 'cost of living crisis' period.**

Households' actual energy bills will depend on how much they actually use, and this conventional picture of energy expenditure is critically missing any information about actual energy expenditure and individual household differences in energy expenditure.

The regulator Ofgem regularly reviews the price cap levels and adjusts it accordingly. Notably during the cost-of-living crisis the cap was raised by unprecedented amounts; a 54% increase in April 2022, which was followed by an 80% increase in October 2022. Households did not pay these prices however because of emergency measures introduced by the Government in the form of the Energy Price Guarantee, shown in red in the above figure. This was set at £2500 (assuming energy consumption for a 'typical' consumer) and during this time households who were on the Energy Price Cap had unit prices set by the Energy Price Guarantee, which therefore reduced their energy costs compared to the Energy Price Cap. Again, households' actual energy bills would depend on how much gas and electricity they use.

A critical aspect of the Energy Price Guarantee is that the Government agreed to pay the difference between the Energy Price Cap and Energy Price Guarantee to the energy suppliers. This resulted in an unprecedented situation where Government subsidised the unit cost of energy out of general taxation, with the result that households that used more energy, who are generally on higher incomes, received higher subsidies compared to low energy use households.

During the winter of 2022/2023, the Government also introduced the Energy Bills Support Scheme which was a £400 payment on electricity bills for every household. As this was applied equally to all households, it will have disproportionately benefited lower income households in relation to their income, though the payment also will have been received by higher income households who arguably may not have needed the financial assistance. The total cost of these Government interventions has been estimated at £42 billion (Lowrey & Mulvany, 2024). Given the lack of information about individual differences, however, estimates about these policies distributional effects are challenging.

While energy prices have reduced from their high points during the winter 2022/2023, we are nonetheless in a 'new normal' period of historically high energy prices, and of general concern about the distributions, patterns, causes and effects of energy expenditure in the residential sector. National debates, and the design and evaluation of effective energy policies to tackle this problem are however held back by the lack of detailed information about actual household energy expenditure and individual differences in the population. Smart meter data can help fill this data gap.

## 4.3. ACTUAL ENERGY EXPENDITURE FROM SMART METER DATA

Figure 2 shows how actual energy prices varied over time for the period covering the winter before and after the cost-of-living crisis winter of 2022/2023, based on the SERL Observatory data. Unit costs and daily standing charges are shown separately for both gas and electricity. The data show broad agreement with the general trends of the conventional picture of energy price variation over time shown in Figure 1, with notable increases around April and October 2022. Unit costs decreased after the winter of 2022/2023 going into the summer of 2023, though daily standing charges stayed flat for gas and even continued to increase for electricity. There is considerably more variance in individual differences for electricity prices than for gas prices, which indicates that there is more actual deviation of individuals from the 'typical' (mean) price for electricity than for gas.

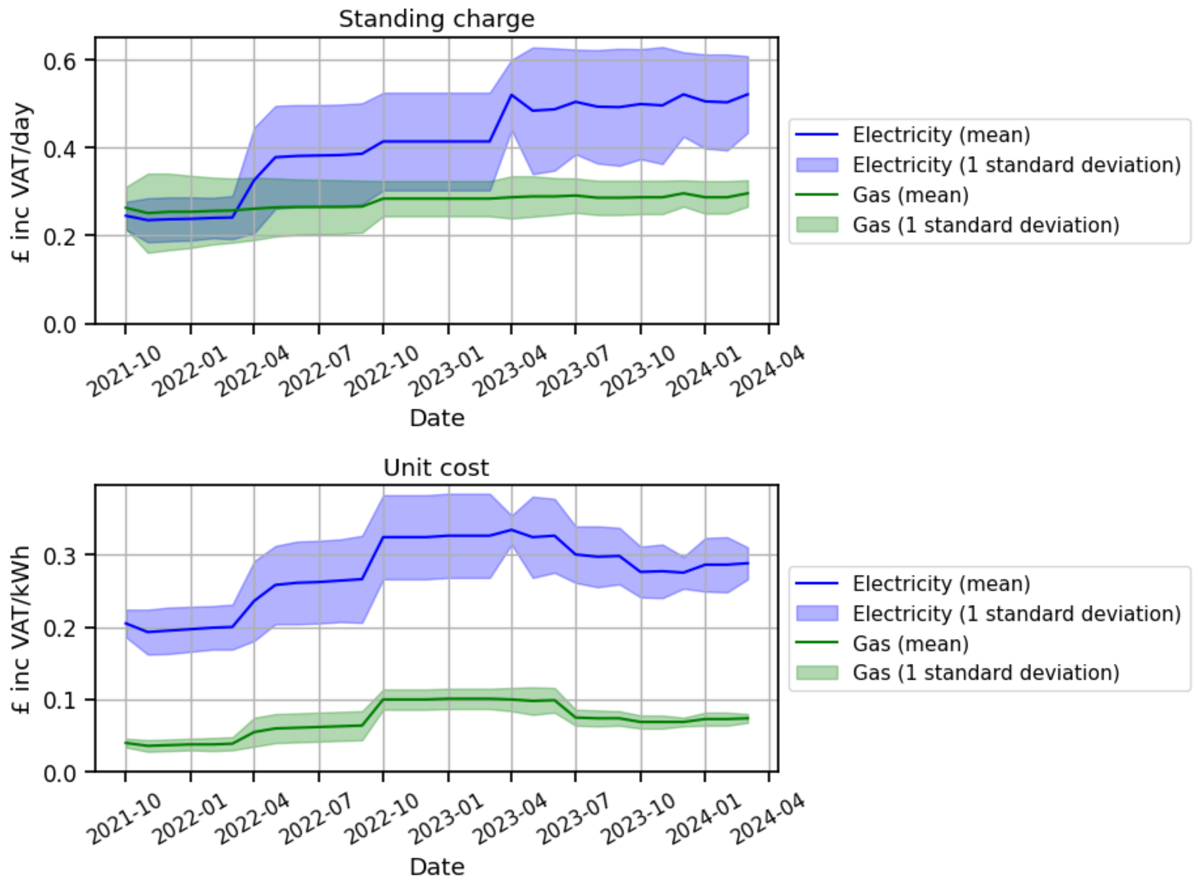


**Figure 2 – Variation in tariff components, unit cost and daily standing charge, based on SERL Observatory data.**

### 4.3.1. MONTHLY VARIATION AND COMPARISON WITH EPC/EPG BILLS FOR TYPICAL CONSUMPTION

We combine the household-level energy tariff data shown above with linked household-level monthly gas and electricity use data for the SERL Observatory participants to get estimates of average monthly gas and electricity expenditure for the period 2021-10 to 2024-03, shown in Figure 3. As mentioned previously, the data are restricted to households who use gas as their primary heating fuel. The results show the pronounced seasonal variation of gas expenditure that is caused by external temperature-driven space heating requirements that increase gas usage during winter. This combined with the rises in gas price shows the approximately ten-fold increase in average monthly gas expenditure from summer 2022 to winter 2022/2023.

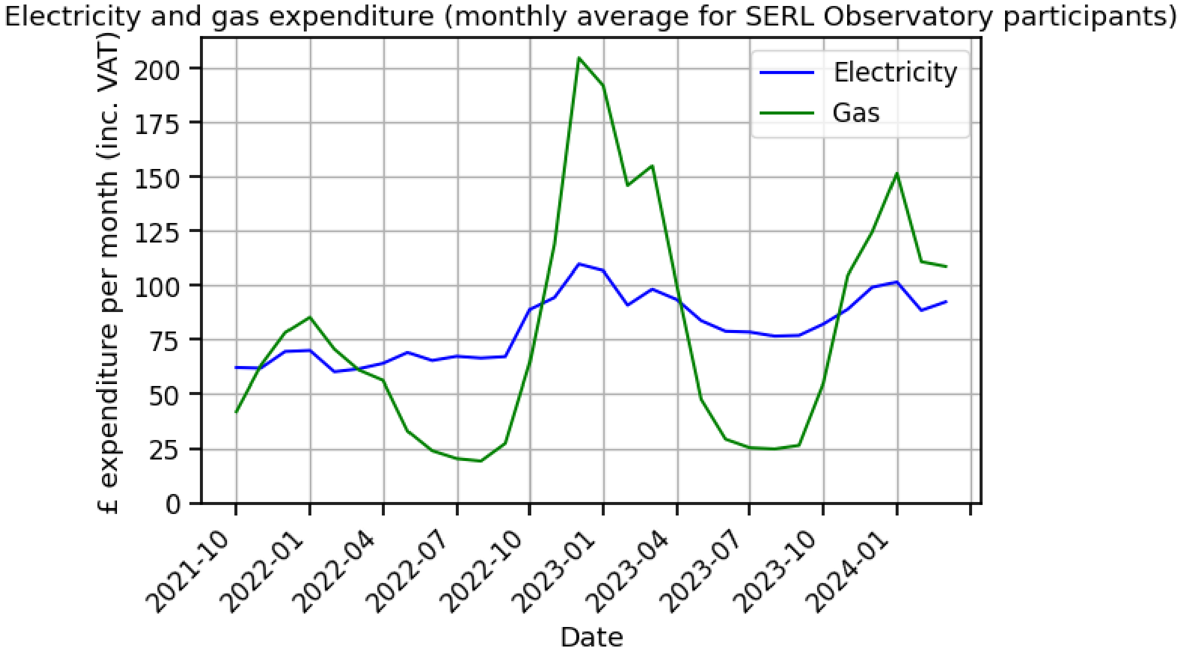


**Figure 3 – Variation in time of actual average (mean) monthly gas and electricity expenditure based on SERL Observatory data.**

Figure 4 combines the average gas and electricity expenditures to estimate total 'dual fuel' energy expenditure and compares this to the data for 'typical' consumers published by the energy regulator, shown in Figure 1, which have been converted from annual to monthly expenditures. Average monthly dual fuel expenditure peaked at £162.5/month during the 2021/2022 heating season. This doubled to a peak of £325.8/month the following heating season. And, due to the reduction in the price cap, peak monthly expenditure dropped the following heating season (2023/2024) to £263.1/month. This plot shows the true seasonal variation in energy expenditure, with peak energy expenditure occurring during the winter months. These peak values are larger than the monthly average values of the Energy Price Cap or Energy Price Guarantee, as the latter assumes no seasonal variation in demand.

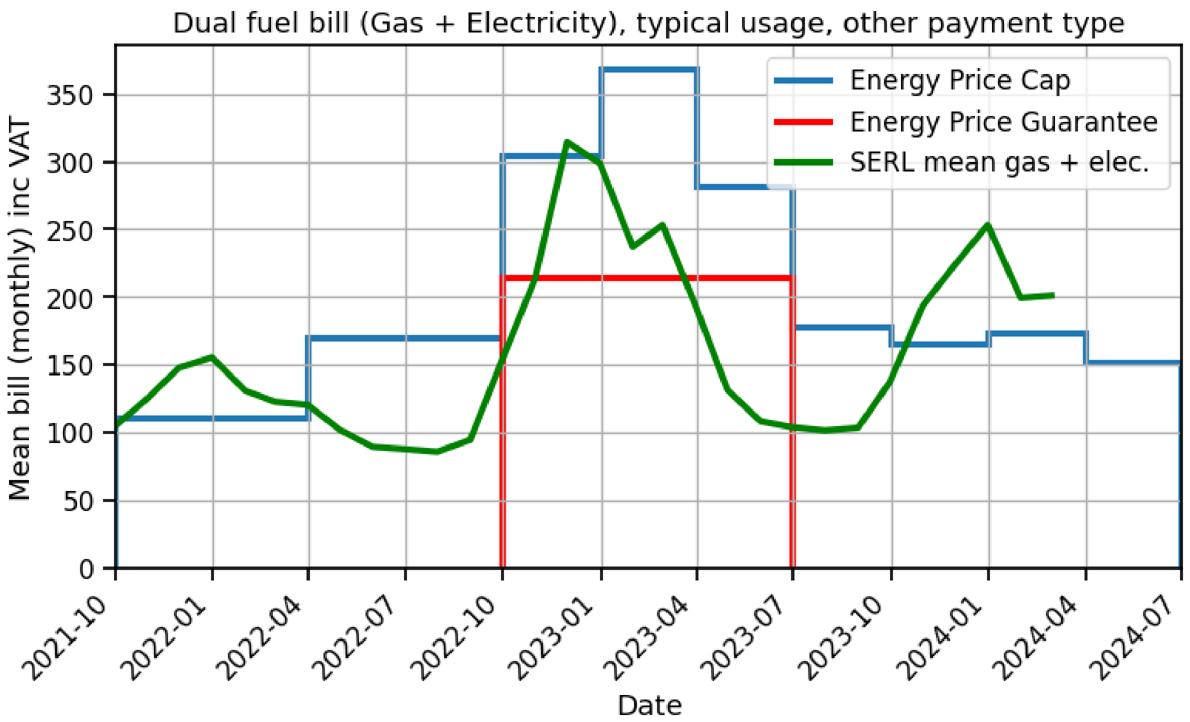


**Figure 4 – Comparison of average monthly 'dual fuel' (gas + electricity) expenditure based on SERL Observatory data and 'typical' monthly energy bills based on energy regulator published data.**

The actual energy expenditure data show minimum expenditure around £100/month during summer months, and show how monthly expenditure rises substantially from summer to winter. A more than three-fold increase going into the 2022/2023 heating season, and 2.5-fold increase going into 2023/2024 heating season. This rapid and large increases in actual energy expenditure are not apparent from the conventional data based on typical annual consumption values.

While the conventional picture shows bills rising steadily from winter 2021/2022 to winter 2022/2023, then declining slightly into 2024, the SERL smart meter data show that in fact energy expenditure is much more variable in practice, and the conventional view masks the true high variability of energy expenditure.

The comparison of actual energy expenditure to the estimated typical energy expenditure that underpins the national debate, shows that the latter masks the true variability of energy expenditure. This is because the conventional data are based on typical annual consumption values, yet in reality energy consumption varies substantially over time, in particular due to heating demand as it gets colder during winter, but also effects such as energy use behaviour change in response to price rises.

The substantial variation in actual monthly energy expenditure highlights the important role of payment type. Customers paying by direct debit are to an extent 'shielded' from these very high price spikes, as they pay for their energy use in a smoothed-out way in monthly instalments. As a consequence, direct debit customers may not experience 'bill shock' in the same way as non-direct debit customers, such as those on standard credit or prepayment meters, as it is likely that it will take time for the direct debit monthly instalments to change. Indeed, this is one of the benefits of direct debit. However, it may also mean that these households are less aware of the extent of how much their bills are going up, they may therefore not reduce their demand as much as they would have if they were not on direct debit, ultimately leading to higher bills later, and increased risk of building up of debt. There is, as a result, a risk that people were unaware of how much their energy expenditure was, or how much it went up during the cost-of-living crisis winter of 2022/2023, potentially leading to unexpected building up of debt. Indeed, residential customer energy debt and arrears have more than doubled from £1.8 billion in Q4 2021 before the cost of living crisis to £3.7 billion in Q2 2024 according to the UK energy regulator (Ofgem, 2024).

Another implication of the conventional view's under-representation of the actual temporal variation in energy expenditure is that it under-represents the short-term 'bill shock' actually faced by non-direct debit customers, such as those on prepayment meters, who may be more likely to be energy poor, as price rises are happening at the same time as demand rises into winter. The conventional view gives a false impression of a limited rise in energy expenditure during the winter of 2022/2023, which appears to persist at a fixed level of just over £200/month, when in fact the average monthly energy expenditure considerably exceeded this, rising to over £300/month in December 2022.

There are clearly benefits to using annual 'typical' values of the kind used in official publications by regulators and governments, such as in terms of ease of interpretation, and providing information in units that most people easily understand. It is however important to be aware that it masks the true variability of energy expenditure, and the impact of changes in energy prices on consumers. Previously this insight was not possible, but with the increasing available of smart meter data we no longer are bound to restrict national debates to this limited picture.

### 4.3.2. HEATING SEASON ENERGY EXPENDITURE

Figure 5 and Figure 6 show distributions of actual energy expenditure using metered energy use and energy tariff data for the three winter heating seasons 2021/2022, 2022/2023 and 2023/2024. 'Heating season' is taken to be October to March inclusive. The purpose of these figures is to facilitate comparison of gas and electricity expenditures from one heating season to the next, and in particular the changes in these expenditures between the cost-of-living crisis winter (2022/2023) and the preceding and following winters. They also illustrate the dramatic difference between figures which are based on mean or typical values (as the previous figures did) and figures which are based on distributions of individual differences in energy expenditure.

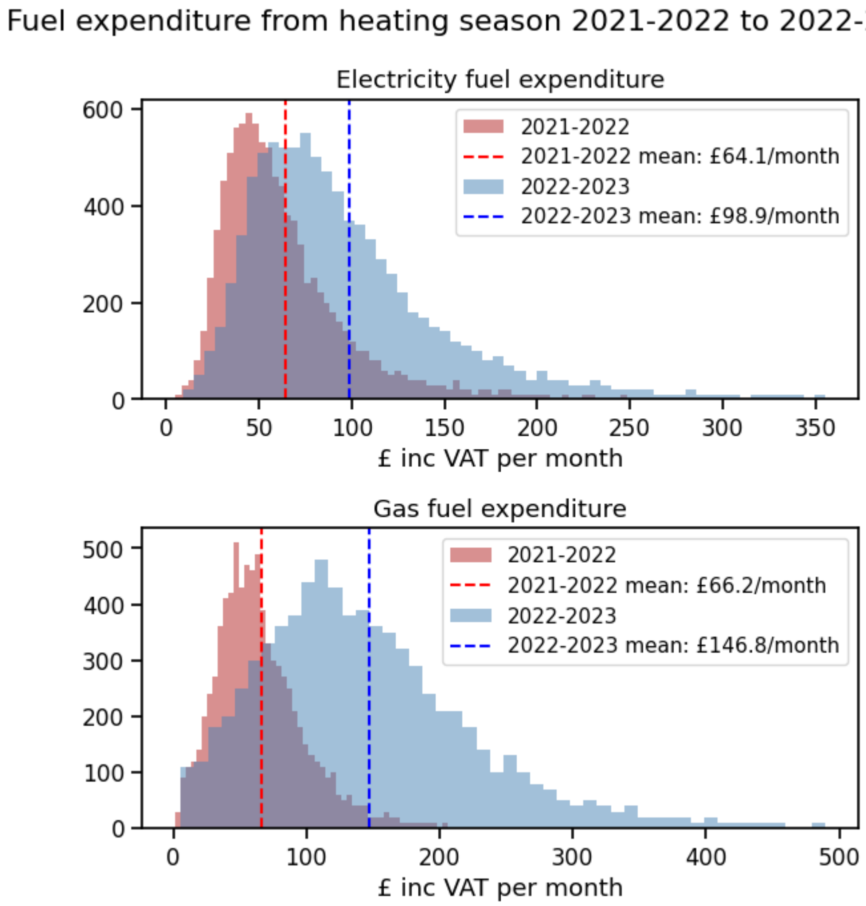


**Figure 5 – Comparison of distributions of individual average monthly gas and electricity expenditure in winter 2021/2022 and winter 2022/2023 (the 'cost of living crisis' winter).**

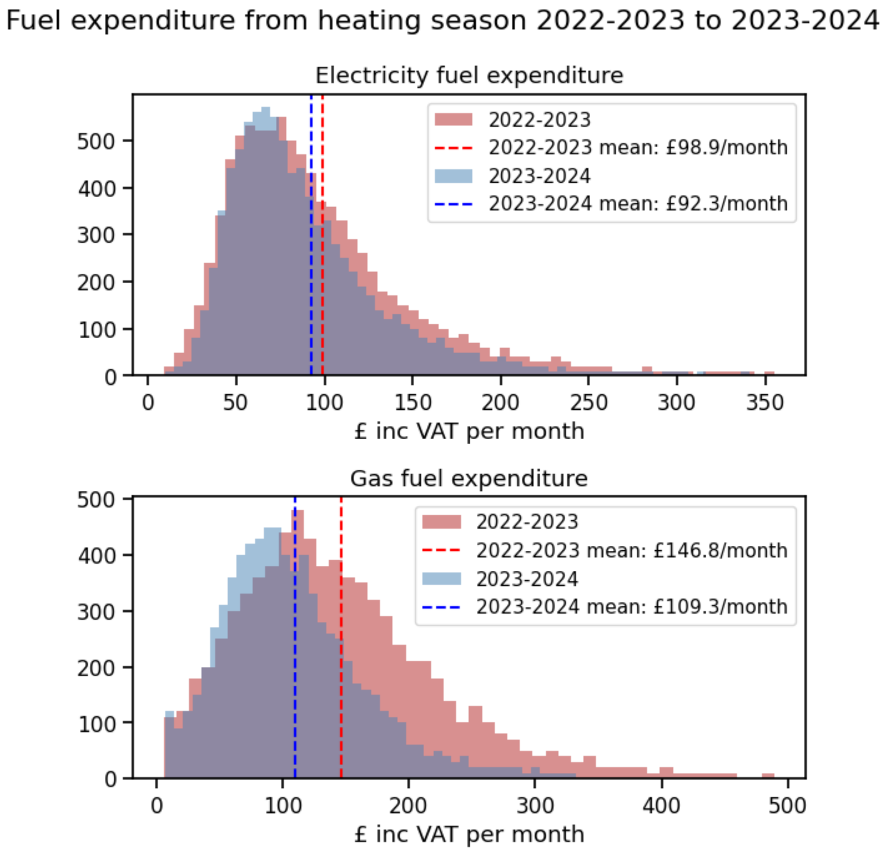


**Figure 6 - Comparison of distributions of individual average monthly gas and electricity expenditure in winter 2022/2023 (the 'cost of living crisis' winter) and the following winter.**

The results show that average monthly gas expenditure rose from £66.2/month during the 2021/2022 heating season to £146.8/month during the 2022/2023 heating season, an increase of 122%, which was followed by a decrease to £109.3/month the following heating season, a drop of 26%, though still an increase of 65% compared to 2021/2022.

Electricity expenditure rose from £64.1/month in 2021/2022 to £98.9/month in 2022/2023, an increase of 54%, which was followed by a decrease to £92.3/month in 2023/2024, a drop of 7%, but still 44% higher than in 2021/2022. These results illustrate that the price rises were particularly pronounced for gas, and that despite a reduction in energy prices compared to the peak, prices are still substantially higher than they were before the cost-of-living crisis.

The results also show that the distributions of individual differences in gas and electricity expenditure are skewed and show considerable variance. (Right) skewed distributions such as these are characterised by long 'tails' of a relatively small number of households with relatively high expenditures. These high values can exert particularly high influence on statistics such as means, 'skewing' them high, which can make the mean a statistical measure of central tendency that is less useful as a picture of the average individual. For this reason, skewed distributions are often summarised statistically in terms of quantiles such as the median, quartiles, etc.

The high variance demonstrates that large proportions of the population of households are spending amounts very different from the average. For example, substantial numbers are spending less than half or more than twice the average. Discussions of residential energy expenditure that are limited to pictures of the central tendency or the 'typical' are therefore simply not accurately representative of large proportions of the population, and this motivates the need for and value of better data on energy expenditure.

### 4.3.3. ANNUAL ENERGY EXPENDITURE

As demonstrated previously, the conventional picture of residential energy expenditure is often framed in terms of annual values, as this is a unit that is particularly useful and comprehensible. Figure 7 therefore presents average annual gas, electricity and total (gas + electricity) energy expenditure based on SERL Observatory data, calculated using a rolling 12-month window. Previous figures have shown how prices increased substantially in heating season 2022/2023. This period is shown to the left side of Figure 7, and what this figure shows is that even those prices spiked during winter 2022/2023 and then proceeded to subsequently drop into the summer of 2023, people's actual energy bills continued to increase for a further year when considered on an annualised basis (a rolling 12 month window). Indeed, annual bills only starting to decrease going into heating season 2023/2024. Note these results include the effect of the Energy Price Guarantee, but do not account for the Energy Bills Supports Scheme (the flat £400 given to all households over heating season 2022/2023).

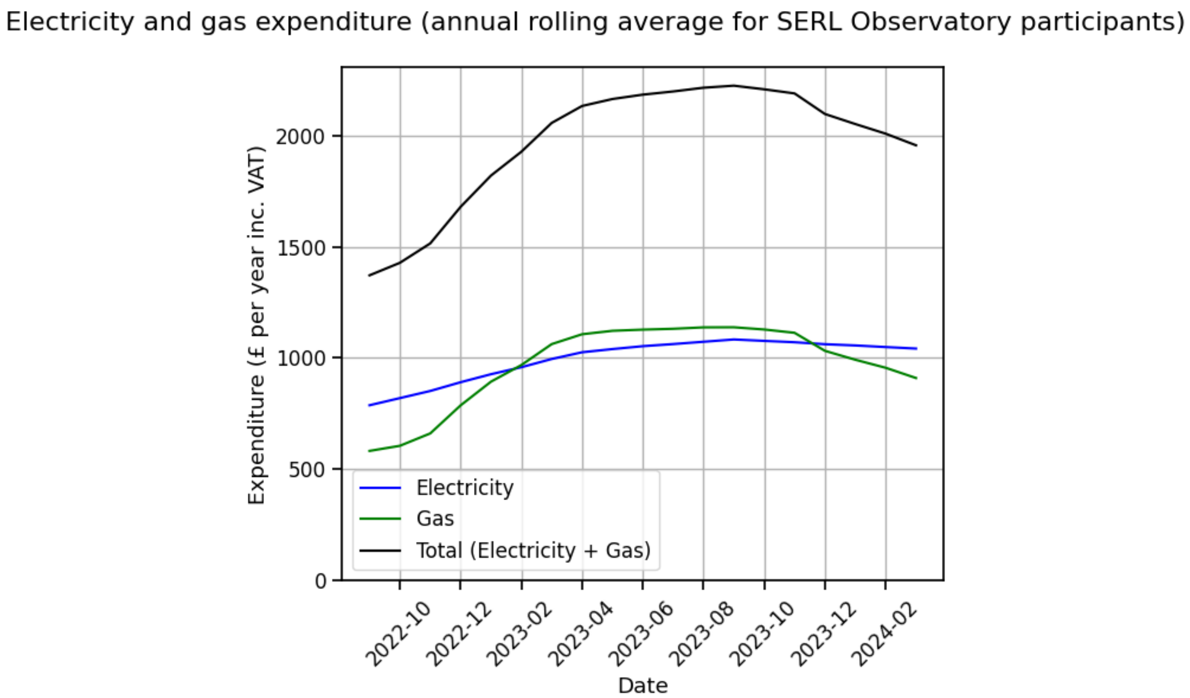


**Figure 7 – Estimates of annual gas, electricity and total energy expenditure based on SERL Observatory data, calculated using a rolling 12 month window.**

As with previous figures that only illustrate the central tendency, Figure 7 masks the considerable variance in individual energy expenditure. Figure 8 therefore shows the distributions of individual annual electricity, gas and total energy expenditure based on SERL Observatory data as of September 2023, the peak of energy expenditure according to Figure 7. The conventional understanding of energy expenditure in the national debate and Government and regulator statistics is of a picture of energy expenditure for a typical household. This gives information about the central tendency of a distribution, but there is little understanding of the underlying dispersion of the distribution. With smart meter data we can understand this. These plots show how there is considerable dispersion in the distribution of energy expenditure and illustrate the extent to which large proportions of the population are not well represented by the central tendency.

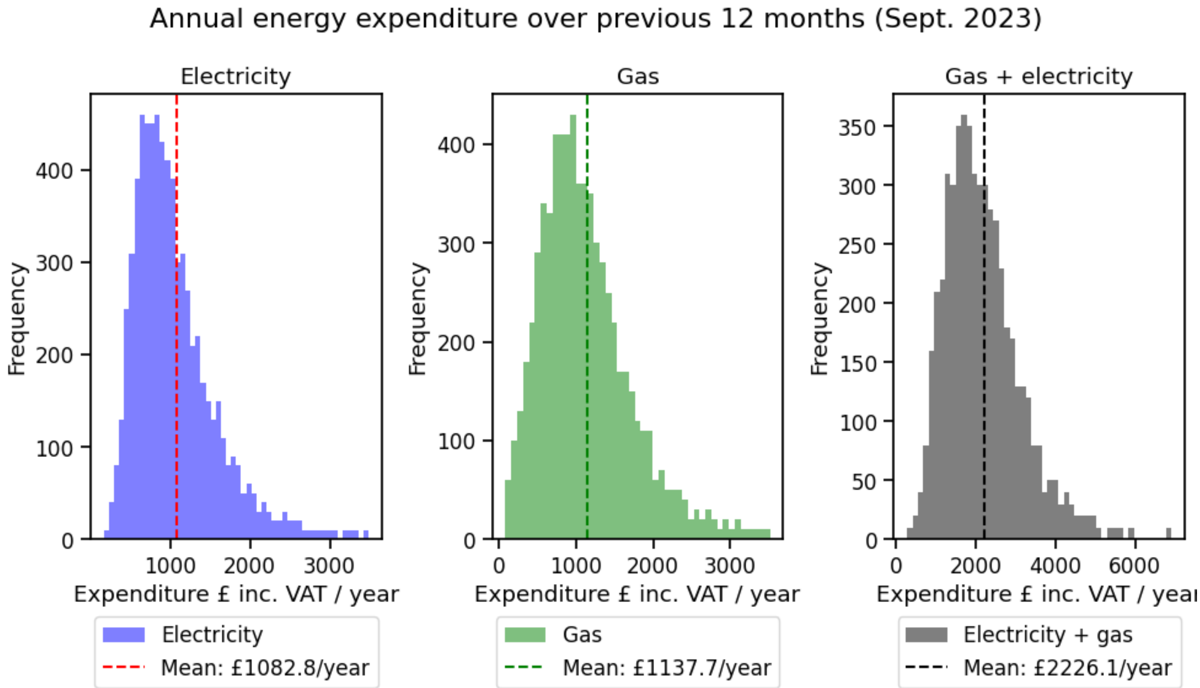


**Figure 8 – Distributions of individual annual electricity, gas and total (electricity + gas) energy expenditure based on SERL Observatory data as of September 2023.**

## 4.4. COMPARISON OF ENERGY EXPENDITURE BETWEEN DIFFERENT HOUSEHOLD GROUPS

Section 3.3.3 discussed the critical role of smart meter data in enabling precise measurement of energy expenditure, a central component in understanding energy poverty. By analysing energy expenditures for different households and groups, smart meter data allow us to move beyond the average and capture the true distribution and diversity of energy costs within the population. The above sections in this chapter have demonstrated significant dispersion in energy expenditures over time, highlighting the variability across households. This section presents the comparative analysis of energy expenditures among different household groups. The analysis focuses on average monthly energy expenditure during the 2022–2023 heating season.

Energy poverty affects households differently, with significant variability across income levels, housing types, and other socioeconomic factors. By examining specific subgroups based on income status, Feeling Energy Poor (FEP), EPC rating, tenure, and employment status, we aim to provide an understanding of significant differences in energy expenditures across different household groups revealed by smart meter data.

Each following subsection (4.4.1 to 4.4.5) provides histograms illustrating the distribution of expenditures for specific household groups, alongside mean values, the standard error of the mean (SEM), and 95% confidence intervals. X axis is average expenditure (£/month). Y axis is "frequency" on the histogram plot which represents the number of households in this case. The counts in each histogram are rounded to the nearest 10 for confidentiality and consistency. To assess differences in expenditures between groups, both parametric and non-parametric statistical tests were conducted. Mean comparisons were performed using Z-tests with p-values, and for distributions and medians, non-parametric tests were applied: Mann-Whitney U tests for comparisons between two groups and Kruskal-Wallis tests for comparisons involving more than two groups. Diagnostic assessments ensured the parametric assumptions were met, and where necessary, expenditures were log-transformed to satisfy these conditions. A p-value threshold of 0.05 was used, with p-values < 0.05 indicating statistically significant differences in expenditures across groups.

### 4.4.1. EXPENDITURE AND INCOME

Figure 9 shows the differences in electricity and gas expenditures between low-income (N= 896) and not-low-income households (N= 2,420). These are lower numbers than the full number of participants in the SERL Observatory because not all of these participants have gas central heating and self-reported their household income in the survey conducted during winter 2022/2023. As shown in the histograms, there is a clear distinction in the energy expenditures between these two groups, with the distribution of expenditures shifted towards lower values for low-income households.

For electricity expenditures, the mean monthly expenditure for low-income households is £80.93 ± 3.45, while for not-low-income households, it is significantly higher at £105.82 ± 2.64. Similarly, for gas expenditures, low-income households have a mean expenditure of £118.13 ± 4.30 compared to £158.42 ± 3.68 for not-low-income households. The Z-test on log-transformed expenditure data indicates a statistically significant difference in means for both electricity ($Z = -13.252$, $p < 0.001$) and gas ($Z = -11.241$, $p < 0.001$) expenditures, confirming that not-low-income households spend more on average. Additionally, the Mann-Whitney U test, a non-parametric test suitable for comparing medians, further supports this finding. For electricity, the U-statistic is 749,555 ($p < 0.001$), and for gas, the U-statistic is 787,500 ($p < 0.001$), indicating significant differences in median expenditures as well. These statistic results highlight a difference in energy expenditure between income levels.

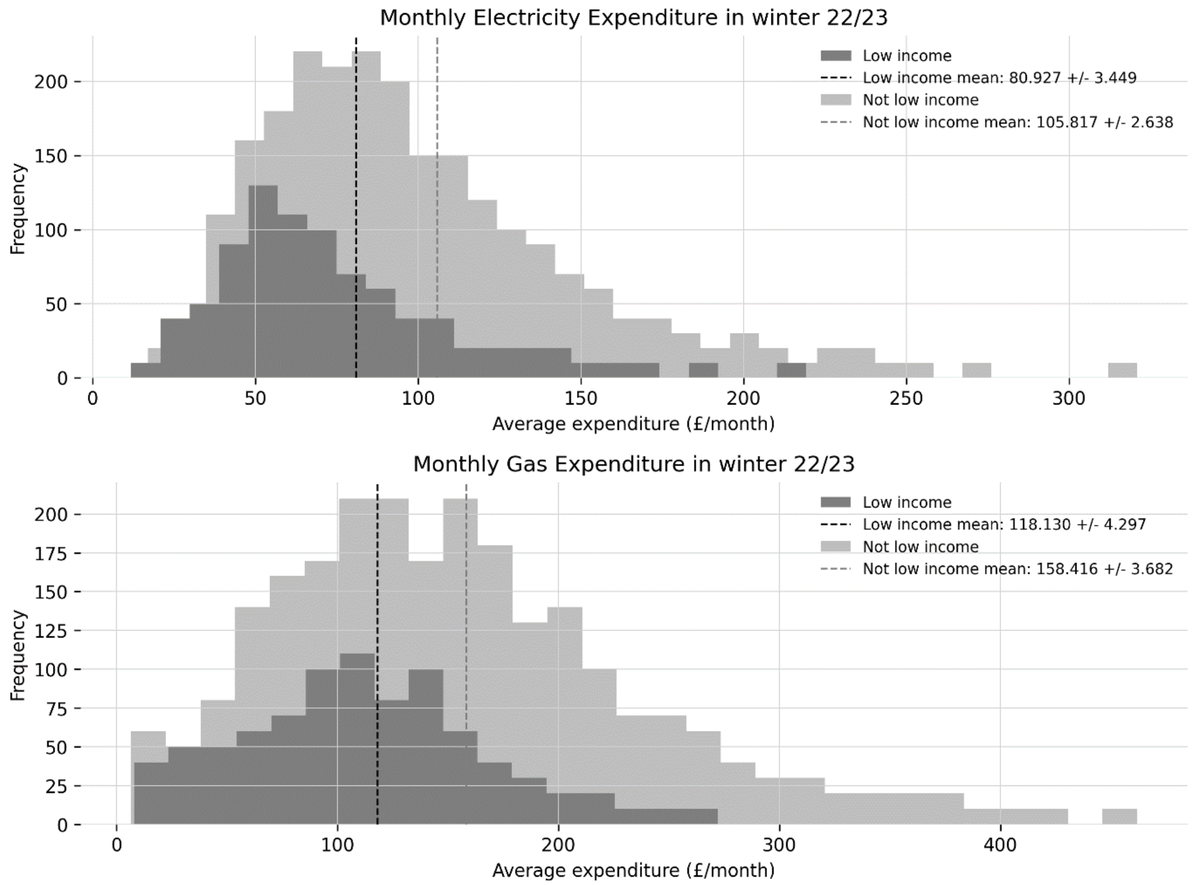


**Figure 9 – Distributions of average monthly electricity and gas expenditures in winter 2022/23 (SERL Observatory Data) between different income status.**

### 4.4.2. EXPENDITURE AND FEELING ENERGY POOR

Figure 10 shows the differences in electricity and gas expenditures between households that identify as "Feeling Energy Poor" (FEP) (N=697) and those that do not feel energy poor (N=3158). The distribution of expenditures shows notable variation, particularly in gas expenditures between the two groups, as indicated in the histograms.

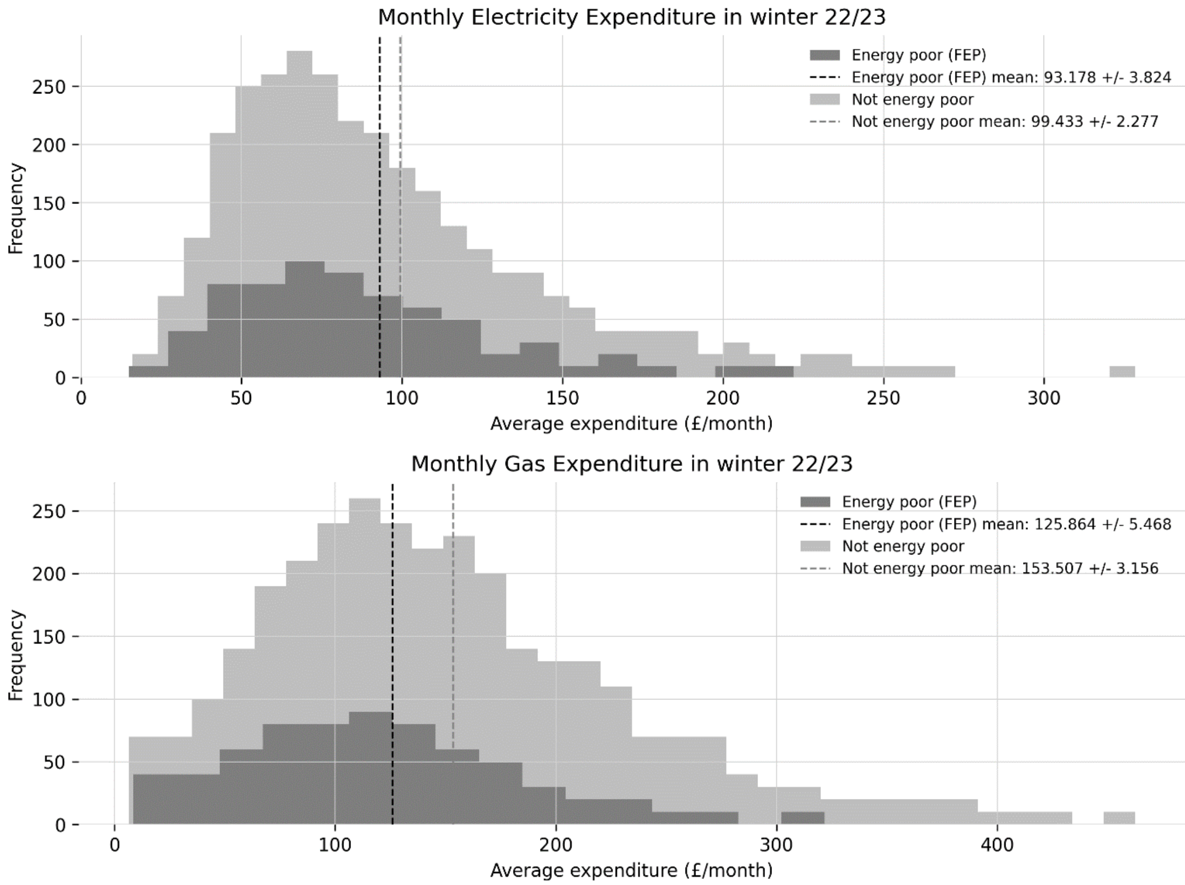


**Figure 10 – Distributions of average monthly electricity and gas expenditures in winter 2022/23 (SERL Observatory Data) between “feel energy poor” and “not feel energy poor” group.**

For electricity, the mean monthly expenditure for FEP households is £93.18 ± 3.82, while for non-FEP households, it is slightly higher at £99.43 ± 2.28. However, the difference in means is not statistically significant, as shown by the Z-test on log-transformed data ($Z = -1.919$, $p = 0.055$). Similarly, the Mann-Whitney U test, which assesses median differences, also found no statistically significant difference in medians for electricity expenditure ($U = 1{,}060{,}518$, $p = 0.132$). For gas expenditure, there is a significant difference between FEP and non-FEP households. The mean gas expenditure for FEP households is £125.86 ± 5.47, while for non-FEP households, it is £153.51 ± 3.16. The Z-test indicates a statistically significant difference in means ($Z = -7.240$, $p < 0.001$). Furthermore, the Mann-Whitney U test confirms a significant difference in medians for gas expenditure ($U = 897{,}053$, $p < 0.001$), indicating that FEP households tend to spend less on gas compared to non-FEP households. These results show that FEP households may intentionally reduce their energy usage to lower their bills, even if it means compromising on comfort. This behaviour often occurs in households that feel they cannot afford adequate heating or energy use. They might keep the thermostat lower, heat fewer rooms, or use energy at reduced times, resulting in lower gas and electricity expenditures.

### 4.4.3. EXPENDITURE AND EPC RATING

Figure 11 shows the variations of electricity and gas expenditures between households with two Energy Performance Certificate (EPC) ratings group: (1) EPC rating of C and above C (labelling by: EPC-AboveC, N= 1807) and (2) rating of D and below D (labelling by: EPC-BelowD, N= 2868). The histogram distributions of expenditures highlight the expenditure differences between these groups.

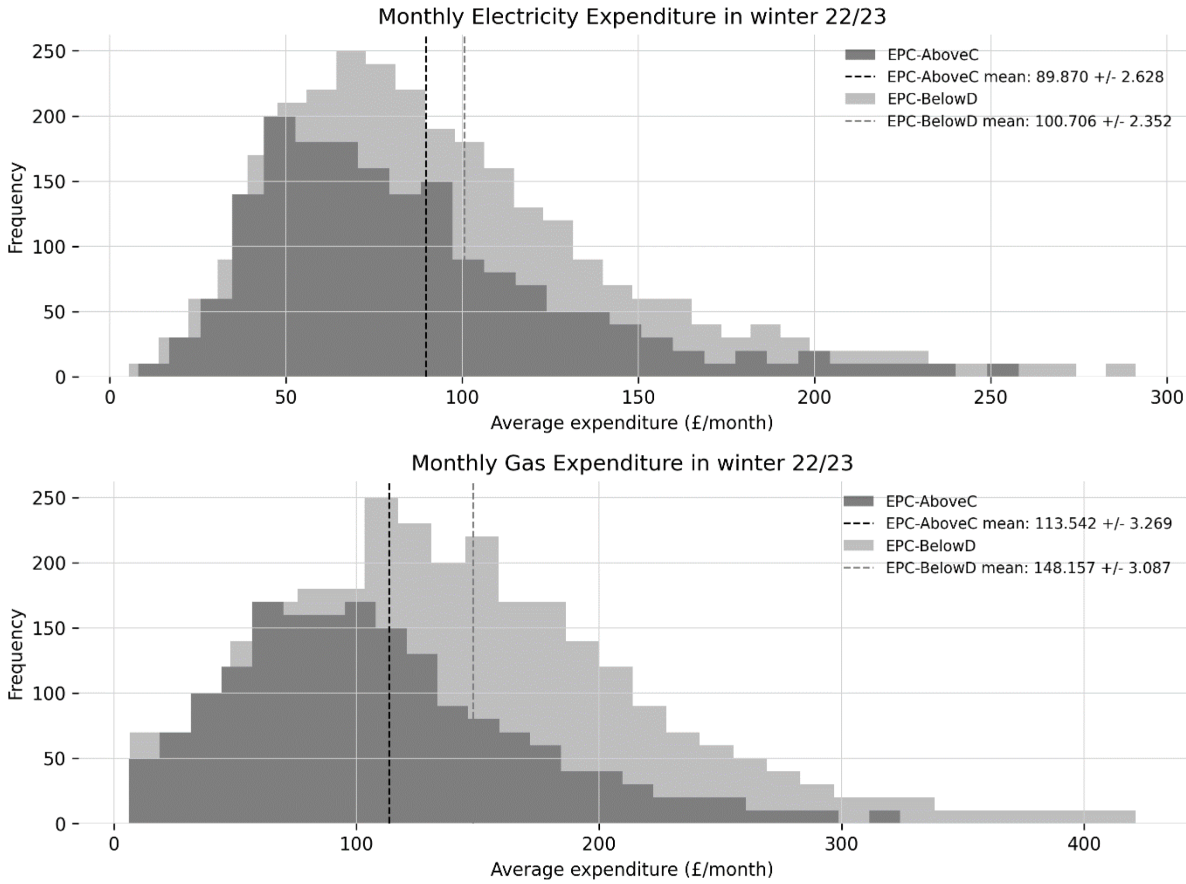


**Figure 11 – Distributions of average monthly electricity and gas expenditures in winter 2022/23 (SERL Observatory Data) between EPC rating. ("EPC-AboveC" represents EPC rating of C and above C; "EPC-BelowD" represents EPC rating of D and below D).**

For electricity expenditure, households with EPC rating of C and above C (labelling by EPC-AboveC) have a mean monthly expenditure of £89.87 ± 2.63, whereas households with EPC rating of D and below D (labelling by EPC-BelowD) show a higher mean of £100.71 ± 2.35. The Z-test on log-transformed electricity expenditure data reveals a statistically significant difference between the means ($Z = -6.936$, $p < 0.001$). The Mann-Whitney U test, which compares median expenditures, also indicates a significant difference ($U = 2,244,876$, $p < 0.001$), confirming that EPC "D and below D" households tend to have higher electricity expenditures. For gas expenditure, the difference between EPC "C and above C" and "D and below D" households are even more obvious. EPC "C and above C" households have a mean gas expenditure of £113.54 ± 3.27, while EPC "D and below D" households exhibit a considerably higher mean of £148.16 ± 3.09. The Z-test confirms a statistically significant difference in means ($Z = -14.028$, $p < 0.001$), and the Mann-Whitney U test supports a significant difference in medians as well ($U = 1,875,993.5$, $p < 0.001$).

These results indicate that households with lower EPC ratings, reflecting lower energy efficiency, lead significantly higher monthly expenditures for both electricity and gas during winter. This disparity highlights the impact of energy efficiency on household energy costs.

#### 4.4.4. EXPENDITURE AND TENURE

Figure 12 shows electricity and gas expenditures between owner-occupier (N= 6453) and renter households (N= 1114). The numbers are higher here because more of the SERL Observatory participants self-reported their tenure status in the survey they were asked to complete when they agreed to participate in the research project. The distribution of expenditures for each group is presented in the histograms, which highlight noticeable differences in energy expenditure based on tenure.

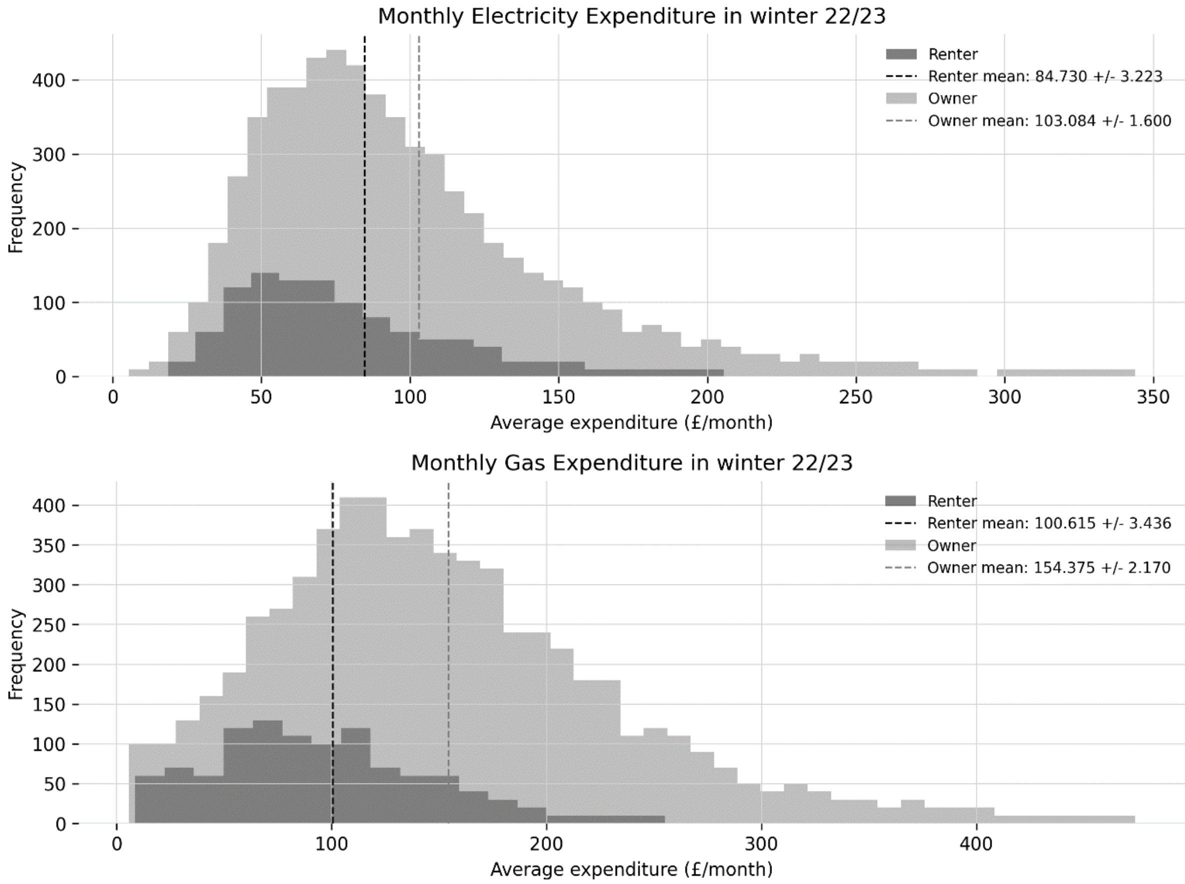


**Figure 12 – Distributions of average monthly electricity and gas expenditures in winter 2022/23 (SERL Observatory Data) between tenure type.**

For electricity expenditure, renters have a mean monthly expenditure of £84.73 ± 3.22, while owners have a higher mean of £103.08 ± 1.60. The Z-test on log-transformed data indicates a statistically significant difference between the means (Z = -10.999, p < 0.001). Additionally, the Mann-Whitney U test shows a significant difference in medians for electricity expenditure between renters and owners (U = 2,834,097, p < 0.001). For gas expenditure, renters have a mean gas expenditure of £100.62 ± 3.44, compared to £154.38 ± 2.17 for owners. The Z-test shows a statistically significant difference in means (Z = -20.008, p < 0.001), and the Mann-Whitney U test confirms significant median differences in gas expenditure between these groups (U = 2,160,651.5, p < 0.001). These findings suggest that owner-occupied households tend to have higher energy expenditures than rented households for both electricity and gas. This could reflect differences in property size, housing type, insulation quality or heating preferences between owners and renters.

### 4.4.5. EXPENDITURE AND EMPLOYMENT STATUS

Figure 13 shows the electricity and gas expenditures for households grouped by employment status, comparing working (N = 1903) versus not working (N= 282) households.

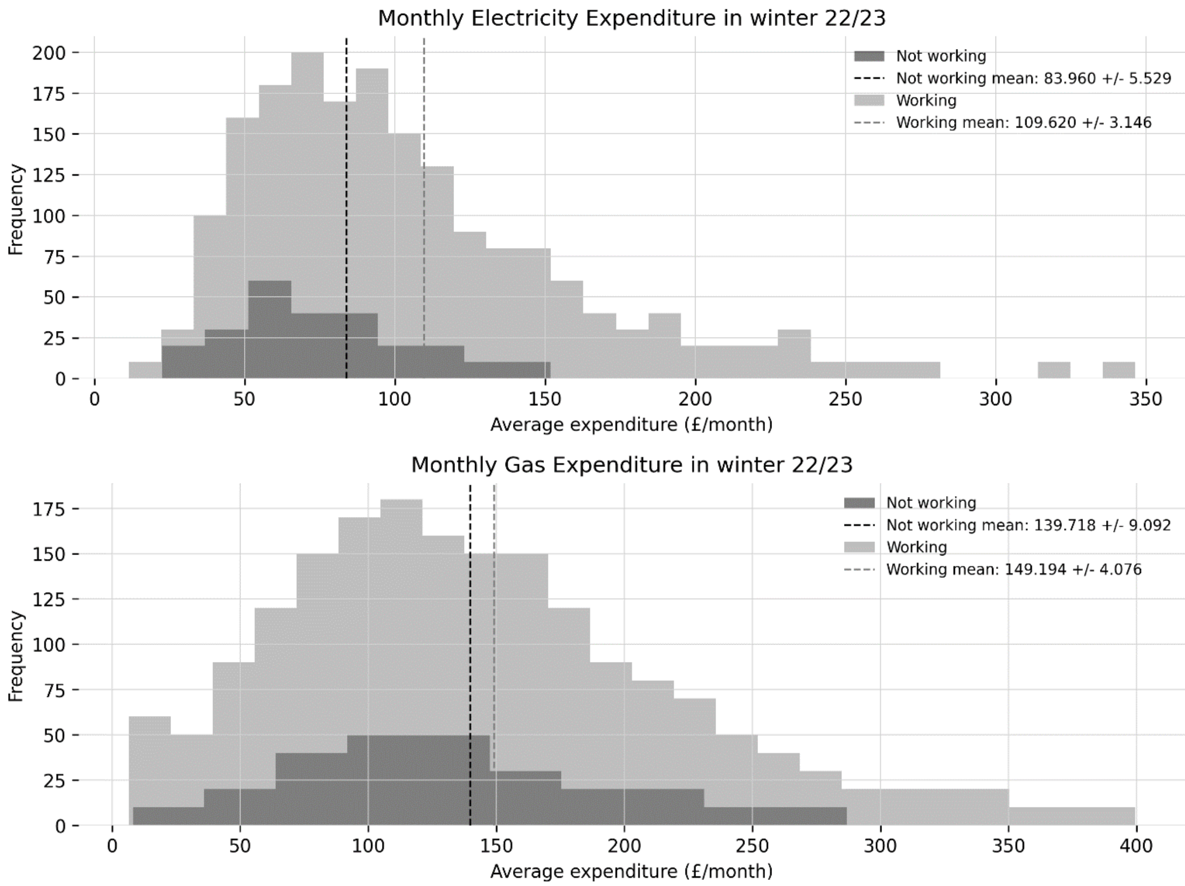


**Figure 13 – Distributions of average monthly electricity and gas expenditures in winter 2022/23 (SERL Observatory Data) between employment status.**

For electricity, households without employed occupants have a mean monthly expenditure of £83.96 ± 5.53, while households have employed occupants has a higher mean expenditure of £109.62 ± 3.15. The Z-test on log-transformed data indicates a statistically significant difference between the two groups ($Z = -7.409$, $p < 0.001$). The Mann-Whitney U test also shows a significant difference in medians ($U = 200{,}069$, $p < 0.001$. In contrast, gas expenditure differences between the two groups are less obvious. Z-test results show that this difference of gas expenditure is not statistically significant ($Z = -1.027$, $p = 0.304$), and the Mann-Whitney U test similarly indicates no significant difference in medians ($U = 254{,}967$, $p = 0.177$).

These findings suggest that while employment status appears to have a significant effect on electricity expenditures, with working households spending more, there is no statistically significant difference on gas expenditures between working and not-working households, possibly due to high occupancy levels for working households due to home-working practices.

## 4.5. CALCULATING ENERGY BURDEN USING SMART METER DATA

Energy burden is a term that refers to the percentage of household disposable income that is spent on total energy expenditure. It is a necessary metric to calculate energy poverty indicators such "as Spending more than a specific percentage of household income on energy services". We estimate energy burden for the SERL Observatory participants using the household-level estimates of annual expenditure shown in Figure 7 and combining these with household-level estimates of disposable income based on self-reported household gross income. Figure 14 shows the variation in time of the average energy burden. Note the following includes effect of the Energy Bills Support Scheme, i.e., all households are assumed to have received £400 during the winter of 2022/2023, which is treated as a £400 increase in their household disposable income.

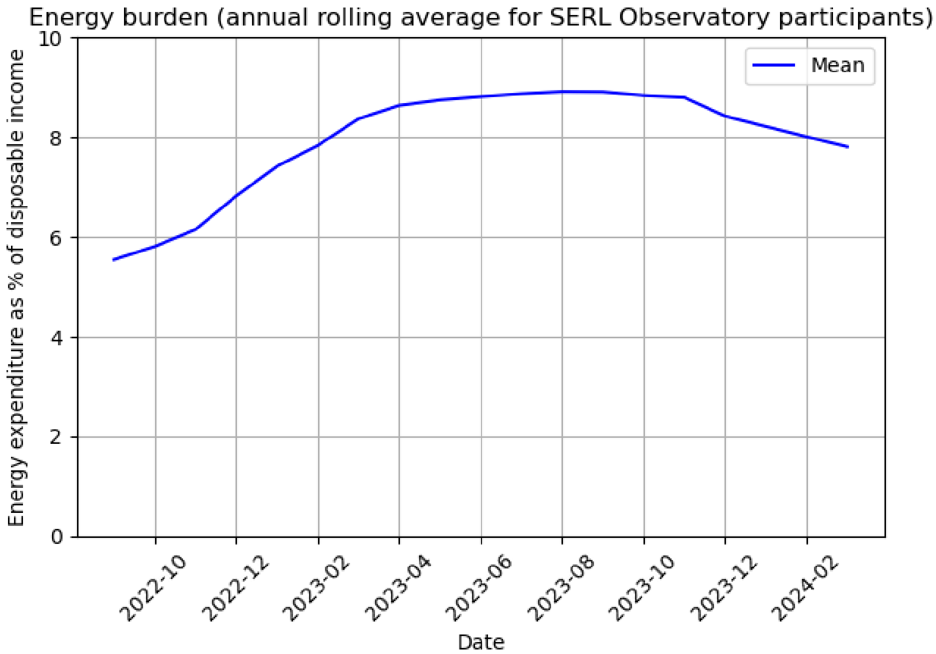


**Figure 14 – Variation in time of average energy burden (total energy expenditure as % of household disposable income) based on SERL Observatory data.**

The results show a similar trend to the variation in annual energy expenditure shown in Figure 7, which is that while the energy price spike of winter 2022/2023 increased and then decreased energy prices, as household annual energy bills continued to rise through to summer 2023, so too did the average energy burden. The average energy burden rose from 5.5% in September 2022 to 8.9% in September 2023.

Figure 15 shows the distribution of individual household differences in energy burden in September 2023. As with previous distributions, the distribution of individual energy burdens is right skewed and shows considerable variance (the standard deviation is 0.078, or expressed as the coefficient of variation it is 0.876). The standard deviation is the average an individual observation deviates from the mean, while the coefficient of variation is a normalised version of the standard deviation given by dividing the standard deviation by the mean. The skewed nature means that the mean 8.9% is considerably higher than the median (4.4%). This illustrates that when it comes to energy burden it is especially important to have detailed data on individual differences as a reliance on a single central tendency value such as the mean is highly unrepresentative of most households, and it completely fails to provide information about the scale of the problem of households with high energy burden.

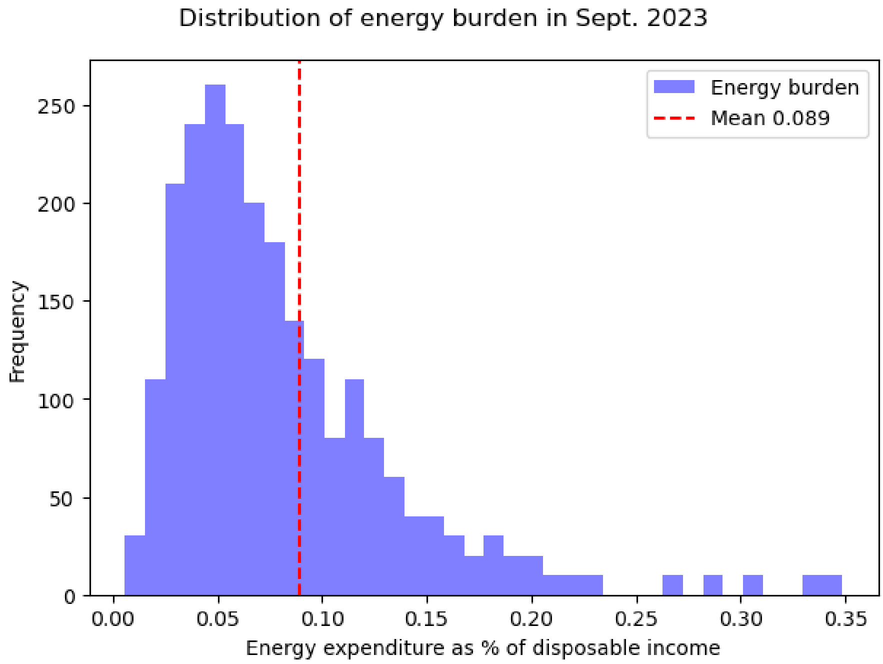


**Figure 15 – Distribution of individual household differences in energy burden (total energy expenditure as percentage of household disposable income) as of September 2023 based on SERL Observatory data. Note the x-axis shows proportions not percentages.**

## 4.6. CALCULATING ACTUAL EXPENDITURE ENERGY POVERTY USING SMART METER DATA

Given household-level energy burden data, it is possible to estimate household-level energy poverty using the Actual Expenditure Energy Poverty (AEEP) indicator using a 10% threshold; households spending 10% or more of their household disposable income on total (gas + electricity) energy expenditure are classified as energy poor. According to the data, September 2023 was the period of peak average energy burden. The following tables show that approximately 28% of households were energy poor according to this indicator during this period of time.

**Table 2 – Number and percentage of households in Actual Expenditure Energy Poverty in September 2023.**

| Actual Expenditure Energy Poverty | Number of households | Percentage of households (%) |
|---|---:|---:|
| False | 1730 | 71.84 |
| True | 678 | 28.16 |

Due to missing data, some households do not have a measurement of annual energy expenditure in September 2023. Therefore, instead of using the annual energy expenditure in September 2023, we will use the maximum value of energy expenditure for each household. This gives a larger total number of households with sufficient data to calculate AEEP, giving the results in the following table, which show similar levels of energy poverty at 28%. Given the larger total number of households, we will use this latter measurement in the analysis going forward as it increases the available sample size.

**Table 3 – number and percentage of households in Actual Expenditure Energy Poverty, based on maximum value of energy expenditure.**

| Actual Expenditure Energy Poverty | Number of households | Percentage of households (%) |
|---|---:|---:|
| False | 2080 | 72.07 |
| True | 806 | 27.93 |

While the calculation of energy poverty using an actual expenditure-based indicator is not novel, what makes this novel is its derivation based on highly accurate smart meter energy use and energy tariff data, and therefore not subject to the same recall biases and errors associated with self-reported energy expenditure. The use of smart meter data means that energy poverty estimates can be derived at higher temporal resolution, longitudinally, with lower participant burden, and lower instrumentation costs than those based purely on surveys.

## 4.7. EVALUATING THE ACCURACY OF SMART METER BASED ACTUAL ENERGY EXPENDITURE ENERGY POVERTY INDICATOR (AEEP)

Broadly speaking, energy poverty is a condition where a household is unable to afford to adequately heat their home when it is cold. There are two parts to this condition: first, the condition of a home being adequately or sufficiently warm, and the second is the costs of doing so being unaffordable. There are, as a result, two related challenges: determining what is "sufficiently warm" and its associated energy costs, and determining when these costs are "too high". In the following we will compare the smart meter-based AEEP indicator with the following two indicators: the objective Required Expenditure Energy Poverty indicator, and the subjective Feeling Energy Poor indicator.

### 4.7.1. THE OBJECTIVE ENERGY POVERTY 'GROUND TRUTH'

There are objective and subjective approaches to addressing these challenges. UK Government definitions have taken objective approaches. Energy costs are determined using the SAP building energy model, combined with normative weather conditions and occupancy, and sufficient warmth is determined by a normative heating schedule (DESNZ, 2023). These 'required' energy costs are combined with household income, and a threshold is set to determine energy poverty status. For example, the Welsh Government uses household disposable income before housing costs and a 10% threshold, which we will call Required Expenditure Energy Poverty (REEP). This is also the official indicator that was used in England prior to the Hills Review which changed the definition to Low Income High Costs (LIHC) (Hills, 2011), and which was further changed to the Low Income Low Energy Efficiency 'LILEE' in 2021 (BEIS, 2021b).

One argument for using required energy costs when measuring energy poverty is that 'this ensures that those households who have low energy bills simply because they actively limit their use of energy at home, by not heating their home for example, are not overlooked' (DESNZ, 2023). Required energy costs are modelled based on normative assumptions: 'a warm, well-lit home, with hot water for everyday use, and the running of appliances'.

A challenge with energy poverty indicators that are based on required energy costs is that it is non-trivial to determine required energy costs. In UK, this requires a detailed building physical survey carried out by a trained professional, and using the collected data as input to a relatively complex building energy model, all of which involves cost, time, and skill. This challenge is a difficult one, and it introduces a significant barrier to measuring, identifying and evaluating energy poverty, all of which are critical to tackling and reducing energy poverty.

The roll-out of smart meters however means that data on actual energy costs are becoming more widely available. The question of interest here is therefore to what extent can actual energy costs based on smart meter data be used to measure energy poverty?

In the previous section, we developed an energy poverty indicator based on actual energy costs using smart meter data. In this section, we focus on interpreting and evaluating this measurement. In particular, the question: *how accurate is it*?

For the purposes of evaluating the AEEP indicator with respect to an objective energy poverty indicator, we will take the Required Expenditure Energy Poverty 'REEP' indicator to be a 'ground-truth' indicator, while acknowledging that no indicator is perfect. By ground truth we mean a benchmark against which we can compare our smart-meter based AEEP indicator, as it is useful to compare our indicator against one that is used in official governmental policy. We do not imply that REEP is true in the sense that it is the most accurate, or best energy poverty indicator.

Note that we do not currently observe the REEP indicator for the SERL Observatory participants, and so the comparison we do later will be speculative.

### 4.7.2. THE SUBJECTIVE ENERGY POVERTY GROUND TRUTH

The Feeling Energy Poor indicator is a subjective measure of energy poverty. A subjective measure of energy poverty like this has advantages in that it only requires asking people a few simple questions about their ability to keep warm in their home and meet their energy costs. It is therefore more simple and cheaper to measure than the REEP indicator, which requires a physical survey and energy model calculation. For the purposes of evaluating the AEEP indicator with respect to a subjective energy poverty indicator, we will take FEP as a 'ground truth' indicator. Again, we make the same caveat as above regarding the term ground truth.

The following shows the number of households in SERL Observatory who are energy poor according to the Feeling Energy Poor indicator, based on their answers to the SERL follow-up survey, conducted in January-February 2023, showing that approximately 19% of households were energy poor according to the Feeling Energy Poor indicator.

**Table 4 – number of households Feeling Energy Poor based on SERL Observatory data.**

| Feeling Energy Poor | Number of households | Percentage of households (%) |
|---|---|---|
| not-FEP | 4681 | 81.44 |
| FEP | 1067 | 18.56 |

### 4.7.3. TO WHAT EXTENT DOES AEEP RESULT IN FALSE POSITIVES?

As mentioned in the Hills Interim Report of the Fuel Poverty Review (Hills, 2011), another criticism of AEEP, and a point in favour of using modelled required energy expenditure in REEP is that AEEP could produce false positives where households are using more than the required amount, because they are 'wasteful in their use of energy'.

Compared to the normative levels of required energy estimated by the SAP building energy model, we know that actual energy use, and therefore costs, are lower, and that this is particularly so for older, less efficient buildings (Few et al., 2023) and that many households under-heat their home compared to the norm, particularly during the cost of living crisis (Hanmer et al., 2024). This is true for the sample analysed here, but it is reasonable to extrapolate this to households in general.

It is therefore a reasonable assumption that actual energy costs are lower than required energy costs, at least on aggregate. A consequence of this is that AEEP will be a *conservative indicator* compared to the ground truth, REEP in this case, provided the only difference between the two is AEEP uses actual energy costs and REEP uses required energy costs, a claim also made by Waddams Price (2012). To be more specific, not only will the number of households identified as energy poor using AEEP be lower than the number identified by REEP, but AEEP households *will also be a sub-set* of the REEP households.

By definition, if AEEP is a sub-set of REEP, then the AEEP indicator will have zero false positives. A false positive would be a household that AEEP identified as energy poor but was not actually energy poor, according to the REEP indicator. A low false positive rate (or its inverse, a high "precision") is one of the critical determinants of whether a test or indicator is accurate and therefore useful. Under this assumption the precision of the AEEP indicator (how many predicted positives are actually positive) would be 100% compared to REEP.

What about the false positive rate with respect to the Feeling Energy Poor indicator? Table 5 compares the numbers of households in SERL Observatory measured as energy poor using the two indicators. The results show that the objective AEEP indicator measures 560 households as energy poor who are not measured as energy poor according to the subjective FEP indicator. These are households who are spending 10% or more of their household disposable income on their energy bills, but who do not feel like they are unable to afford to keep comfortably warm in their living room during cold weather and who do not feel like they are struggling to meet their energy bills, at least at the time that the survey was conducted. If we treat the FEP indicator as a ground truth, and these households as "false positives", the AEEP has false positive rate of around 24%, or viewed another way a specificity of 76%. So approximately 1 in 4 households who are not energy poor will be falsely identified as energy poor using the AEEP indicator.

**Table 5 – A "confusion matrix" comparing numbers of households in SERL Observatory measured as energy poor using the AEEP indicator compared to the FEP indicator.**

| | AEEP | Not AEEP | Total |
|---|---|---|---|
| FEP | 240 | 280 | 520 (18%) |
| Not FEP | 560 | 1800 | 2360 |
| | | | |
| Total | 800 (28%) | 2080 | 2880 |

The precision is another important accuracy metric, it is the proportion of true positives out of all positives identified (true positives plus false positives). In this case the AEEP indicator has a precision of 30% compared to the FEP indicator, indicating that approximately 1 in 3 households identified as energy poor using the AEEP indicator were actually Feeling Energy Poor.

How does this compare to other studies? Waddams Price et al. (2012) conducted a similar study comparing an equivalent indicator to AEEP to an equivalent indicator to FEP. They found similar levels of energy poverty to our results, with 16% Feeling Energy Poor and 28% Actual Expenditure Energy Poor. They reported 527 households identified as expenditure energy poor using an equivalent indicator to AEEP out of a total of 2165 households *not* identified as energy poor using an equivalent indicator to FEP. This is a similar result to ours, with a false positive rate of 24%, or a specificity of 76%. They reported a precision of 26%, similar to our reported precision of 30%.

#### 4.7.4. TO WHAT EXTENT DOES AEEP RESULT IN FALSE NEGATIVES?

While a low false positive rate is clearly desirable for an energy poverty indicator, a low false negative rate is even more so. A false negative would be a household that AEEP identified as *not* being energy poor but that *actually* was. The consequences of a false negative are worse than those of a false positive, as clearly it risks 'overlooking' households who are in need of help.

Compared to the Feeling Energy Poor (FEP) indicator, the AEEP indicator measured 280 households as *not* energy poor who were actually energy poor according to the FEP indicator. This is a false negative rate of 54%, which can also be described as a recall rate of 46%. Along with high specificity, a high recall is also a critical measure of the accuracy or performance of an indicator. A recall of 46% is poor, as it means that about 1 in 2 households who are actually energy poor are not identified.

Waddams Price (2012) reports similar results, with 231 households *not* identified as energy poor according to their AEEP-equivalent indicator out of 413 households who were actually energy poor according to their FEP-equivalent indicator, yielding a false negative rate of 56% or a recall of 44%.

What about the false negative performance of AEEP in relation to the objective "ground truth" REEP? Unfortunately, REEP is not currently measured for SERL Observatory participants and so we cannot evaluate this performance directly. As a rough estimate however we can hypothesise that the false negatives of the AEEP indicator compared to the FEP indicator would also be false negatives of AEEP compared to REEP. This is because the AEEP to FEP false negatives are households who are feeling energy poor, who say they are unable to afford to keep warm, and struggling to meet their energy costs, but who have an energy expenditure below the 10% threshold, which means these are households that are very likely to be actively making efforts to reduce their energy use, such as by under-heating their home. We can hypothesise that these are households who would spend more than the 10% threshold if they were not making these efforts, and thus who would be energy poor according to the REEP indicator.

This is clearly a rough and speculative estimate, however if we take these households to be a guess at the false negative rate of AEEP compared to the REEP indicator, then this results in a false negative rate of about 26% (a recall of about 74%), i.e., about 1 in four households who are in energy poverty, according to the REEP indicator, would be falsely identified as not energy poor according to the AEEP indicator.

### 4.7.5. HOW TO REDUCES FALSE NEGATIVES FOR THE AEEP INDICATOR?

Reducing false negatives is particularly important for an energy poverty indicator, because of the actual, potential or perceived negative impacts of a false negative, i.e., "overlooking" households who are in need of help. This is why reduction in false negatives is generally prioritised in tests, or indicators, where the risks or costs associated with false negatives are greater than those associated with false positives, e.g., cancer tests.

This leads to the question: how can the false negative rate associated with the AEEP indicator be reduced?

There are two options we can consider as follows, and each has different use cases or applications.

#### *4.7.5.1. Finding an optimal decision threshold for AEEP*

So far, as in Waddams Price (2012), we have based the definition of the AEEP indicator on the "ground truth" REEP indicator, and specifically that includes its 10% threshold. This value is what is known as a decision threshold in classification modelling. In this case, if the energy burden is greater than or equal to the threshold of 10% then the decision is that the household is classified as energy poor.

Previously however we claimed that the actual energy costs used in the AEEP indicator will in general always be less than or equal to required energy costs of the REEP indicator, and as a result that the AEEP indicator was a conservative proxy for the REEP indicator. In particular, that compared to REEP, AEEP will produce no false positives, but will also produce false negatives at an estimated rate of about 26%.

Given this systematic difference between actual energy costs and required costs, an obvious change would be to use a lower threshold for the AEEP indicator. The concept is that as the threshold is lowered below 10%, more of the households that were "overlooked" previously, i.e. false negatives, will now be correctly identified as energy poor with a lower threshold.

While on the face of it, it would seem beneficial therefore to lower the decision threshold, a negative consequence however is that doing so will also inevitably increase the false positive rate. A balance needs to be struck therefore between reducing false negatives without an unacceptable increase in false positives.

Figure 16 demonstrates this visually by showing the effect of varying the decision threshold for the AEEP indicator on its performance compared to the FEP indicator. As a reminder, in this content the decision threshold is the threshold of the proportion of household disposable income spent on energy that would classify a household as energy poor. The results show that decreasing the decision threshold has the effect of increasing the recall (decreases the false negative rate) which means more of the households actually Feeling Energy Poor get identified as energy poor using the AEEP indicator (with modified decision threshold). While clearly that's a beneficial change, unfortunately it comes at a cost. The results show that lowering the decision threshold decreases the specificity (increases the false positive rate).

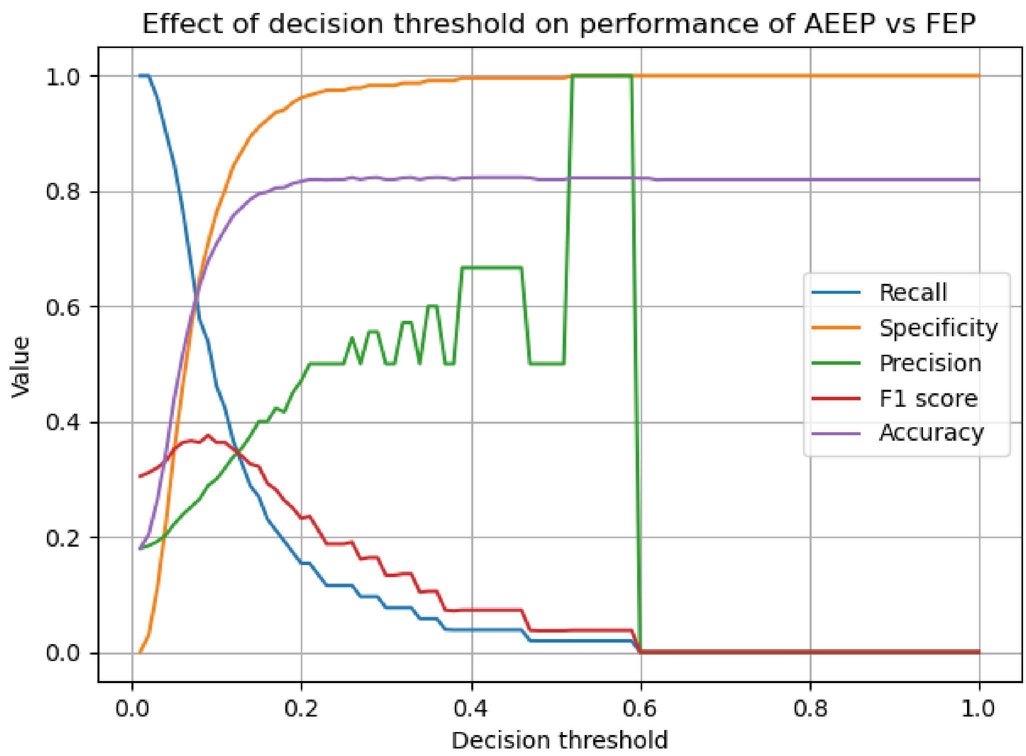


**Figure 16 – Effect of varying the decision threshold for the Actual Expenditure Energy Poverty indicator on its performance compared to a 'ground truth' subjective energy poverty indicator (Feeling Energy Poor).**

Accuracy is the proportion of all identifications that are correct. If we wanted to maximise *accuracy*, we would take the approach of raising the threshold so high that it was equivalent of simply saying all households are not energy poor. Because only 18% of households are Feeling Energy Poor, that would give an accuracy of 82%, which sounds good, but would be a terrible indicator. The figure also shows how the "accuracy" metric can be an unhelpful performance metric in contexts such as these where we have imbalanced groups, i.e., there are relatively few energy poor compared to non-energy poor.

What is the decision threshold that produces the optimal balance between false positives and false negatives? The F1-score is a metric intended to balance the recall and precision by calculating their harmonic mean. It gives more weight to lower scores, and ranges from 1 (indicating perfect precision and recall) to 0 (indicating poor performance). In fact, the optimal decision threshold to maximise the F1-score is 9%, very close to the original 10% threshold. This provides an optimal balance between reducing false negatives without an unacceptable increase in false positives.

**Table 6 – Performance of AEEP indicator using 9% threshold compared to the Feeling Energy Poor indicator.**

| | AEEP (9%) | Not AEEP (9%) |
|---|---|---|
| FEP | 280 | 240 |
| Not FEP | 690 | 1680 |

Using a 9% decision threshold rather than a 10% threshold reduces the number of false negatives from 280 to 240, a reduction of 40. This is equivalent to increasing the recall rate from 46% to 54%. However, the total number of households identified as energy poor has increased from 800 to 970, an increase of 170. Given that 40 of these are true positives, that means an additional 130 are false positives. This means the precision drops from 30% to 29%, and the specificity drops from 76% to 71%.

Regarding the performance of AEEP with 9% threshold compared to REEP, if we make the same speculative assumptions as previously, then the results show that using 9% decision threshold increases the (estimated) recall rate with respect to REEP to 78%, or a reduction in false negative rate from 26% to 22%, but with a reduction in precision from 100% to 87%, or an increase in false positive rate from 0% to 13%.

In summary, where the objective is to measure energy poverty for a group of households, and where the ground truth indicator of interest is REEP, and where it is unfeasible or impractical to measure REEP directly, then if data are available to calculate AEEP, then based on the results of this analysis a threshold of 9% for AEEP is recommended to measure energy poverty as this achieves a balance between minimising false negatives without an unacceptable increase in false positive rate. Note that this analysis has included the impact of the Energy Bills Support Scheme (the £400 increase in disposable income for every household). Without this subsidy the results for optimal decision threshold would be different.

The following compares the numbers of households measured as energy poor using the AEEP with 10% and 9% thresholds.

**Table 7 – Number of households in Actual Expenditure Energy Poverty (10% threshold).**

| Actual Expenditure Energy Poverty (10% threshold) | Number of households | Percentage of households (%) |
|---|---|---|
| False | 2080 | 72.07 |
| True | 806 | 27.93 |

**Table 8 – Number of households in Actual Expenditure Energy Poverty (9% threshold)**

| Actual Expenditure Energy Poverty (9% threshold) | Number of households | Percentage of households (%) |
|---|---|---|
| False | 1921 | 66.56 |
| True | 965 | 33.44 |

### *4.7.5.2. Developing a hybrid indicator that is a proxy for REEP*

A second option to reduce false negatives relating to the REEP indicator, is to use a hybrid indicator for measuring energy poverty. The option available here is to use *both* the AEEP indicator (with the original 10% decision threshold) and the FEP indicator. The argument is that AEEP 10% indicator has zero (or very low) false positive rates, but with an estimated false negative rate of approximately 26%. The FEP indictor could therefore be used to lower the false negative rate, reducing the number of households that we have good reason to believe are actually energy poor according to the ground truth indicator REEP, which we do not observe, but which the AEEP 10% indicator does not identify as energy poor.

The following tables show counts and percentages for the three indicators: AEEP (10%), FEP, and the proposed 'hybrid' proxy for REEP, so that they can be compared.

**Table 9 – results for Actual Expenditure Energy Poverty Indicator using 10% decision threshold:**

| AEEP (10%) | Number of households | Percentage of households (%) |
|---|---|---|
| False | 2080 | 72.1 |
| True | 806 | 27.9 |

**Table 10 – results for Feeling Energy Poor indicator:**

| Feeling Energy Poor | Number of households | Percentage of households (%) |
|---|---|---|
| not-FEP | 4681 | 81.4 |
| FEP | 1067 | 18.6 |

**Table 11 – results for hybrid 'proxy' for Required Expenditure Energy Poverty indicator.**

| Hybrid Required Expenditure Energy Poverty proxy | Number of households | Percentage of households (%) |
|---|---|---|
| False | 4117 | 71.6 |
| True | 1631 | 28.4 |

Why use this hybrid indicator? First, it is likely to be a less biased proxy for the "ground truth" REEP indicator than either FEP or AEEP alone. Second, assuming smart meter data is available, it will also be easier to collect the necessary data to produce it, compared to the requirement for a physical survey conducted by an expert surveyor for REEP and a knowledgeable practitioner of the SAP building energy model. Where both the FEP and AEEP indicators are available, therefore, and where the objective is to have a measurement that is the best possible estimate of the ground truth (REEP in this case), we therefore recommend using this hybrid indicator. Clearly however there are downsides to this hybrid indicator, in that it has greater data requirements than AEEP or FEP alone.

## 4.8. WHY IS A SMART METER DATA ENABLED ENERGY POVERTY INDICATOR IMPORTANT?

As mentioned previously, indicators based on required energy costs have significant barriers to their measurement, and this means that there are more barriers to their use for measuring, identification and evaluation of energy poverty. The AEEP indicator therefore is important because, where smart meter data are available, it is easier to implement, and therefore there are lower barriers to its implementation, and this opens more opportunities for improving the understanding of energy poverty and tackling it effectively. For example, AEEP could be used relatively easily for evaluation of energy efficiency retrofit measures which could be evaluated on their impact on outcomes (in this case energy affordability, energy poverty). AEEP therefore fits into, or supports a move towards a greater focus on evaluation of policies, measures, solutions in terms of outcomes and performance, and the subsequent beneficial feedback loop in terms of prioritising solutions, installers, and policies that achieve targeted levels of performance.

As an example, the following presents analysis of evaluating the impact of the Energy Price Guarantee and the Energy Bills Support Scheme (the key policies used during the cost-of-living crisis described in section 4.2) on energy poverty levels as measured by AEEP.

### 4.9. IMPACT OF ENERGY POLICIES ON ENERGY POVERTY

The two key policies that were introduced in GB to reduce household energy bills were the Energy Bills Support Scheme (EBSS) and the Energy Price Guarantee (EPG) (see section 4.2). Figure 17 illustrates the estimated impact that these policies had on reducing the average energy burden (the percentage of household disposable income spent on gas and electricity expenditure in the previous 12 months) for the SERL Observatory participants. The counterfactual to the EBSS assumes that each household did not receive £400 in the winter 2022/2023, and that this directly affected their disposable income. The counterfactual for the Energy Price Guarantee assumes that households paid the Energy Price Cap unit cost for gas and electricity rather than the subsidised Energy Price Guarantee during the period from October 2022 to June 2023 inclusive. On average, over this period, the EBSS reduced the average energy burden by 0.3%, while the EPG reduced it by 2.4%. In combination they reduced the average energy burden by 2.8%, and at their peak they reduced the average energy burden for the SERL Observatory participants from what would have been a maximum of 13.2% to 8.9%, a reduction of 4.3%.

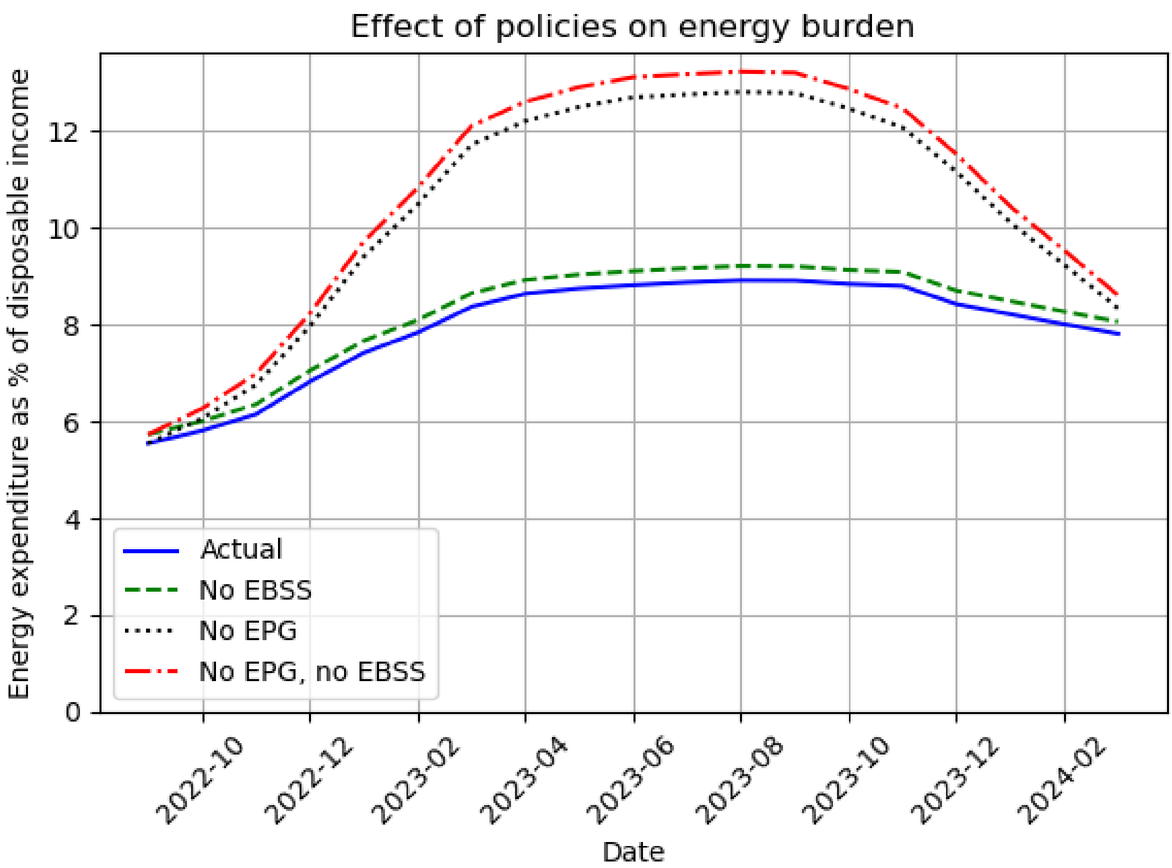


**Figure 17 – Effect of two policies, the Energy Bills Support Scheme (EBSS) and Energy Price Guarantee (EPG), on average energy burden for SERL Observatory participants.**

The following tables show the impact of these reductions in energy burden due to these energy policies on energy poverty, as defined by the AEEP 10% threshold indicator, by showing how many households in the SERL Observatory would have been classified as in Actual Expenditure Energy Poverty if the support had not been in place. The results show the substantial impact these policies had on reducing energy poverty levels. Without the EPG and EBSS, 48% of households in the SERL Observatory would have been in energy poverty according to the AEEP 10% indicator, as opposed to 28%, a decrease of 20%. While clearly this came at a substantial cost to the Government (an estimated £42 billion (Lowrey & Mulvany, 2024)), without this unprecedented intervention a possible 20% of households in GB would have been pushed into energy poverty.

**Table 12 – number of households in Actual Expenditure Energy Poverty assuming no EBSS.**

| Actual Expenditure Energy Poverty | Number of households | Percentage of households (%) |
|---|---:|---:|
| False | 2049 | 71 |
| True | 837 | 29 |

**Table 13 – number of households in Actual Expenditure Energy Poverty assuming no EPG.**

| Actual Expenditure Energy Poverty | Number of households | Percentage of households (%) |
|---|---:|---:|
| False | 1537 | 53.22 |
| True | 1351 | 46.78 |

**Table 14 – number of households in Actual Expenditure Energy Poverty assuming no EPG and no EBSS.**

| Actual Expenditure Energy Poverty | Number of households | Percentage of households (%) |
|---|---:|---:|
| False | 1511 | 52.32 |
| True | 1377 | 47.68 |

# 5. USING SMART METER DATA TO IDENTIFY ENERGY POVERTY: COMPARATIVE ANALYSIS OF ENERGY USE PATTERNS OF ENERGY POOR HOUSEHOLDS

Machine learning could help solve the problem of identifying households who are in or at risk of energy poverty (Deloitte LLP, 2020). To do this however requires input data that are available at scale (for the whole population ideally), training data to train the model (and critically this means the need for both the input data and the linked classification data) and a model that is sufficiently accurate. With smart meters installed or being installed in most homes in EU (De Paola et al., 2023), smart meter data are a promising potential new source of input data for such models, and the use of smart meter data to improve methods of identifying energy poverty is a topic of research that merits investigation.

The SERL Observatory is a novel dataset that contains the labelled data required to train a machine learning model that could identify energy poverty using smart meter data (smart meter data linked to energy poverty status at the household-level), and this gives the opportunity to develop models to identify energy poverty using smart meter data and test their accuracy.

The development of such a machine learning model is based on the fundamental assumption that there are significant differences in patterns in the input data (smart meter data) between the different groups to be identified (energy poor vs non-energy poor). If there are no differences in smart meter data between the energy poor and the non-energy poor, then it is not reasonable to assume that a machine learning model can be trained to identify the groups based on smart meter data. This chapter therefore conducts exploratory data analysis to investigate the presence (or lack of) differences in smart meter data between energy poor and other households in the SERL Observatory. The more there are apparent differences then the greater motivation, or justification for developing a machine learning classification model that uses smart meter data as an input to predict energy poverty status.

To frame the analysis, we will test the following hypotheses.

**Table 15 – Hypotheses to test regarding differences in patterns of energy use between energy poor and non-energy poor.**

| Hypothesis | Rationale | Analysis |
|---|---|---|
| H1: the energy poor use significantly less energy than non-energy poor households, especially during extreme cold weather | Households in energy poverty under-consume because they cannot afford adequate heating. Analysis of gas usage data for 143 GB households revealed that households in the lowest income groups and those in energy poverty increased their gas usage during cold weather less than other households (BEIS, 2021a). | Compare distributions of gas and electricity use between the two groups in particular, distributions of mean energy use, annual, peak demand, diurnal and during coldest periods, e.g., December 2022 |

| | | |
|---|---|---|
| H2: energy poor households display irregular energy usage patterns compared to non-energy poor households | Energy poor households may have irregular energy use caused by fluctuations in financial stability or their ability to afford energy. A UK Government-commissioned study indicated that energy poor households often face difficulties in affording their energy bills, leading them to adopt coping mechanisms such as reducing energy consumption, which can lead to irregular usage patterns as they balance comfort and affordability over time (London Economics, 2023). | Compare household-level statistics related to dispersion of energy use, e.g., standard deviation, coefficient of variation, skewness and kurtosis between energy poor and non-energy poor |

As in the previous chapter, we only include households whom we believe have gas central heating. The original number of households with energy poverty status data is 5748, and this is reduced to 4704 (81.8%) with gas central heating included in this analysis.

In the following we will present analyses for the two energy poverty indicators we directly measure, and which are described in detail in the previous chapter: the objective indicator Actual Expenditure Energy Poverty (AEEP) using a 10% threshold, and the subjective indicator Feeling Energy Poor. For each indicator we compare the two groups of 1) energy poor according to the given indicator and 2) not energy poor according to the given indicator.

Tests of significance are performed to compare the statistics of central tendency between the groups. As the distributions are generally skewed, we perform two tests: log-transforming the distributions to reduce skewness and using a Z-test to test for differences in means, and the Mann-Whitney U-test to test for differences in medians.

## 5.1. ANNUAL AVERAGE ENERGY USE

Do energy poor households use less energy than non-energy poor households? Figure 18 and Figure 19 show frequency distributions of average gas and electricity use (in kWh/day) for 2023 based on SERL Observatory data for households who are energy poor versus households who are not energy poor. Figure 18 compares these two groups using the Feeling Energy Poor (FEP) indicator, while Figure 19 uses the Actual Expenditure Energy Poverty (AEEP) indicator. The results show that, on average, FEP households use less electricity and gas compared to other households, with a daily average usage of 7.2 kWh/day for electricity and 24.0 kWh/day for gas as compared to 7.9 kWh/day and 30.5 kWh/day. The differences in average use are statistically significant. *Electricity: Z-statistic -3.575. P-value 0.000. U-stat: 844252.0, p-value: 0.0108. Gas: Z-statistic -9.785. P-value 0.000. U-stat: 656170.0, p-value: 6.7969e-19.*

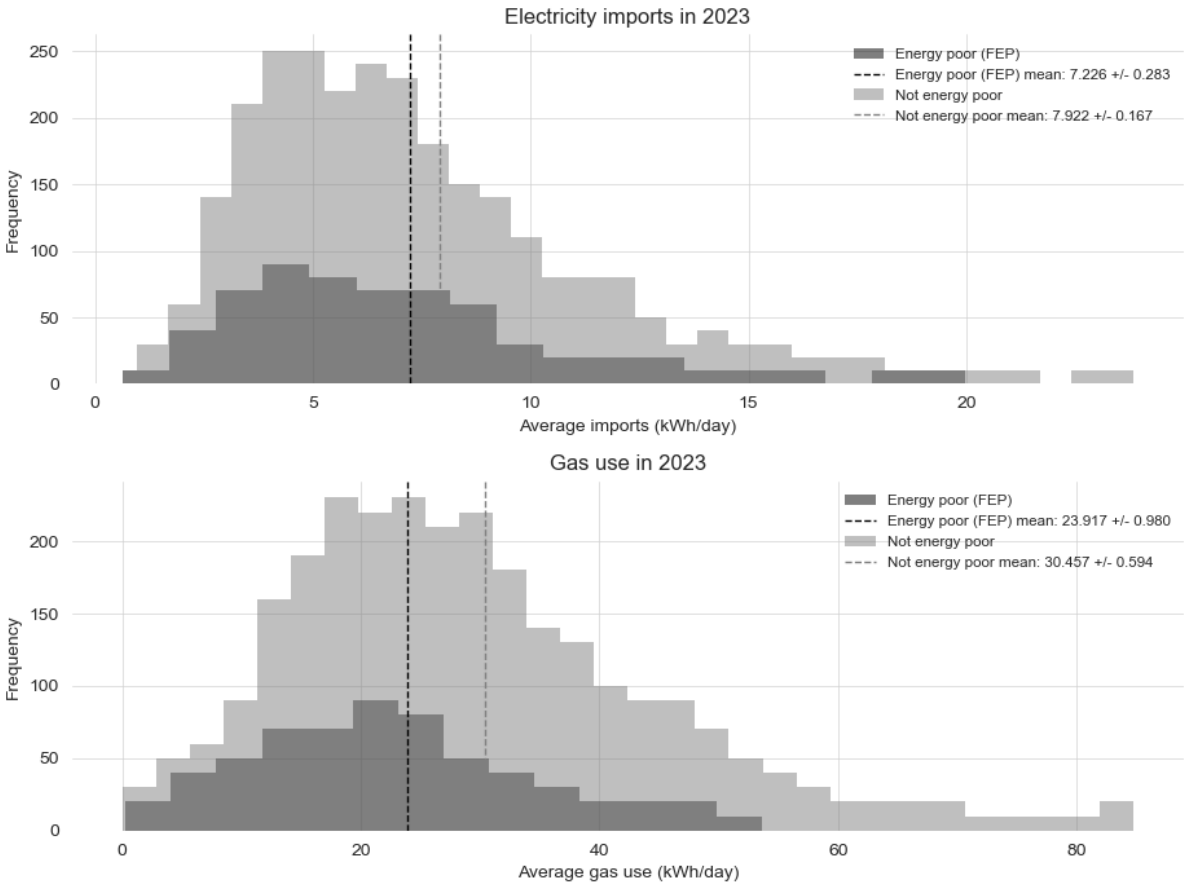


**Figure 18 – Frequency distributions of household-level average daily gas and electricity use in 2023 for energy poor households using the Feeling Energy Poor indicator and other non-energy poor households.**

For AEEP households the results in Figure 19 show that compared to non-energy poor households on average they use similar amounts of electricity (7.9 kWh/day vs. 7.8 kWh/day) but more gas (32.8 kWh/day vs. 27.9 kWh/day). The differences in central tendencies between the two groups were not statistically significant for electricity, but were for gas. *Electricity: Z-statistic 0.393. P-value 0.694. U-stat: 666086.0, p-value: 0.7054. Gas: Z-statistic 6.594. P-value 0.000. U-stat: 881581.5, p-value: 5.7797e-11.*

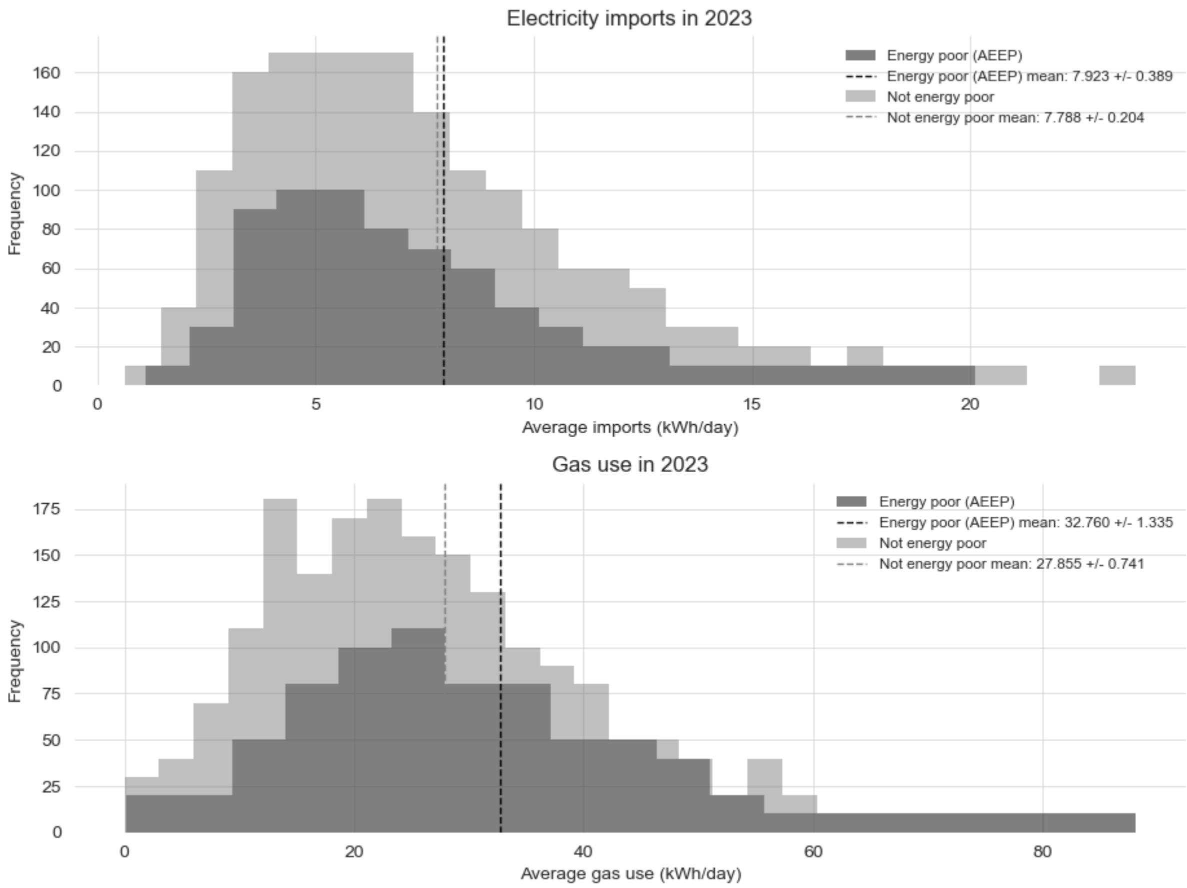


**Figure 19 – Frequency distributions of household-level average daily gas and electricity use in 2023 for energy poor households using the Actual Expenditure Energy Poverty indicator and other non-energy poor households.**

The results are therefore supportive of the hypothesis that energy poor households use less energy than non-energy poor households, *when energy poverty is measured using the Feeling Energy Poor indicator*. When using the AEEP indicator however the results refute the hypothesis as the (AEEP) energy poor actually use significantly more gas than the non-energy poor. These results are intuitive if we assume that FEP households are more likely than non-energy poor to have reduced their heating in response to energy price rises, while for AEEP the indicator is by definition identifying households with high energy usage i.e. those that are *less likely* to have reduced their energy usage.

## 5.2. COLD WEATHER ENERGY USE

Does cold weather make a difference to these findings? Figure 20 and Figure 21 show distributions for energy use during December 2022, which was a particularly cold month, with an average mean temperature below +5 degrees Celsius. Overall, the pattern of results seen in 2023 is repeated but the differences in averages are substantively larger. During December 2022, Feeling Energy Poor households (Figure 20) used less electricity than non-energy poor households (8.7 kWh/day vs. 9.9 kWh/day) and less gas (53.3 kWh/day vs. 67.1 kWh/day). These differences are statistically significant. *Electricity: Z-statistic -4.112. P-value 0.000. U-stat: 1282953.5, p-value: 0.0006. Gas: Z-statistic -8.146. P-value 0.000. U-stat: 765048.5, p-value: 1.65049e-18.*

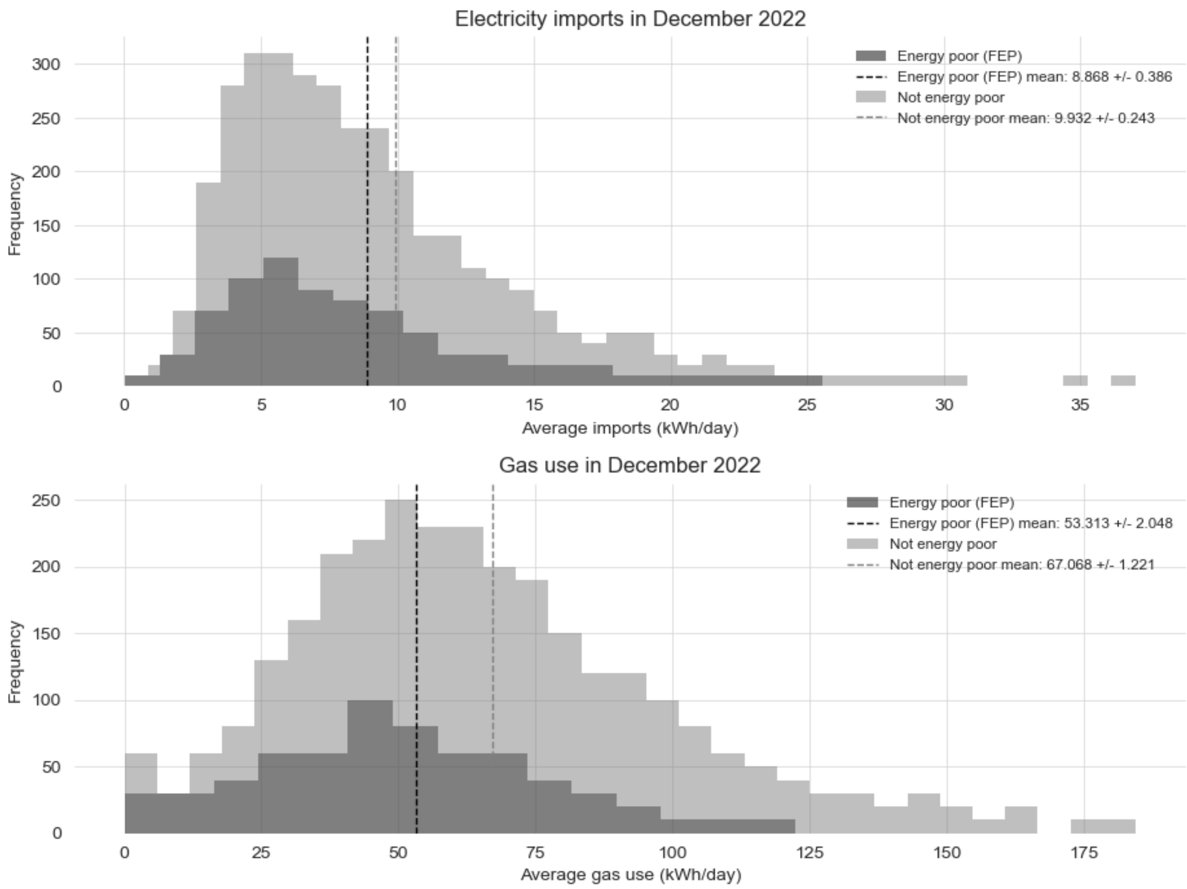


**Figure 20 – Frequency distributions of household-level average daily gas and electricity use in December 2022 for energy poor households using the Feeling Energy Poor indicator and other non-energy poor households.**

Actual Expenditure Energy Poor households (Figure 21), on average, did not use more or less electricity than non-energy poor households during December 2022, but they did use more gas (71.3 kWh/day vs. 61.9 kWh/day). The differences in gas use are statistically significant. *Electricity: Z-statistic 0.879. P-value 0.379. U-stat: 829905.5, p-value: 0.84767. Gas: Z-statistic 6.473. P-value 0.000. U-stat: 946613.0, p-value: 1.02101e-09.*

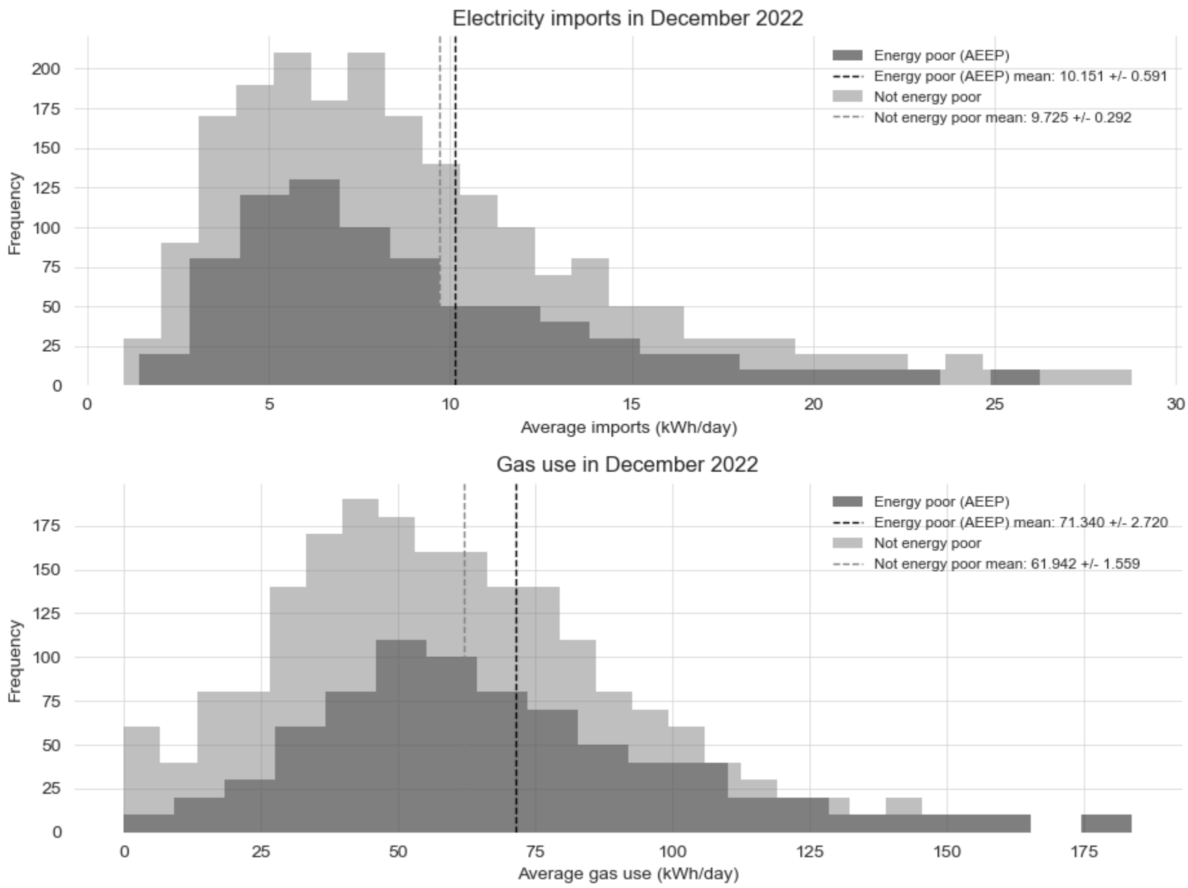


**Figure 21 – Frequency distributions of household-level average daily gas and electricity use in December 2022 for energy poor households using the Actual Expenditure Energy Poverty indicator and other non-energy poor households.**

Again, the results therefore support the hypothesis that energy poor households use less energy than non-energy poor households particularly during cold weather, but only for households who are Feeling Energy Poor. The results for Actual Expenditure Energy Poor refute this hypothesis, as these households use more gas than non-energy poor households and the difference is substantively bigger during cold weather periods.

## 5.3. DEMAND PROFILE ANALYSIS

The previous figures were based on average daily energy consumption. They were useful for investigating the presence of systematic differences in overall gas and electricity consumption between energy poor and non-energy poor households. Smart meter data however record energy consumption at high-resolution, 30-minutes in the case of the SERL Observatory data. In addition to overall levels of energy usage, therefore, smart meter data also allow the investigation in differences in the time-of-day patterns of gas and electricity usage ('energy demand profiles') between energy poor and non-energy poor households. Households who use similar amounts of energy may nonetheless have different demand profiles due to differences in when energy is used throughout the day, driven by differences in behaviours and activities. Any differences can be thought of as group-specific 'energy signatures' which machine learning models could be trained to detect. The more there are differences in demand profiles between energy poor and non-energy poor households, the more justification there is to pursue the development of a machine learning model to identify energy poverty based on smart meter data.

Figure 22 and Figure 23 show average electricity and gas demand profiles during 2023 for Feeling Energy Poor households versus non-energy poor households. The results show that both groups display demand profiles that follow similar time-of-day profiles: low "off peak" energy use during the night, high "peak" energy use during the evening, intermediate levels of energy use during the day with a small increase around lunchtime, and a second period of "peak" energy use for gas during the morning. The demand profiles for Feeling Energy Poor households are however lower than those for non-energy poor households, particularly so for gas, and show that the energy poor households generally use less energy than non-energy poor households at all times of the day, with some exceptions such as gas use at night and electricity use during "ramp up" periods immediately preceding morning and evening peaks.

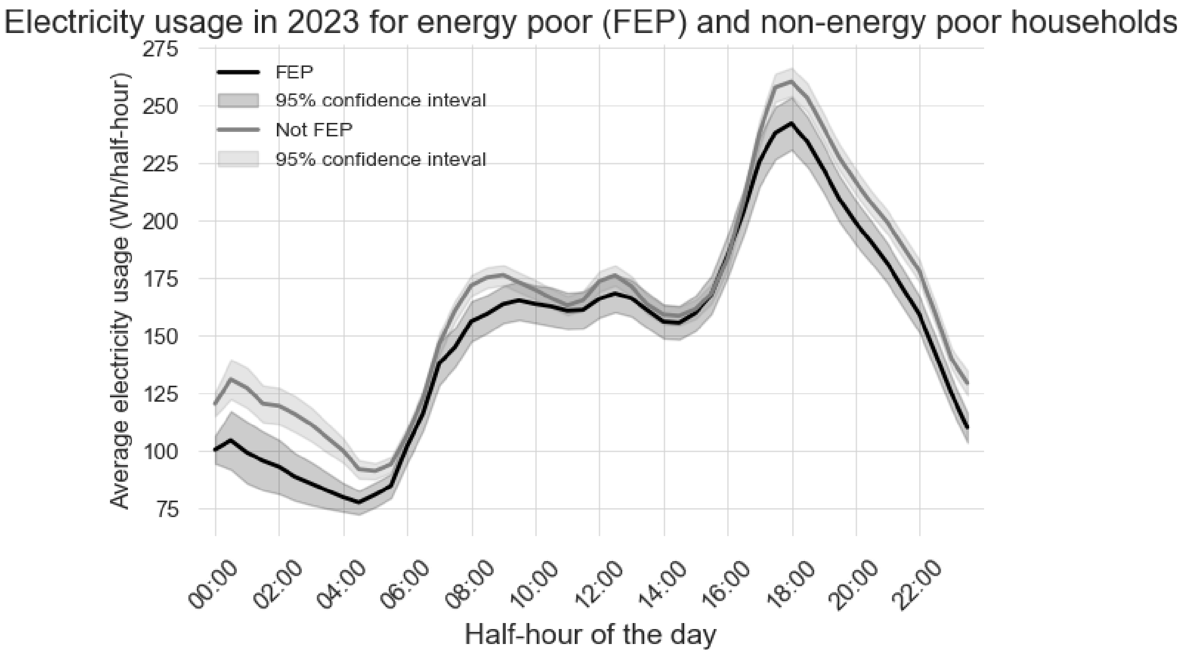


**Figure 22 – Average electricity demand profile in 2023 for energy poor households (measured using the Feeling Energy Poor indicator) versus non-energy poor households.**

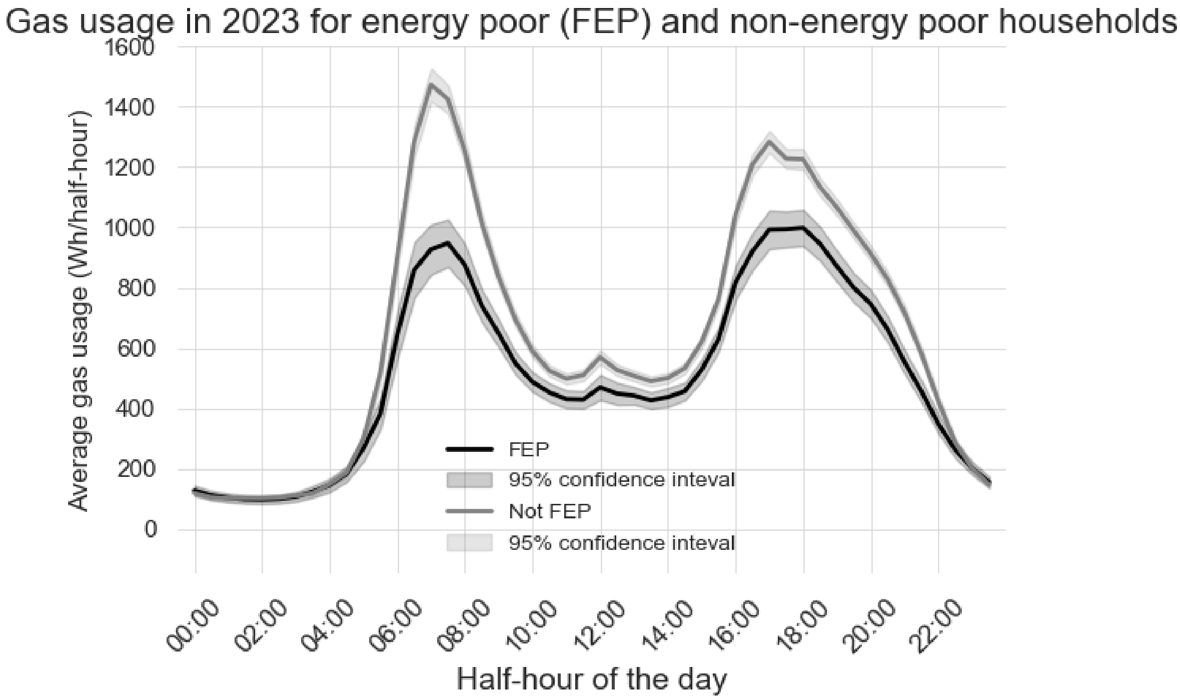


**Figure 23 – Average gas demand profile in 2023 for energy poor households (measured using the Feeling Energy Poor indicator) versus non-energy poor households.**

Are the differences in demand profiles significant? While the 95% confidence intervals provide an indication, the following compares distributions of 'peak' gas and electricity use for the two groups, which we test for statistically significant differences in central tendency. We will take peak demand to be 4pm to 9pm for electricity, and for gas we take it to be 6am to 9am and 4pm to 7pm. Figure 24 shows that while Feeling Energy Poor households on average use less electricity during peak times than non-energy poor households (212.7 Wh/half-hour vs. 225.4 Wh/half-hour) this is not a statistically significant at the 95% confidence level. For gas however the difference is statistically significant, with Feeling Energy Poor households using substantially less gas during peak periods than non-energy poor households (830.8 Wh/half-hour versus 1133.2 Wh/half-hour). *Electricity: Z-statistic -1.928. P-value 0.054. U-stat: 921038.0, p-value: 0.11241. Gas: Z-statistic -9.589. P-value 0.000. U-stat: 578378.0. p-value: 8.5206e-27.*

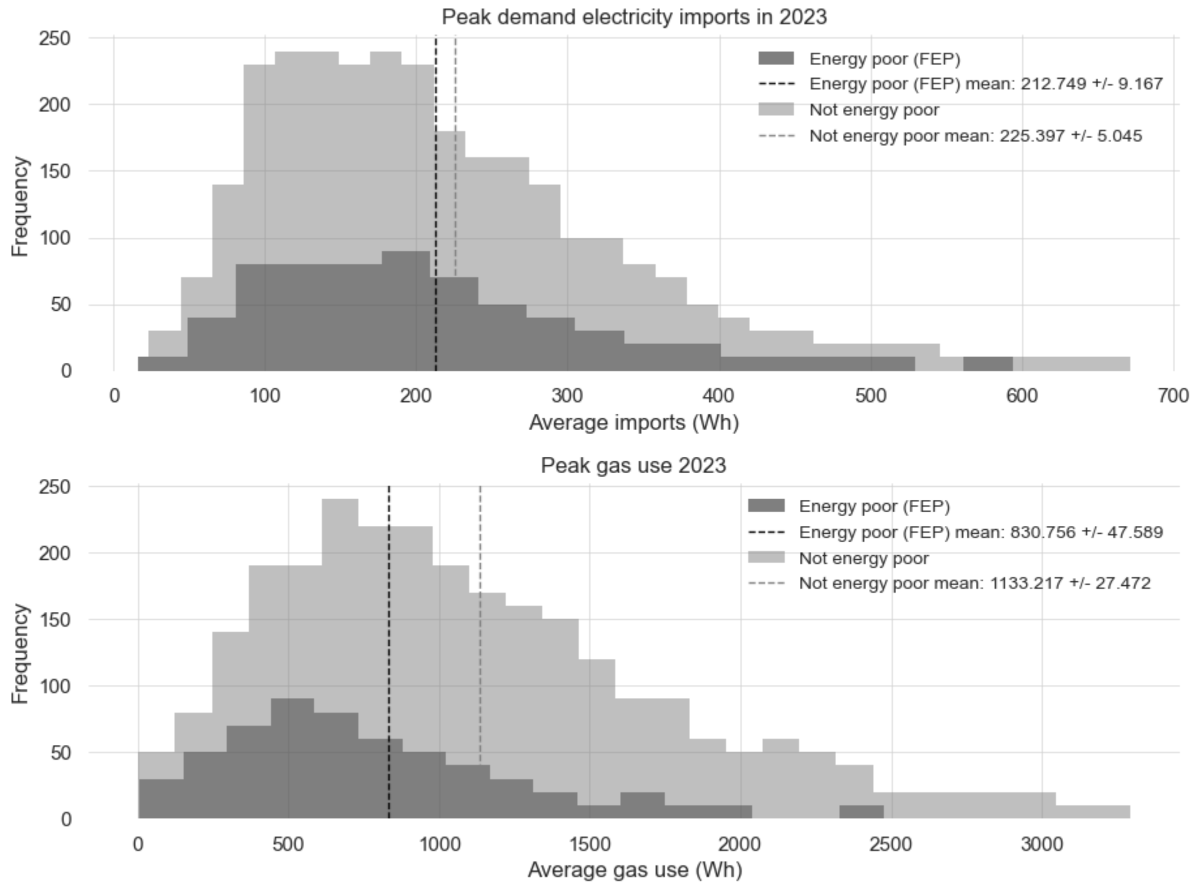


**Figure 24 – Frequency distributions comparing household-level average gas and electricity usage during peak periods for energy poor (measured using the Feeling Energy Poor indicator) and non-energy poor households.**

Figure 25 and Figure 26 show the average electricity and gas demand profiles in 2023 for energy poor households measured using the Actual Expenditure Energy Poverty indicator with a 10% threshold and non-energy poor households. Both groups follow the same broad time-of-day pattern as described previously. When it comes to electricity, however, AEEP households appear to use less electricity at night but more during the day, possibly driven by differences in household occupancy patterns. For gas, AEEP households appear to use more gas than non-energy poor households throughout the day, particularly during the day, again suggesting differences in occupancy patterns between the two groups. When it comes to peak usage, the differences between the two groups are not statistically significant for electricity but are for gas. *Electricity: Z-statistic 0.494. P-value 0.621. U-stat: 700988.0, p-value: 0.6476. Gas: Z-statistic 2.326. P-value 0.020. U-stat: 769149.0, p-value: 0.01119.*

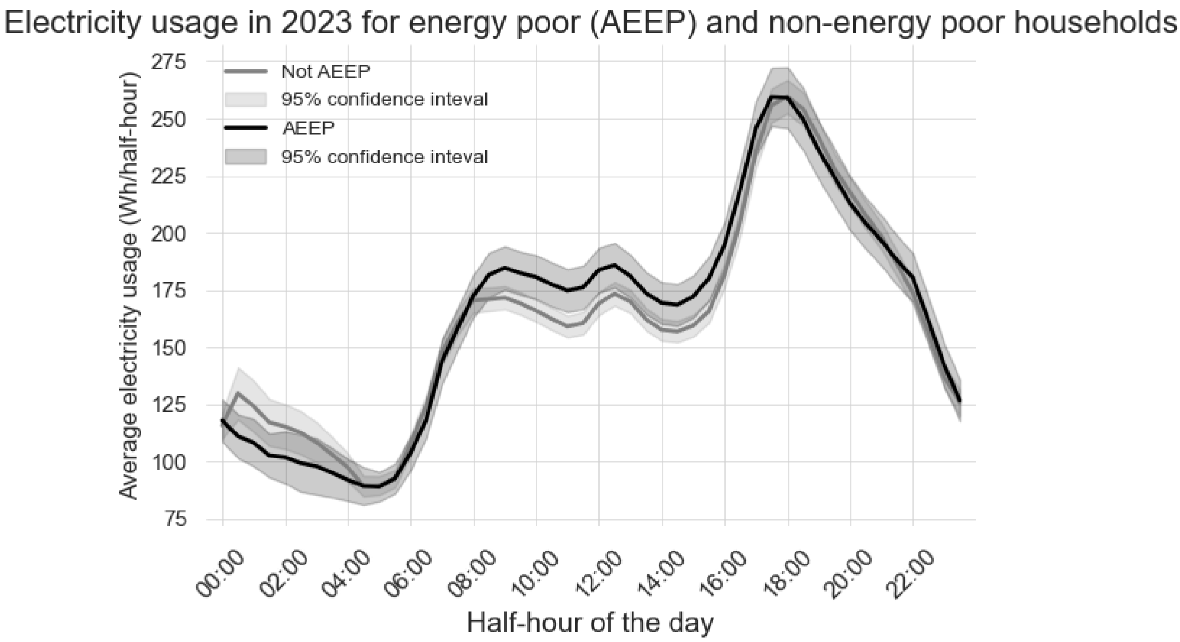


**Figure 25 – Average electricity demand profile in 2023 for energy poor households (measured using the Actual Expenditure Energy Poverty indicator with 10% threshold) versus non-energy poor households.**

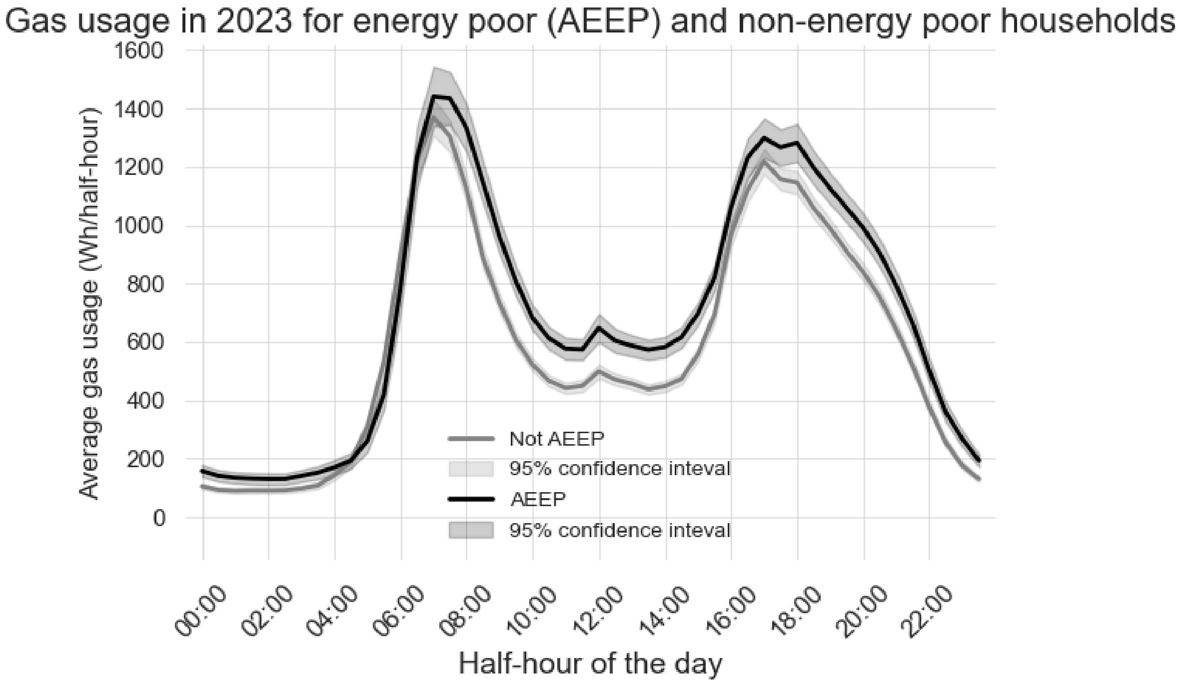


**Figure 26 – Average gas demand profile in 2023 for energy poor households (measured using the Actual Expenditure Energy Poverty indicator using 10% threshold) versus non-energy poor households.**

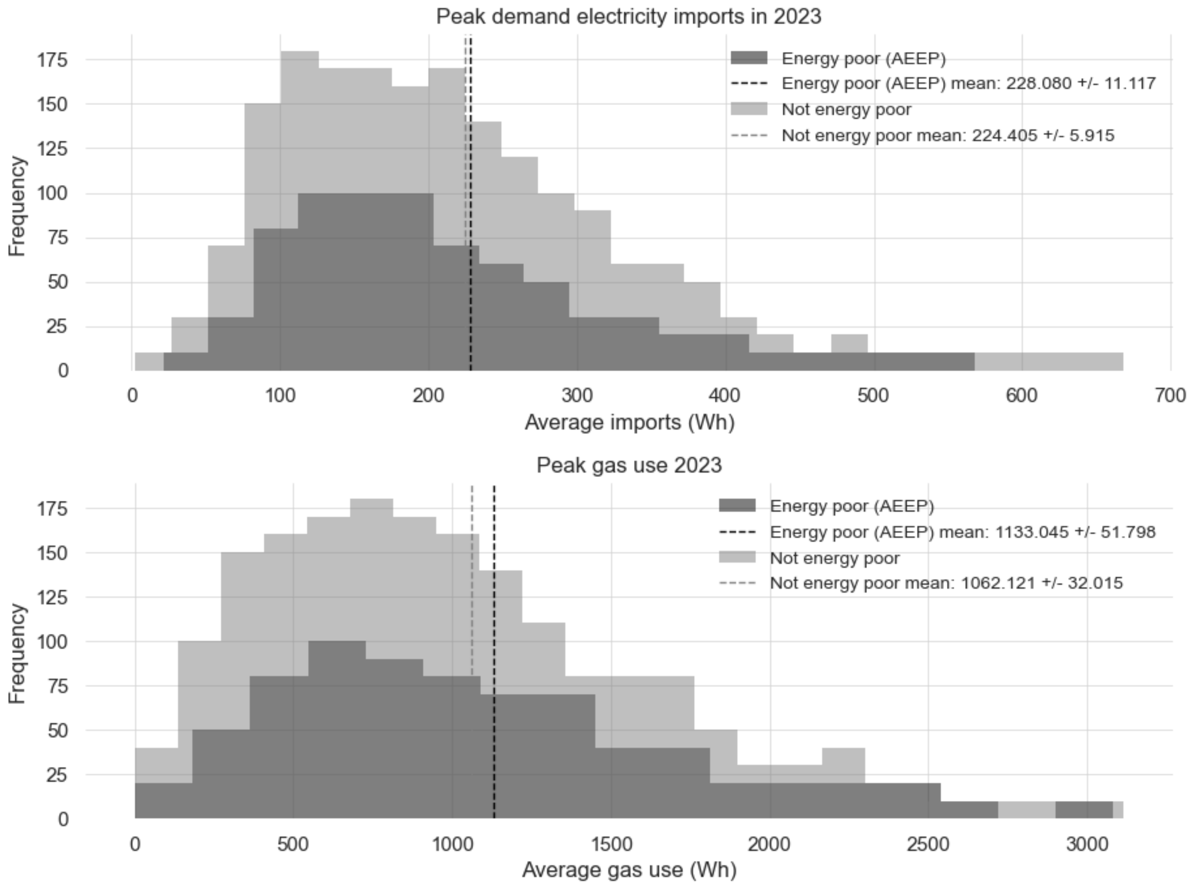


**Figure 27 – Frequency distributions comparing household-level average gas and electricity usage during peak periods for energy poor (measured using the Actual Expenditure Energy Poverty indicator) and non-energy poor households.**

In summary, the results of the demand profile analysis reveal substantial and significant differences in patterns of gas usage by time-of-day between energy poor and non-energy poor households, and with some qualitative differences in electricity usage, though not statistically significantly at least relating to peak demand periods. We see the trend of Feeling Energy Poor households using less gas than non-energy poor households throughout the day, while AEEP energy poor households tend to use more than non-energy poor households, particularly during the daytime. The average difference in demand profiles therefore supports the idea of using high-resolution smart meter data to detect differences in energy poverty status as these differences in patterns or energy signatures might be learned during the training of a machine learning energy poverty identification model.

## 5.4. DISPERSION OF HALF-HOURLY ENERGY USE

Here we examine statistics of dispersion of the household-level half-hourly energy use data, as measures of irregularity, and to determine if these are significantly different between energy poor and non-energy poor households. We will compare distributions of household-level statistics of standard deviation, coefficient of variation, skew, and kurtosis for the two groups. For the calculation of all statistics, we use half-hourly gas or electricity data for each household for the year 2023. We then compare distributions of the groups of the household-level statistics for energy poor and non-energy poor households.

The **standard deviation** measures the average deviation from the mean for a distribution of data. It represents the dispersion of data in the distribution. In the context of household-level energy use data, higher standard deviation represents greater variability in half-hourly energy use. It is calculated as

$$s = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$$

Where $N$is the number of observations, $x_i$ is each individual observation (i.e., each individual gas or electricity usage for each half-hour for a household), and $\bar{x}$ is the mean of the individual observations.

The **coefficient of variation** is the ratio of the standard deviation to the mean, and it is a normalised version of the standard deviation. It is useful when comparing dispersion across distributions with different means, as the standard deviation can scale with the mean, i.e., groups with higher average energy consumption can have higher standard deviation, and the coefficient of variation accounts for that scaling. It is calculated as

$$CV = \frac{s}{\bar{x}}$$

Similar to the standard deviation, a higher coefficient of variation can indicate greater irregularity in energy use.

**Skewness** quantifies the asymmetry of the distribution. Many of the energy use distributions shown previously are right skewed, meaning that the majority of observations are around the lower end of the distribution with a relatively small number of observations that are high, which pulls the distribution towards the right. Right skewed distributions will have positive skewness, while left skewed distributions will have negative skewness. Skewness is calculated as

$$\gamma_1 = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^3}{s^3}$$

In the context of household-level energy use statistics, more positive values of skewness can reveal distributions with more extreme values, potentially highlighting irregular usage patterns.

**Kurtosis** measures the 'tailedness' of a distribution, with higher values indicating more frequent spikes or drops in energy usage compared to the average.

$$\gamma_2 = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^4}{s^4} - 3$$

Values above zero indicate heavier tails in distributions, and potentially reveal more erratic energy use patterns.

### 5.4.1. FEELING ENERGY POOR

We will first consider the distributions of these statistics of dispersion for the Feeling Energy Poor households compare to the feeling non-energy poor households. The distributions for the four statistics are shown in Figure 28, Figure 29, Figure 30 and Figure 31. The results indicating the presence of differences in the distributions between the two groups are summarised in Table 16 and Table 17. The results show that the differences in energy use patterns between energy poor (as measured using the FEP indicator) are greater for gas, which is driven by heating behaviour, than they are for electricity. On average, Feeling Energy Poor households show distributions of half-hourly energy use that are more variable (higher coefficient of variation), more skewed and with higher proportion of extreme values (both high and low). These results support the hypothesis that energy poor households have patterns of energy use that are more irregular than non-energy poor households.

**Table 16 – Summary of differences in statistics of household-level electricity half-hourly energy use in 2023 for energy poor (measured using Feeling Energy Poor indicator) and non-energy poor groups of households in the SERL Observatory.**

| Statistic (half-hourly electricity use) | Feeling Energy Poor (mean of distribution) | Not Feeling Energy Poor (mean of distribution) | Statistically significant difference in means? | Statistically significant difference in medians? |
|---|---|---|---|---|
| Standard deviation | 181.2 Wh/half-hour | 195.5 Wh/half-hour | No (*Z-statistic -1.828, P-value 0.067*) | No (*U-stat: 1395663.0, p-value: 0.44410*) |
| Coefficient of variation | 1.27 | 1.25 | No (*Z-statistic 1.254, P-value 0.210*) | No (*U-stat: 1475924.0, p-value: 0.083188*) |
| Skewness | 4.23 | 3.96 | Yes (*Z-statistic 3.195, P-value 0.001*) | Yes (*U-stat: 1488334.0, p-value: 0.034117*) |
| Kurtosis | 31.8 | 24.8 | No (*Z-statistic 1.108, P-value 0.268*) | Yes (*U-stat: 1501500.0, p-value: 0.011457*) |

**Table 17 – Summary of differences in statistics of household-level gas half-hourly energy use in 2023 for energy poor (measured using Feeling Energy Poor indicator) and non-energy poor groups of households in the SERL Observatory.**

| Statistic (half-hourly gas use) | Feeling Energy Poor (mean of distribution) | Not Feeling Energy Poor (mean of distribution) | Statistically significant difference in means? | Statistically significant difference in medians? |
|---|---|---|---|---|
| Standard deviation | 1198.8 Wh/half-hour | 1394.6 Wh/half-hour | Yes (*Z-statistic -7.904, P-value 0.000*) | Yes (*U-stat: 832437.0, p-value: 5.87649e-16*) |

| | | | | |
|---|---|---|---|---|
| Coefficient of variation | 2.82 | 2.51 | Yes *(Z-statistic 6.788, P-value 0.000)* | Yes *(U-stat: 1203294.0, p-value: 6.05273e-11)* |
| Skewness | 3.74 | 3.19 | Yes *(Z-statistic 7.443, P-value 0.000)* | Yes *(U-stat: 1226763.0, p-value: 8.281510e-14)* |
| Kurtosis | 24.3 | 16.6 | Yes *(Z-statistic 7.926, P-value 0.000)* | Yes *(U-stat: 1232102.0, p-value: 1.643640e-14)* |

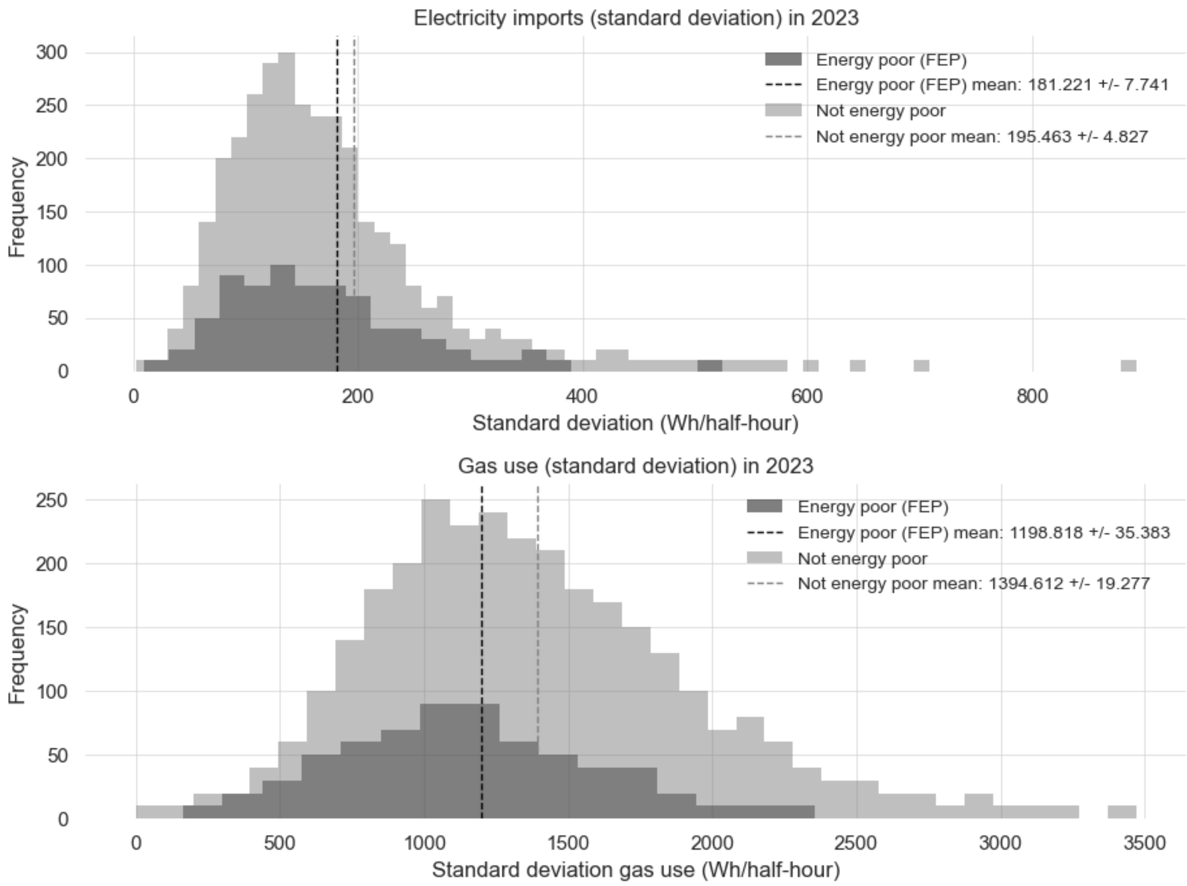


**Figure 28 – Comparison of standard deviations of household-level electricity and gas half-hourly energy use in 2023 for energy poor (measured using Feeling Energy Poor indicator) and non-energy poor groups of households in the SERL Observatory.**

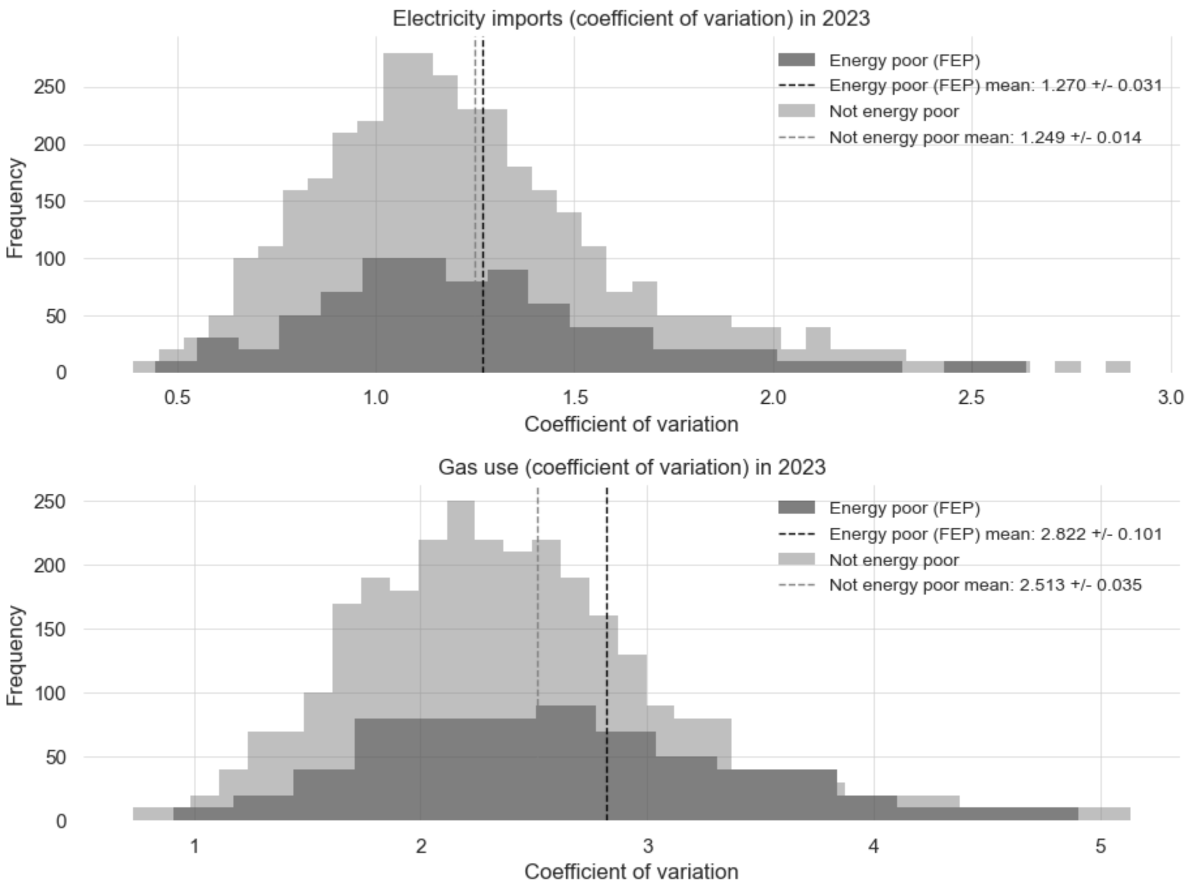


**Figure 29 – Comparison of distributions of coefficients of variation of household-level electricity and gas half-hourly energy use in 2023 for energy poor (measured using Feeling Energy Poor indicator) and non-energy poor groups of households in the SERL Observatory.**

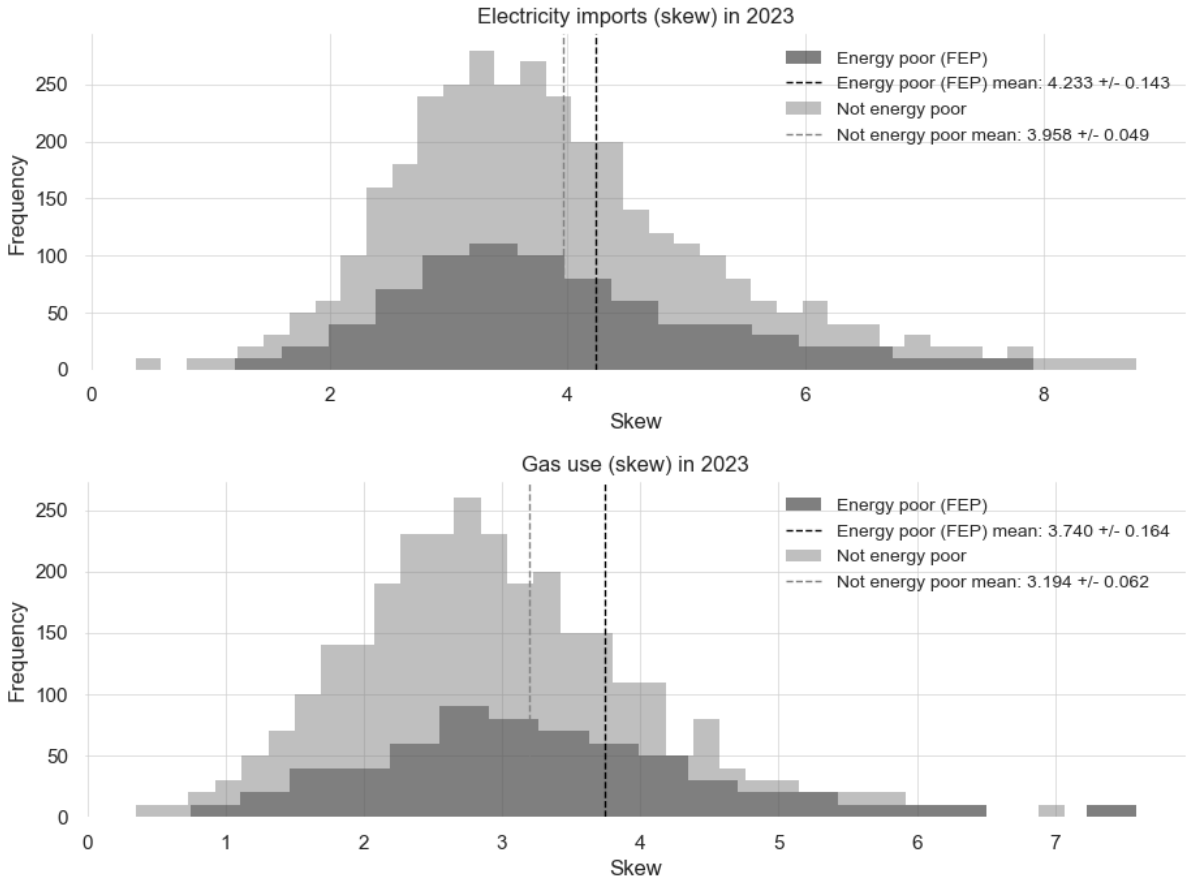


**Figure 30 – Comparison of distributions of skewness of household-level electricity and gas half-hourly energy use in 2023 for energy poor (measured using Feeling Energy Poor indicator) and non-energy poor groups of households in the SERL Observatory.**

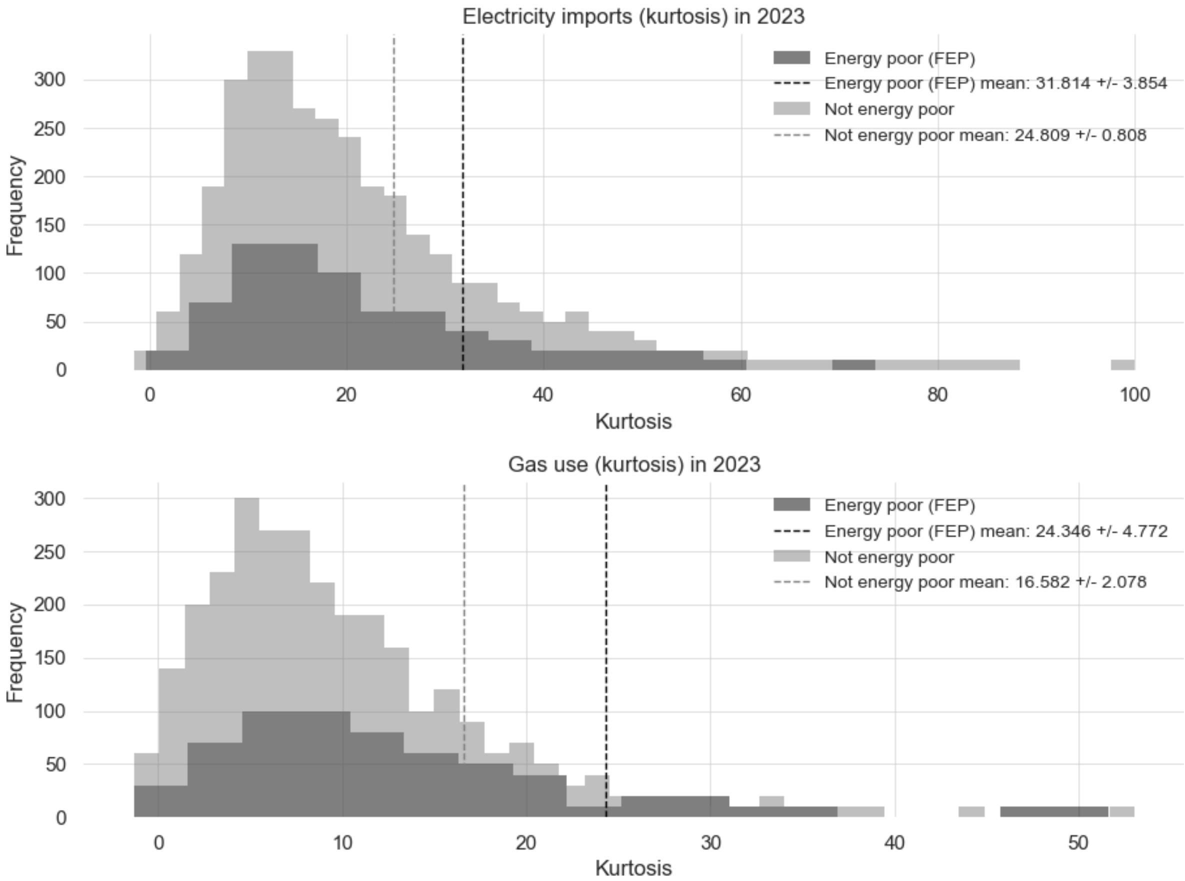


**Figure 31 – Comparison of distributions of kurtoses of household-level electricity and gas half-hourly energy use in 2023 for energy poor (measured using Feeling Energy Poor indicator) and non-energy poor groups of households in the SERL Observatory.**

### 5.4.2. ACTUAL EXPENDITURE ENERGY POOR

We now consider the results for energy poor households as measured using the Actual Expenditure Energy Poverty indicator with a 10% threshold. Figure 32, Figure 33, Figure 34, and Figure 35 illustrate the differences in distributions of the four statistics (standard deviation, coefficient of variation, skewness and kurtosis), while Table 18 and Table 19 summarise the results and whether there are statistically significant differences in the means of the distributions between the Actual Expenditure Energy Poor and those who are not. Similar to the previous results, these show that the differences between the two groups are more pronounced for half-hourly gas use distributions than for electricity. In general, the Actual Expenditure Energy Poor are more likely to have distributions of half-hourly energy use that are less variable, less skewed and have less extreme values (both high and low) than the non-energy poor. These results therefore indicate that the Actual Expenditure Energy Poor have energy usage patterns that are *less* irregular than the non-energy poor, and therefore refutes the hypothesis.

**Table 18 – Summary of differences in statistics of household-level electricity half-hourly energy use in 2023 for energy poor (measured using Actual Expenditure Energy Poverty indicator) and non-energy poor groups of households in the SERL Observatory.**

| Statistic (half-hourly electricity use) | Actual Expenditure Energy Poor (mean of distribution) | Not Actual Expenditure Energy Poor (mean of distribution) | Statistically significant difference in means? | Statistically significant difference in medians? |
|---|---|---|---|---|
| Standard deviation | 185.5 Wh/half-hour | 202.3 Wh/half-hour | Yes (Z-statistic -3.156, P-value 0.002) | Yes *(U-stat: 767967.0, p-value: 0.000659)* |
| Coefficient of variation | 1.19 | 1.30 | Yes *(Z-statistic -6.661, P-value 0.000)* | Yes *(U-stat: 702835.0, p-value: 2.82102e-11)* |
| Skewness | 4.08 | 4.05 | No *(Z-statistic -0.292, P-value 0.770)* | No *(U-stat: 837922.0, p-value: 0.932540)* |
| Kurtosis | 27.8 | 26.7 | No *(Z-statistic 0.912, P-value 0.362)* | No *(U-stat: 857521.0, p-value: 0.287979)* |

**Table 19 – Summary of differences in statistics of household-level gas half-hourly energy use in 2023 for energy poor (measured using Actual Expenditure Energy Poverty indicator) and non-energy poor groups of households in the SERL Observatory.**

| Statistic (half-hourly gas use) | Actual Expenditure Energy Poor (mean of distribution) | Not Actual Expenditure Energy Poor (mean of distribution) | Statistically significant difference in means? | Statistically significant difference in medians? |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| Standard deviation | 1386.4 Wh/half-hour | 1337.5 Wh/half-hour | Yes *(Z-statistic 2.194, P-value 0.028)* | Yes *(U-stat: 873318.0, p-value: 0.046839)* |
| Coefficient of variation | 2.35 | 2.69 | Yes *(Z-statistic -9.118, P-value 0.000)* | Yes *(U-stat: 637471.0, p-value: 1.659478e-22)* |
| Skewness | 2.90 | 3.52 | Yes *(Z-statistic -10.390, P-value 0.000)* | Yes *(U-stat: 618469.0, p-value: 8.904597e-27)* |
| Kurtosis | 12.4 | 21.2 | Yes *(Z-statistic -9.140, P-value 0.000)* | Yes *(U-stat: 625430.0, p-value: 3.624211e-25)* |

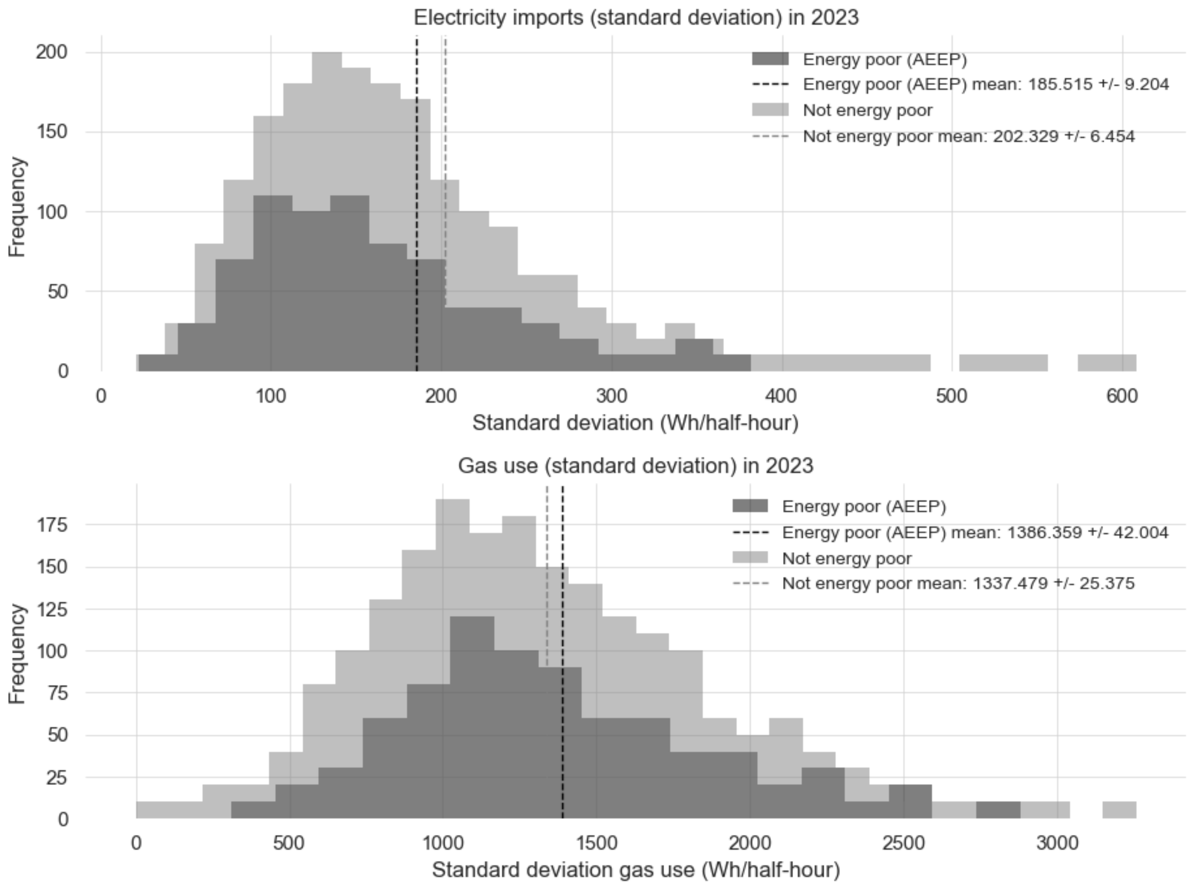


**Figure 32 – Comparison of distributions of standard deviations of household-level electricity and gas half-hourly energy use in 2023 for energy poor (measured using Actual Expenditure Energy Poverty 10% indicator) and non-energy poor groups of households in the SERL Observatory.**

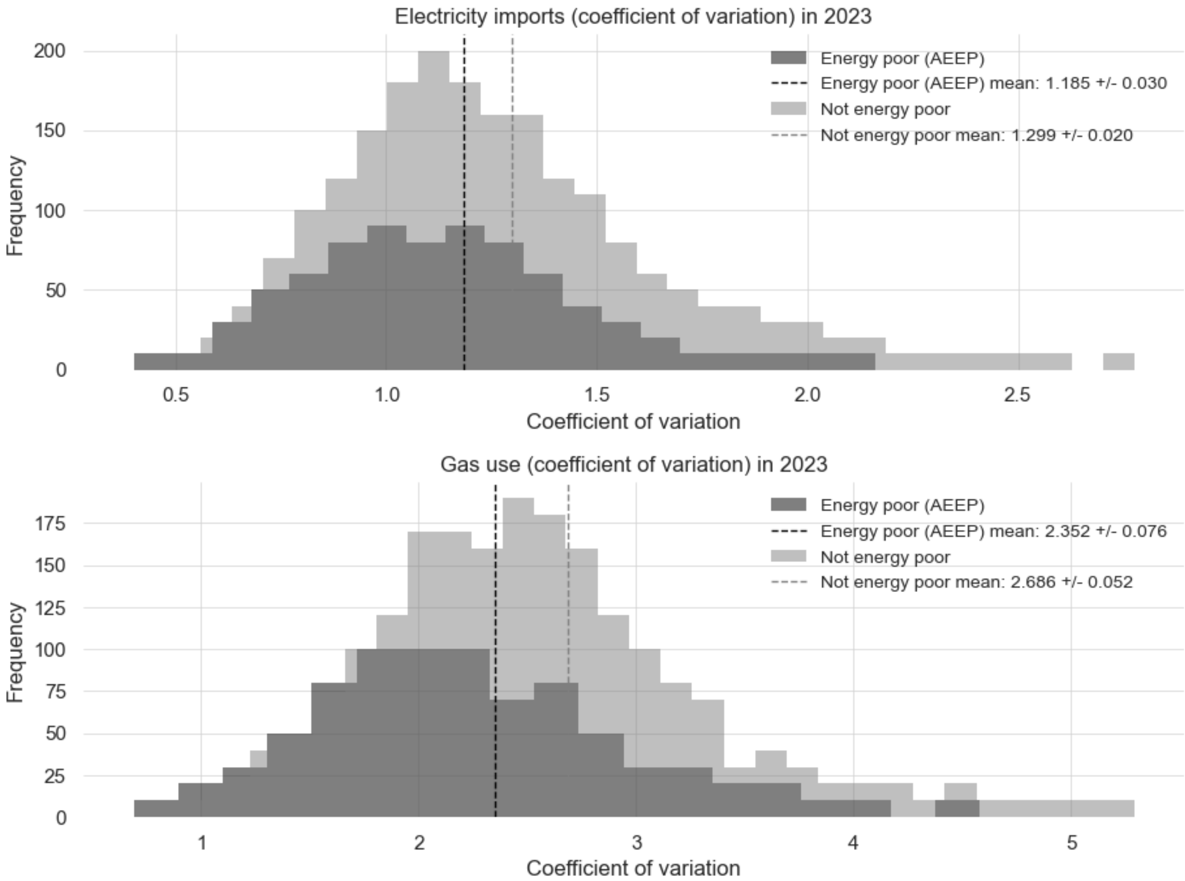


**Figure 33 – Comparison of distributions of coefficients of variation of household-level electricity and gas half-hourly energy use in 2023 for energy poor (measured using Actual Expenditure Energy Poverty 10% indicator) and non-energy poor groups of households in the SERL Observatory.**

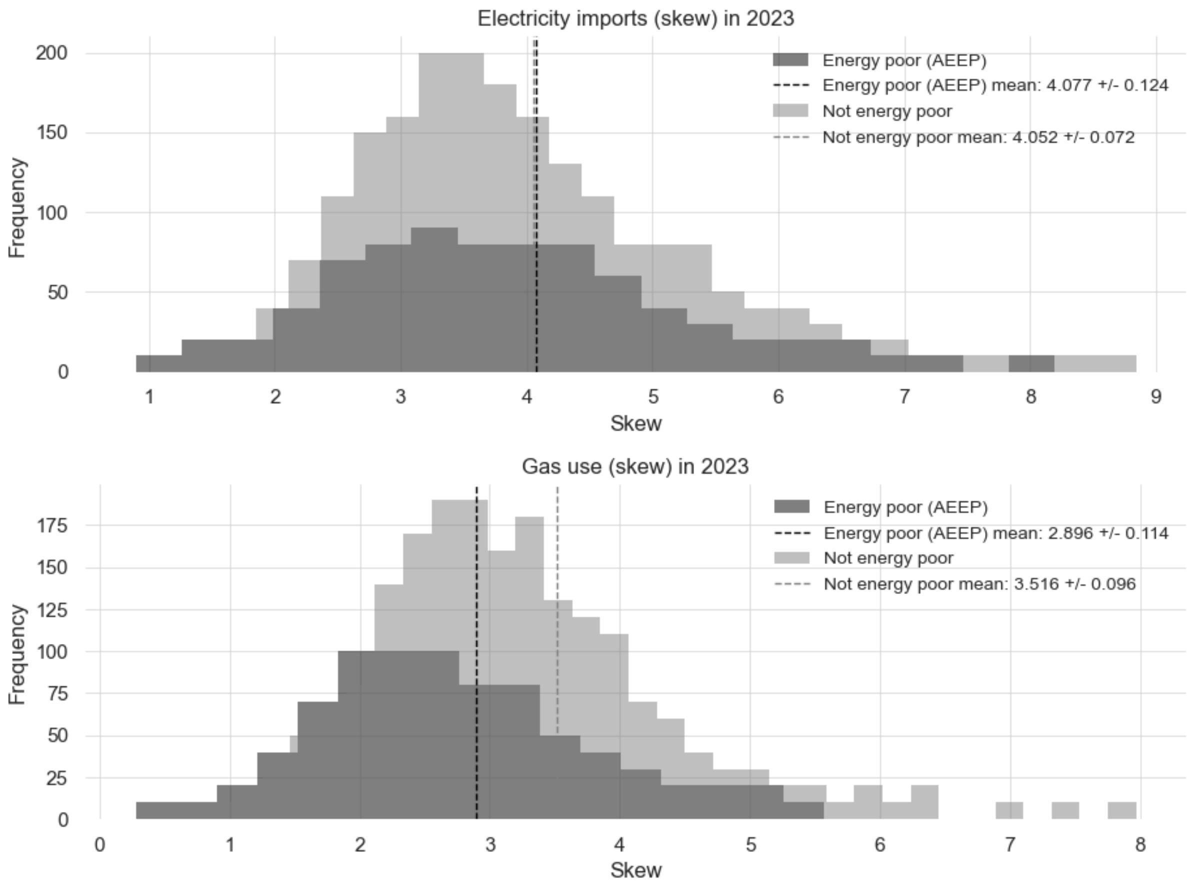


**Figure 34 – Comparison of distributions of skewness of household-level electricity and gas half-hourly energy use in 2023 for energy poor (measured using Actual Expenditure Energy Poverty 10% indicator) and non-energy poor groups of households in the SERL Observatory.**

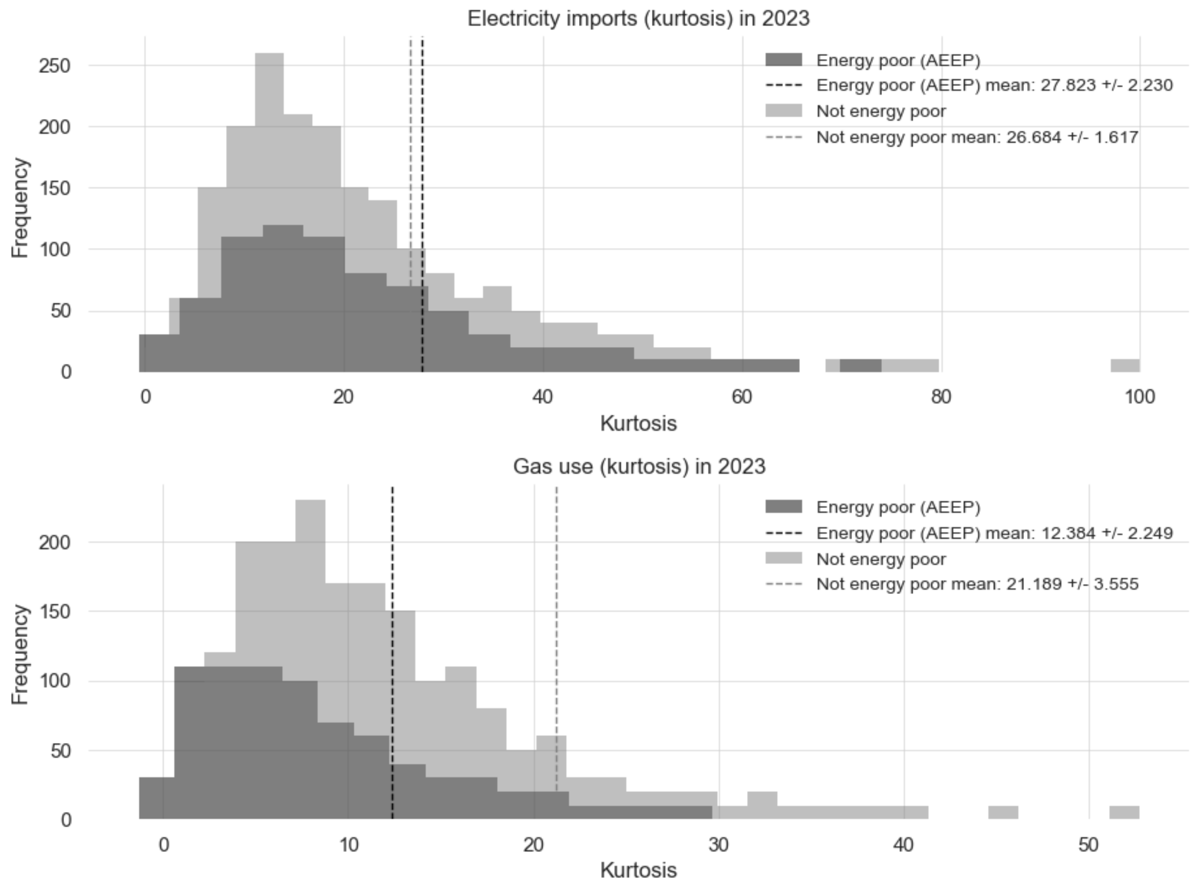


**Figure 35 – Comparison of distributions of kurtoses of household-level electricity and gas half-hourly energy use in 2023 for energy poor (measured using Actual Expenditure Energy Poverty 10% indicator) and non-energy poor groups of households in the SERL Observatory.**

## 5.5. CHAPTER SUMMARY

The purpose of this chapter was to investigate the patterns of gas and electricity of energy poor households, to compare these to non-energy poor households and to test whether any differences were statistically significant. In particular, we were motivated to test the hypotheses that energy poor households used less energy than non-energy poor households, and had patterns of energy use that were more irregular than non-energy poor households.

For energy poor and non-energy poor households, as measuring using two energy poverty indicators (Feeling Energy Poor, and Actual Expenditure Energy Poverty), for both gas and electricity, we analysed and compared distributions of annual energy use, energy use during periods of particularly cold weather, demand profiles and statistics of dispersion of half-hourly energy use (standard deviation, coefficient of variation, skewness and kurtosis).

The results showed the presence of significant differences in energy use distributions and patterns between energy poor and non-energy poor households. Moreover, the results show that the differences between energy poor and non-energy poor are *different for the two different energy poverty indicators*.

Households who are Feeling Energy Poor, on average and compared to non-energy poor households: use less gas and electricity, particularly during cold weather; less gas during peak periods of the day; and have energy use that is more variable, more skewed and more likely to have extreme (high and low) values.

By contrast, households who are Actual Expenditure Energy Poor, on average and compared to non-energy poor households: use more gas, particularly during cold weather; more gas during the daytime; and have energy use that is less variable, less skewed, and less likely to have extreme (high and low) values.

These results suggest that FEP households were more likely than non-FEP households to have reduced their energy usage in response to energy price rises, for example by reducing heating use, while AEEP households were those households *less likely* to reduce their energy usage, and so by definition more likely to be identified as energy poor by the AEEP indicator. This relative change or lack of change of energy usage could also have a causal effect on the dispersion statistics and explain the related results.

To the extent that there are substantial and significant differences in patterns of energy use, and more specifically smart meter data, between energy poor and non-energy poor households, the results also give evidence that supports the development of machine learning models to predict the energy poverty status of households that are trained on and use smart meter data as an input.

The results emphasise the greater importance of using gas smart meter data as an input than electricity, at least where gas use is driven by heating behaviour, as well as the importance of contextual data as input such as weather data, and calendar and time data.

The results confirm the hypotheses but only for Feeling Energy Poor households. For Actual Expenditure Energy Poor households, the results disprove the hypotheses. As a result, given the marked differences in patterns of energy use between Feeling Energy Poor and Actual Expenditure Energy Poor households, this indicates that it would be sensible to consider training separate models to identify the two different types of energy poverty.

# 6. DISCUSSION

## 6.1. ACTUAL EXPENDITURE ENERGY POVERTY: AN INCREASINGLY USEFUL "TOOL IN THE BOX"

In this report we investigated the use of smart meter data to improve how energy poverty is measured. We showed that smart meter data can be used to produce household-level energy poverty indicators including: high-resolution gas and electricity use, energy prices, energy expenditure, and, when combined with income data, Actual Expenditure Energy Poverty (AEEP).

Due to the smart meter roll-outs, which are either completed or well-underway in EU and UK, and the nature of smart meters as a technology, these smart meter-enabled indicators have characteristics that address some of the limitations associated with current energy poverty indicator data collection methods, notably household surveys. These beneficial characteristics include: data accessibility, low cost, universality, longitudinal, and consistency.

As a result, smart meters and the data they collect can enable a range of statistics and insights relating to energy poverty that are a considerable improvement over the conventional picture that is typically limited to views of central tendencies, without understanding of the underlying dispersion of individual differences in the population, as well as subject to biases dues to self-reporting by households.

Are we therefore advocating the use of the smart meter-enabled AEEP indicator over other EP indicators? No. As stated by the UK Committee on Fuel Poverty, there is no consensus on how to capture the full range of energy poverty, and we believe our results do not change this fact. There are, for example, a number of weaknesses with the AEEP indictor. Our results provide further evidence that different indicators can identify different segments of the population and that AEEP can fail to identify 'Feeling Energy Poor' (FEP) households that are actively cutting back on their energy usage the most.

People that are under-heating are therefore much more likely to be overlooked by the AEEP indicator. This is because by cutting back on their energy use, they are reducing their energy expenditure, and so more likely that their energy burden share of income spent on energy bills) falls under the AEEP threshold (10% in this case).

This is an example of a 'false negative' and, like cancer screening, when it comes to energy poverty classification, the consequences of false negatives are more substantial than those of false positives. This means we should be cautious about the use of AEEP alone, without any other supporting method of compensating for this weakness, and identifying these 'overlooked' households. We have seen that this could be done by combining AEEP with other indicators like FEP, or by lowering the AEEP threshold below 10%. However, we note that while lowering the threshold can reduce the false negative rate it does not come without a cost, as unavoidably it will also increase the false positive rate. The choice of an appropriate balance between false positives to false negatives is non-trivial and one that should be taken in consultation with appropriate stakeholders.

All energy poverty indicators have downsides therefore and we do not advocate the use of one over others. Energy poverty is multi-faceted, it is appropriate that a range of indicators should be brought to bear on the problem and its solutions. In this way we echo the recommendations of the Energy Poverty Advisory Hub that the diagnosis of energy poverty at a local level requires the selection of a set of indicators (EPAH, 2022).

Nonetheless, the roll-out of smart meters is an opportunity to improve the quality and quantity of data relating to one particular energy poverty indicator (AEEP), and the related indicators like energy price/tariff, energy use and energy expenditure. From that perspective, the Actual Expenditure Energy Poverty indicator is simply one of the 'tools in the box' that we have when it comes to measuring and ultimately tackling energy poverty, but with smart meter roll-outs it is a tool that is becoming increasingly useful. We therefore advocate the greater use of the smart-meter based AEEP indicator alongside other indicators where appropriate. Where smart meters are widely deployed, we recommend Governments, regulators, stakeholders make better use of smart meter data for energy poverty monitoring, and particularly for program evaluation. Not using smart meter data where they are available for these purposes is a wasted opportunity to iteratively improve the effectiveness of how limited resources are used to tackle energy poverty.

## 6.2. DEVELOPING A SMART METER MODEL FOR IDENTIFICATION OF ENERGY POVERTY: AN ENCOURAGING FIRST STEP

What about using smart meter data to identify households in or at risk of energy poverty? We started this investigation inspired by the goal of developing a machine learning energy poverty identification model using smart meter data as input. The principle of such models is that with machine learning they could be trained to reliably detect differences in patterns of energy use between energy poor and non-energy poor households. The approach is however reliant on their being real and apparent differences in patterns of energy use between the two groups of households that could be detected. As an initial first step, therefore, we investigated whether there were obvious differences in patterns of energy use between energy poor and non-energy poor households and we found this to be true.

Our results have shown that energy poor households according to two indicators show substantial and statistically significant differences in patterns of energy use, particularly gas usage associated with heating, compared to non-energy poor households. We compared gas and electricity use annually, during cold weather, by time of day and in terms of its irregularity as measured by statistics of dispersion (standard deviation, coefficient of variation, skewness and kurtosis).

Households identified as energy poor according to the FEP indicator use less gas and electricity than other households, likely associated with these households taking active measures to reduce their energy use in response to high energy prices, while households identified as energy poor according to the AEEP indicator use more gas than other households. The results show that households who are Feeling Energy Poor, on average and compared to non-energy poor households, have energy use that is more variable, more skewed, and more likely to have extreme (high and low) values. By contrast, households who are Actual Expenditure Energy Poor, on average and compared to non-energy poor have energy use that is less variable, less skewed, and less likely to have extreme (high and low) values. Future research could investigate the causes of the differences in results between these two groups, as well as comparing households who are both FEP and AEEP with those that are neither.

These results are therefore a promising first step in the journey towards the goal of developing a machine learning model of energy poverty identification that uses smart meter data as input. We see evidence that smart meter data are an information source that has signals within it that are strongly associated with energy poverty, similar to Palmer et al. (Palmer et al., 2023) who found that smart meter data enabled the identification of sub-sets of households appearing to be in extreme need due to using very little energy for heating and experiencing a high number of energy self-disconnections, periods where households forgo access to gas and electricity to save on energy costs. This finding strongly motivates the continuation of this journey, and the development of machine learning models that use smart meter data input.

Smart meter data are already being collected by utilities, entities that are often also interested in or obligated to help the energy poor. We therefore strongly encourage further research to develop and test these models. While historically data needed to develop them have not been available, with SERL Observatory that is no longer a barrier, at least for UK. We also therefore strongly encourage the development of further Observatories for other EU member states, given their potential for enabling previously impossible research and development that is needed for tackling energy poverty and achieving a clean energy future.

Some further observations about implications and challenges associated with this goal:

Energy poverty generally affects a minority of the population, and this has implications for the task of training a model using machine learning. If one of the classes is small, then the model can learn to reliably identify the majority class but fail to reliably identify the minority class. As energy poverty is the minority class, this can result in higher false negative rates, which is particularly unwelcome in cases such as this where the consequences of false negatives are worse than the consequences of false positives. As a result, it is recommended to train the model on a balanced dataset, with approximately equal numbers of the different classes. Note that even if the model is trained on balanced data, the performance metrics of the final trained model should be reported on unbalanced data.

Another consequence of imbalanced data, where the majority group (non-energy poor) substantially outnumbers the minority group (energy poor), is that the choice of model performance metric is important. In particular, the use of accuracy as a performance metric can be misleading. If the minority group is only 10% of the population, then a model that fails to identify any of the minority group can still have an accuracy of 90%. We therefore particularly recommend the use of the recall metric for energy poverty identification, given the importance of minimising false negatives.

Regarding choice of indicator to predict, our finding that the patterns of energy use are substantially different between FEP-identified households and AEEP-identified households implies that separate models should be trained for different indicators. Furthermore, we assume that households identified as energy poor according to Required Expenditure Energy Poverty (REEP) would include both FEP and AEEP-identified households, it is likely that models trained to identify REEP will have poorer performance than models trained to identified FEP or AEEP, as FEP and AEEP-identified households are unlikely to share common energy use patterns.

## 6.3. ACCELERATE THE ROLL-OUT OF SMART METERS

The roll-out of smart meters is determined by governments and EU member states, and depends on whether there is deemed to be a cost benefit to their installation.

The use of smart meter data for addressing the problem of energy poverty, through improved measurement, evaluation, and identification is however not generally included among the benefits of smart meters.

We have shown here however that there are potential benefits of smart meter data relating to energy poverty reduction. The improved design of energy poverty reduction programs and the better identification of the energy poor are improvements that would have considerably societal benefits which should be added to the balance when considering the cost-benefit of smart meter roll-outs.

This makes the roll-out of smart meters more important, and urgent given the cost-of-living crisis, and we recommend that governments and EU member states consider including the role that smart meters could play in reducing energy poverty in smart meter deployment cost-benefit analyses.

## 6.4. INCREASE THE AVAILABILITY OF SMART METER DATA

It is not just the deployment of smart meters that is required, however, but also the ability for the data they collect to be used for public interest research and development use cases.

The UK and Estonia are leaders in this area, with advanced smart meter data communications infrastructure that greatly facilitate the secure sharing of smart meter data with approved users for public interest use cases.

This is an area in which the EU can usefully set out a vision and greater ambition for how smart meter data should become more available for public interest research and innovation, with initiatives for knowledge sharing of best practice across member states, and ultimately requirements for member states to comply.

Data are increasingly the fuel of innovation, and smart meter data could be one of the fundamental building blocks of the many solutions that are required to reduce energy poverty and achieve the clean energy transition. Without open data however the risk is that the large investments we are making in smart meter infrastructure will not be put to best use.

## 6.5. LIMITATIONS

Our study has several limitations which should be noted. Firstly, while smart meter data resolves some of the potential limitations and participant burden regarding survey-based energy expenditure data collection, nonetheless this study has relied upon self-reported income data, collected via survey. While our analysis has shown that the median income for the SERL Observatory is reasonable, it is nonetheless likely that this self-reported variable will have errors due to recall bias, or misrepresentation.

While we advocate the greater use of smart meter data in energy poverty measurement and identification, it is true that smart meters are not universally deployed everywhere yet, and as a result a reliance on methods that use smart meter data alone could lead to biases that could adversely impact households in need of help. For example, in GB smart meters are less likely to have been installed in apartments due to the nature of the roll-out, and these are more likely to accommodate private rental households, who are disproportionately affected by energy poverty compared to owner-occupiers. There are therefore some disadvantages to reliance on smart meter data, and this should be considered in any energy poverty measurement or identification programme.

The debate between relative and absolute measures of energy poverty poses challenges for standardisation. Our study employs the 10% energy expenditure threshold as a fixed percentage, which may not adequately reflect trends during periods of fluctuating energy prices. Alternative measures, such as "twice the median energy expenditure" have been proposed as potentially more reflective of relative energy poverty. However, these approaches present significant challenges in their application, particularly at the household level, where variability in income and energy use complicates direct comparisons.

Our study heavily relies on the Feeling Energy Poor (FEP) indicator, derived from self-reported survey data. However, the FEP measure has inherent limitations: Ambiguities in the survey question, such as references to heating "living rooms" rather than specific spaces, and lack of clarity on the timeframe for reported difficulties (e.g., how often or how long energy affordability issues persist). Potential biases in reporting, particularly among older adults who may underreport their struggles due to reluctance to admit difficulties, even to themselves. These factors reduce the precision of FEP-related analyses and limit confidence in the associated false positive and false negative rates.

# 7. CONCLUSIONS

Energy poverty is a critical societal issue with severe negative consequences, including increased health risks to individuals, excess winter deaths, and strains on national health services. Addressing energy poverty requires robust, accurate data and targeted interventions.

Existing methods for measuring energy poverty at the household-level are however primarily based on household surveys, and face significant challenges such as high costs, recall bias and lack of longitudinal insights. These issues create barriers to effective data collection for energy poverty monitoring and program evaluation. Furthermore, existing methods for identifying households in or at risk of energy poverty are either expensive or inaccurate, leading to wasted resources, misallocation of funding and reduced societal benefit.

The roll-out of smart meters presents an opportunity to improve the measurement and identification of energy poverty and as a result this report investigates the use of smart meter data to improve measurement and identification of energy poverty by conducting a detailed case study using a dataset of 13,000 households in Great Britain equipped with smart meters and with linked socio-technical contextual data: the SERL Observatory dataset.

Smart meter data enable the Actual Expenditure Energy Poverty (AEEP) indicator, where a household is classified as energy poor if they spend 10% or more of their household disposable income before housing costs on energy bills. The smart meter-based AEEP indicator has advantages over other traditional indicators: it reduces recall biases, has high temporal resolution and allows for longitudinal tracking, it is cost-effective and easier to implement where smart meter infrastructure exists.

Comparing the AEEP indictor to the Feeling Energy Poor (FEP) indicator (or "inability to keep warm during winter") using data for the SERL Observatory participants reveals that the two indicators identify largely different groups, demonstrating that AEEP should be viewed as a complement rather than a replacement to other indicators.

An analysis of the UK policies of the Energy Price Cap and Energy Price Guarantee revealed these policies substantially reduced energy poverty rates and illustrates the value of smart meter data and the AEEP indicator in evaluating the effectiveness of policy interventions.

Significant differences in patterns of gas and electricity use between energy poor and non-energy poor households and suggest the potential for machine learning models to identify energy poverty status using smart meter data as input. The key findings were that households who are Feeling Energy Poor, on average and compared to non-energy poor households: use less gas and electricity, particularly during cold weather; less gas during peak periods of the day; and have energy use that is more variable, more skewed, and more likely to have extreme (high and low) values.

By contrast, households who are Actual Expenditure Energy Poor, on average and compared to non-energy poor households: use more gas, particularly during cold weather; more gas during the daytime; and have energy use that is less variable, less skewed, and less likely to have extreme (high and low) values.

We recommend that governments, regulators, and stakeholders make better use of smart meter data where they are available for energy poverty monitoring and program evaluation, and that further research is conducted to develop and test machine learning models for energy poverty identification using smart meter data as a key input variable.

To enable such research and development, we also recognise and recommend the critical enabling role of Energy Demand Observatory datasets such as the GB's SERL Observatory, and strongly encourage the development of similar Observatories across the EU to facilitate the innovative research required to tackle energy poverty and the transition to a clean energy future. This is an area where we believe European institutions and research funding can and should play a critical enabling role.

## 8. ACKNOWLEDGEMENTS

The SERL Observatory dataset used in this research continues to be collected and periodically released for use by GB researchers on approved projects. The SERL Observatory dataset has been collected and made available to the UK research community by the Smart Energy Research Lab (SERL) via funding from EPSRC-funded research project EP/P032781/1. We would like to thank the 13,000+ SERL Observatory households who have consented access to their smart meter data, without whom it would not have been possible to undertake this research. The SERL Observatory data is available to UK accredited researchers via the UK Data Service.

Data: Elam, S., Webborn, E., Few, J., McKenna, E., Pullinger, M., Oreszczyn, T., Anderson, B., Ministry of Housing, Communities and Local Government, European Centre for Medium-Range Weather Forecasts, Royal Mail Group Limited. (2023). *Smart Energy Research Lab Observatory Data, 2019-2022: Secure Access.* [data collection]. *5th Edition.* UK Data Service. SN: 8666, DOI: http://doi.org/10.5255/UKDA-SN-8666-6

Data descriptor: Webborn E, Few J, McKenna E, Elam S, Pullinger M, Anderson B, et al. *The SERL Observatory Dataset: Longitudinal Smart Meter Electricity and Gas Data, Survey, EPC and Climate Data for Over 13,000 GB Households*. Energies (Basel) 2021;14. https://doi.org/10.3390/en14216934.

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This project has been approved by UCL Research Ethics, and access to SERL Observatory data for the purposes of this project has been approved by the SERL Data Governance Board. All researchers accessing SERL Observatory data are Accredited Researchers.

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