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The Modern Problematisation of Fuel Poverty in England: Quantification, Obfuscation and Energy Transitions

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Abstract

The conceptualisation and quantification of fuel poverty remain contentious, particularly in England, where the Low Income High Costs (LIHC) and Low Income Low Energy Efficiency (LILEE) definitions have dominated the UK Government's modern fuel poverty agenda. As relative measures, the LIHC and LILEE definitions are demonstrably prone to underestimating fuel poverty in low- and middle-income households. Moreover, this relativity can obfuscate the true impact of macroeconomic shocks, such as energy price inflation, by decoupling poverty rates from real-world economic conditions.

To address the deficiencies of the LIHC and LILEE definitions, this thesis presents the Two-Step Measurement Framework (TSMF) to provide a more robust assessment of fuel poverty. The first step leverages a budget standard-based clause, inspired by the Scottish Government's approach and drawing on the Minimum Income Standard (MIS). This provides a more objective and needs-based foundation for including an energy costs criterion in fuel poverty quantifications. The second step introduces fuel poverty depth indicators, including the fuel poverty quotient, which is proposed as a new indicator of energy costs equality that measures the area-level, aggregate depth of poverty. The framework's effectiveness is demonstrated via a sensitivity analysis of two potential future scenarios: one reflecting improved energy efficiency and the other simulating worst-case scenario energy price inflation. The results show that the new framework and its associated quotient respond more logically to changing external conditions than the LIHC and LILEE definitions. Ultimately, this thesis emphasises the need to urgently reconsider the official fuel poverty definition in England, suggesting that a modern definition must be more able to accurately quantify the condition in financially vulnerable households, while also responding to macroeconomic shocks (e.g., energy price volatility).

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- Guy's and St Thomas' NHS Foundation Trust funded a subjective fuel poverty survey of London residents, which was hosted by the OLIO sharing app during the winter of 2022. These data were foundational for my empirical critique of the LILEE fuel poverty definition.
- Broxtowe City Council assisted with the dissemination and collection of responses for a replication of the subjective fuel poverty survey among Broxtowe residents during the winter 2024/2025 period.
- NatWest Group, via their partnered organisation Smart Data Foundry, contributed individual-level financial records for UK residents, which were invaluable in the development of individual-level fuel poverty and financial security metrics.

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Publications

Note: the chapter to which each publication is related is displayed in parentheses.

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Abbreviations

AHC – After Housing Costs

BEIS – Department for Business, Energy and Industrial Strategy

BHC – Before Housing Costs

DECC – Department of Energy and Climate Change

DEFRA – Department for Environment, Food and Rural Affairs

DESNZ – Department for Energy Security and Net Zero

DLUHC – Department for Levelling Up, Housing and Communities

EPAH – Energy Poverty Advisory Hub

EPOV – EU Energy Poverty Observatory

EPC – Energy Performance Certificate

FPDEF – Fuel Poverty Definition Evaluation Framework

FPEER – Fuel Poverty Energy Efficiency Rating

FPOP – Fixed Parameters Ordered Probit (model)

GDHI – Gross Disposable Household Income

HIHC – High Income High Costs

HIHEE – High Income High Energy Efficiency

HILEE – High Income Low Energy Efficiency

HILC – High Income Low Costs

IMD – Index of Multiple Deprivation

LIHC – Low Income High Costs

LIHEE – Low Income High Energy Efficiency

LILEE – Low Income Low Energy Efficiency

LILC – Low Income Low Costs

MIS – Minimum Income Standard

OECD – Organisation for Economic Co-operation and Development

Ofgem – Office of Gas and Electricity Markets

ONS – Office for National Statistics

RPOP – Random Parameters Ordered Probit (model)

SAP – Standard Assessment Procedure (score)

Introduction

This introductory chapter provides necessary framing for the remainder of the thesis. First, the theoretical background is summarised, and the motivations for the current study are stated. Predicated on this, four primary research questions are proposed. The multidisciplinary methodological approach used to address the research questions is summarised, and the research questions are subsequently described in terms of constituent research objectives. Finally, the thesis structure is outlined, and an overview of each chapter is provided, including the thesis's main contributions to knowledge.

Background

Fuel poverty (or energy poverty) is generally defined as a household's inability to afford adequate energy services. Despite previous pledges to eradicate fuel poverty (UK Parliament, 2009), it persists in millions of UK homes and has worsened recently due to the intertwined effects of the cost-of-living and energy crises (DESNZ, 2024a). The uniquely hostile economic environment of the early 2020s has left many already-deprived homes even more vulnerable to the main symptom of fuel poverty: prolonged exposure to cold living conditions, which is known to exacerbate various health conditions and contribute to excess winter morbidity and mortality (Lawlor, 2001; Rudge & Gilchrist, 2005). The condition of being *fuel poor* is intrinsically dependent on internal (e.g., household-level characteristics) and external factors (e.g., energy economics). As a result, attempts to quantify fuel poverty should account for both internal and external root causes of fuel poverty wherever possible. It is the overlapping nature of these internal and external factors, however, that contributes to the continued lack of consensus regarding the most effective fuel poverty definition.

In England, the current Low Income Low Energy Efficiency (LILEE) definition implies that fuel poverty cannot be experienced by those living in homes with higher-than-average energy efficiency (i.e., with an EPC rating of C or above). This also suggests that energy efficiency upgrades are the cardinal solution to fuel poverty and that its eradication could be achieved by all homes achieving an EPC rating of C or above. This is a dangerous assumption, as placing too great an emphasis on household energy efficiency as a fuel poverty measurement criterion, while disregarding other root causes like low income or energy prices, demonstrably leads to the systematic underestimation of fuel poverty in many low- and middle-income households. It is highly likely that many of the low-income homes that are overlooked by the LILEE definition would be considered fuel poor according to other fuel poverty definitions. This fact reiterates the importance of definitions in any poverty-related discussion. It is the government's definition of

poverty that sets the constraints of remedial action; for example, at the local policymaking level, the alleviation of fuel poverty is guided by the UK Government's conceptualisation of fuel poverty (i.e., the LILEE approach) and, thus, those erroneously deemed *not fuel poor* by the LILEE definition are implicitly not worthy of state support.

There is a unique urgency surrounding the quantification of fuel poverty in the modern context, given the unfavourable coalescence of geopolitical and public health issues in the 2020s, including the Russian invasion of Ukraine, the COVID-19 pandemic and the ensuing cost-of-living and energy crises. These events have had dire implications for consumer energy costs and the cost of other necessities more generally, the effects of which were felt most acutely by already-poor and economically precarious people (Joseph Rowntree Foundation, 2023; The Oxford Institute for Energy Studies, 2021). Moreover, the *Climate Change Act 2008* states that net zero carbon emissions, of which ~20% is attributable to domestic energy use, must be achieved by 2050 (UK Parliament, 2008). However, the distributional effects of phasing out fossil fuel-based energies in the home are not yet known. In the context of fuel poverty, energy transitions are highly likely to impact energy prices (and end-user costs) in unpredictable ways; as a consequence, fuel poverty definitions must be able to *respond to changing economic circumstances*. Throughout this thesis, it is argued that the LILEE definition does not respond adequately to economic change, leading to a particularly egregious oversight of fuel poverty in low-income homes as the price of energy becomes more volatile. The Committee on Fuel Poverty (2024) mirror this sentiment, recommending that the LILEE metric 'be reviewed as it no longer captures the full range of households facing unaffordable bills'. As such, this thesis presents multiple analyses of LILEE and competing fuel poverty definitions and develops a novel fuel poverty measurement framework that is fairer, resilient to macroeconomic shocks and, as a consequence, fit for modern use.

Motivations and aims

The measurement, alleviation and eventual eradication of fuel poverty is ultimately dependent on the veracity of the definition or metric in use. Apart from the detrimental impact in the short term, there are broader concerns over the compatibility of fuel poverty definitions like LILEE and decarbonisation efforts. A fair energy transition, in which social inequalities are not exacerbated by systemic changes to the energy sector, is reliant on fair and accurate temporal measures of inequality and poverty. This raises questions regarding the long-term suitability of the LILEE definition, or, for that matter, other existing definitions. Therein lies the motivations of this thesis: i) empirically understand the shortcomings of the LILEE definition; ii) critically evaluate the modern applicability of LILEE and other existing definitions, whilst also considering novel methods; and iii) empirically demonstrate whether alternative (or novel) fuel poverty definitions

are more able to account for changing economic circumstances (e.g., those induced by energy transitions). The central aim of this thesis is to quantify the extent to which the LILEE fuel poverty definition underestimates fuel poverty and, in response, propose an amended or novel approach that provides a more robust and responsive assessment.

Positionality

My positionality as a researcher is a product of my foundational background in Civil Engineering (MEng). During my undergraduate studies, I became increasingly drawn to the intersection of engineering, public health, and societal well-being, interests I have diversified through the Horizon CDT programme. My doctoral research is supported by a multidisciplinary supervision team spanning Engineering, Medical Sciences, and Business, which has enabled me to approach fuel poverty through several distinct analytical lenses. I am a proponent of social and climate justice; consequently, I approach the problematisation of fuel poverty not merely as a technical failure of housing efficiency, but as a systemic form of injustice. This perspective is further shaped by my collaborations with major financial and health institutions. While this provided privileged access to large-scale datasets, my central motivation remains the identification of a hard-to-identify social ill. I combine an engineer's propensity for problem-solving with a critical focus on the energy transition's potential for inequity, ensuring that the obfuscated lived experiences of precarious households remain central to my analysis.

Research questions

The initial research questions (see Table 0-1) were based on the hypothesis that the LILEE fuel poverty definition likely underestimates the true rate of homes whose occupants lack the financial means to secure adequate energy. Further, the overarching aim contextualises each research question as a necessary step towards the central ambition of this research: to quantify the extent to which fuel poverty is underestimated in England. Specifically, the purpose of *Research Question A* was to empirically demonstrate whether LILEE, the current English definition, undercounts fuel poverty and, if so, to what extent. *Research Question B* instead explores the current determinants of subjective fuel poverty, using self-reported indicators, which is used to further demonstrate the extent of LILEE's inaccuracy. *Research Questions A* and *B* correspond to **Chapter 3** and **Chapter 4**, respectively. The findings of these chapters provided sufficient evidence to reject the LILEE definition as an effective approach to measuring fuel poverty, which led to the proposal of two further research questions. *Research Question C*, corresponding to **Chapter 5**, and *Research Question D*, corresponding to **Chapters 6**, **7** and **8**, comprehensively examine competing fuel poverty measurement approaches, to arrive at an optimal measurement framework.

Table 0-1. Overarching aim and constituent research questions

Overarching aim:

Quantify the extent to which the LILEE fuel poverty definition underestimates fuel poverty and, in response, propose an amended or novel approach that provides a more robust and responsive assessment.

Research Question A:

Given the LILEE definition's universal omission of energy-efficient households, is fuel poverty (i.e., the actual ability of occupant(s) to afford adequate energy) currently underestimated in England, and if so, to what extent?

Research Question B:

What are the salient determinants of subjective fuel poverty during a cost-of-living crisis?

Research Question C:

Are existing fuel poverty definitions compatible with parallel political agendas, including the decarbonisation of housing and a just energy transition?

Research Question D:

How effective are competing definitions of fuel poverty (existing and novel) in terms of identifying homes that are unable to afford sufficient energy?

Methodological approach and ethical considerations

This section summarises the thesis's overarching methodological approach. The multidisciplinary nature of the thesis, which takes inspiration from engineering, statistics, geography, and the social sciences, means that the methods used to answer the research questions vary by chapter. To facilitate the thesis's methodological approach, a detailed chapter-specific description of methods is included in every core contribution chapter, immediately preceding the relevant analysis, negating the need for an independent methods chapter.

The supplementary material includes R code (where applicable) that describes each analytical process in depth and ensures the reproducibility of findings. These are located in the thesis's associated repository (see: https://github.com/torransemple/thesis_supplementary_material).

The majority of analyses in this thesis utilise highly sensitive personal data, including self-reported data pertaining to poverty experiences and financial data obtained from external partners. All studies involving human participants adhered to the University of Nottingham's Data Protection Policy and the UK's General Data Protection Regulation, to ensure legal compliance and best practice (University of Nottingham, 2024, p.3). The University of Nottingham (2024) also requires that studies using primary personal data complete study-specific ethics applications. The **Chapter 4** analysis of household energy security (or subjective fuel poverty) was based on a survey of 2,886 London residents; however, the survey was commissioned by Guy's and St Thomas' NHS Foundation Trust, therefore, an ethics application was unnecessary in this case, since the data were both from a secondary source and pre-anonymised. **Chapter 6** involved the analysis of more than one million financial records, which were obtained via a collaboration with Smart Data Foundry, who anonymise and repackage NatWest Group financial data. Although these are also technically secondary data, an ethics application was submitted to the University of Nottingham's Faculty of Engineering (approved on 10/01/25) to provide extra assurances to the industrial partner.

Thesis structure

The thesis contains nine chapters in total. **Chapter 1** is a review of the literature, whereas **Chapter 2** is a focused policy review of fuel poverty definitions in England; **Chapters 3–8** are novel contributions to knowledge (i.e., core contribution chapters) and **Chapter 9** concludes the thesis with a recapitulation of the main contributions to knowledge. Figure 0-1 displays the order of the thesis's chapters, with core contribution chapters highlighted. Figure 0-2 describes the linkage of each core contribution chapter to an associated research question (as outlined in Table 0-1), which are then disaggregated to research objectives. A high-level description of the data and methods used to achieve the research objectives is also included. As noted previously, the multidisciplinary and chapter-specific methodological approach meant that an independent methods chapter was deemed inappropriate.

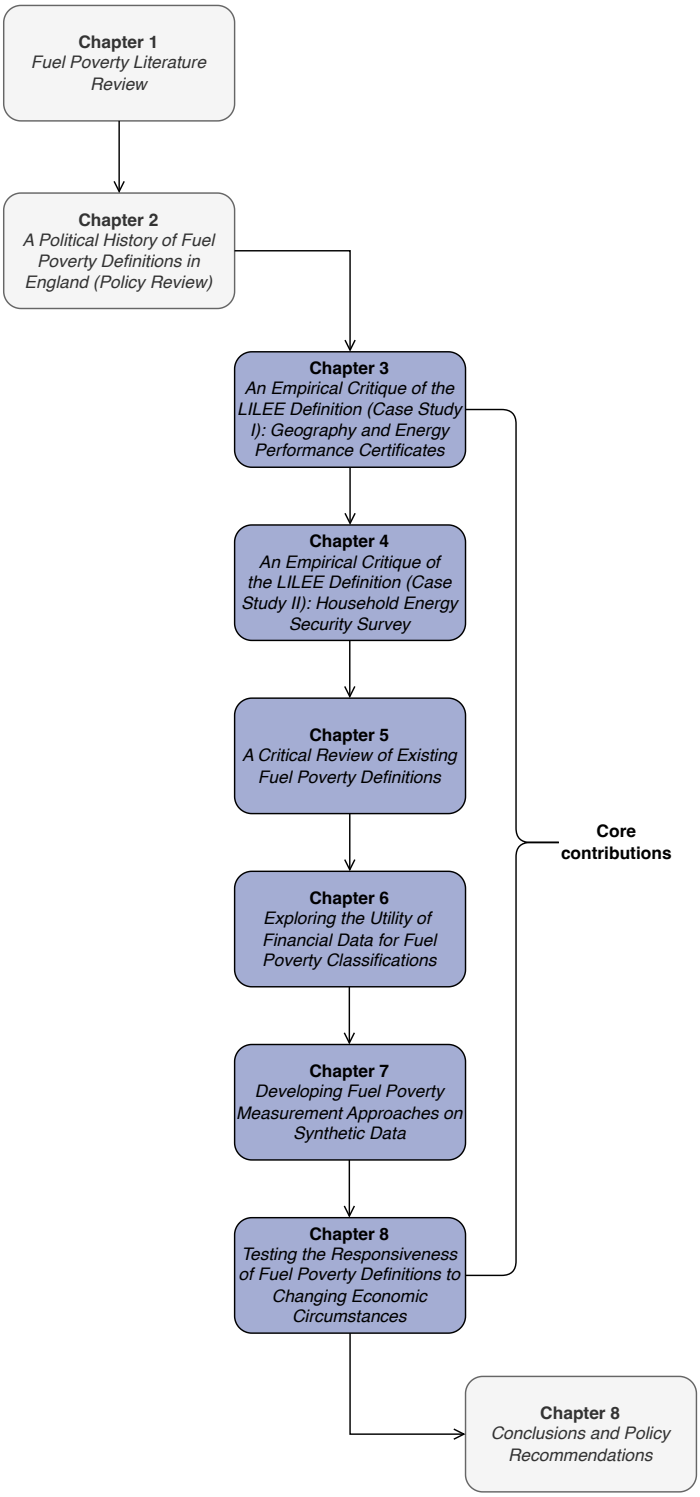


Figure 0-1. Thesis chapter order

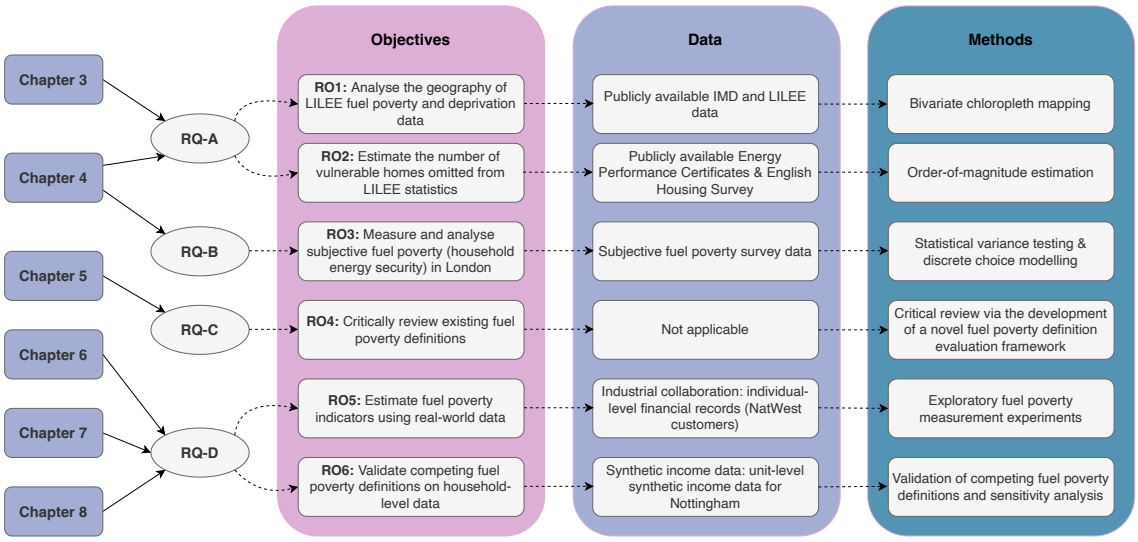


Figure 0-2. Thesis overview: core chapters, research questions, objectives and methods

Chapter overview

This section provides a chapter-by-chapter summary of the thesis's contents to facilitate navigation and highlight its main contributions.

Chapter 1: A History of Fuel Poverty Definitions in England

This chapter provides a literature review of the theoretical background for the thesis. It examines the distinction between fuel poverty's root causes, risk factors, and symptoms, as well as the distinction between income poverty and fuel poverty. A brief history of fuel poverty, from pre-quantifiable conceptualisations to the first quantifiable definition, is also discussed, and existing fuel poverty definitions in the UK and Europe are summarised. This chapter serves as the first stage of the literature review.

Chapter 2: A Political History of Fuel Poverty Definitions in England

This chapter presents a focused policy review of fuel poverty definitions in England. It discusses the political context that led to the rapid evolution of fuel poverty definitions, from the 10% indicator (active 2001–2015) to LIHC (2015–2019) and finally to LILEE (2019–present). Of particular interest is the Hills Review, which was noted as a critical turning point that led to the UK Government adopting LIHC as the official fuel poverty definition and problematising the condition as a relative issue. Theoretical issues concerning all previously adopted English definitions (10%, LIHC, and LILEE) are discussed at length. The findings suggested that the LILEE definition was likely to underestimate fuel poverty in low-income, energy-efficient homes, due to its questionable SAP-based criterion and its treatment of fuel poverty as a relative issue.

Chapter 3: An Empirical Critique of the LILEE Definition, Case Study I

This chapter provides an empirical critique of the LILEE definition via the analysis of publicly available data on energy performance, deprivation, and household surveys. The analysis of the energy performance and deprivation data found that a considerable proportion of financially vulnerable households were wrongly omitted from LILEE statistics based on energy performance alone. A bivariate mapping analysis was also conducted to evidence disparities between LILEE and deprivation statistics in the cities of Nottingham and London. The findings generally corroborated the thesis that the LILEE definition could not capture the full extent of fuel poverty, especially in low-income homes.

Chapter 4: An Empirical Critique of the LILEE Definition, Case Study II

This chapter presents a statistical analysis of London survey data (n=2,886) that captured respondents' experiences of subjective fuel poverty. Subjective fuel poverty was used as a direct comparator to LILEE fuel poverty rates, and the analysis unveiled the degree to which LILEE likely underestimated the true rate of the condition. The rate of subjective fuel poverty in the survey sample was compared to the rate of LILEE fuel poverty in London, which showed that it was experienced at a considerably higher rate. The analysis also showed that the rate of subjective fuel poverty was statistically equivalent in energy-efficient and non-energy-efficient properties, casting significant doubt on the LILEE definition's energy performance-based criterion.

Chapter 5: A Critical Review of Existing Fuel Poverty Definitions

This chapter offers a critical review of a range of existing fuel poverty definitions through the development of a novel Fuel Poverty Definition Evaluation Framework (FPDEF). The findings suggested that many traditional fuel poverty definitions were outmoded and unable to measure the full extent of fuel poverty, particularly in a volatile economic environment. The Scottish Government's two-clause (10% + MIS) approach was identified as the most promising existing method for measuring the condition.

Chapter 6: Exploring the Utility of Financial Data for Fuel Poverty Classifications

This chapter explores the utility of a large financial dataset (n=~1.11 million) for fuel poverty classifications. Several individual-level metrics of financial security and energy affordability were developed, and the findings showed that they held some promise as a supplementary means of quantifying fuel poverty. However, the financial data could not be used to test the performance of competing fuel poverty definitions, which are based on household-level characteristics.

Chapter 7: Developing and Validating Fuel Poverty Measurement Approaches Using Synthetic Data

This chapter develops a synthetic dataset of Nottingham homes to serve as a platform for various poverty-related experiments. The synthetic data were used to compare the overlapping profiles of fuel poverty identified by competing definitions. This round of experimentation led to the development of the Two-Step Fuel Poverty Measurement Framework, a combination of indicators that solves the measurement deficiencies of previously employed definitions.

Chapter 8: Testing the Responsiveness of Fuel Poverty Definitions to Changing Economic Circumstances

This chapter builds upon the experiments of Chapter 7 by performing a sensitivity analysis of competing fuel poverty definitions, including the preferred Two-Step approach. Two distinct scenarios were explored: one reflecting improved energy efficiency and the other simulating energy price inflation. The findings showed that the Two-Step framework responded more logically to changing economic circumstances (i.e., factors that are outside the direct control of individual households) than competing definitions.

Chapter 9: Conclusions and Policy Recommendations

This chapter recapitulates the findings of each core contribution chapter and presents comprehensive policy recommendations. The central recommendation of this thesis is that the English fuel poverty definition requires urgent reconsideration.

Chapter 1: Fuel Poverty Literature Review

> *He spends his days loafing in the public library or any other place where he can keep warm. That – keeping warm – is almost the sole preoccupation of a single unemployed man in winter.*
>
> George Orwell: *The Road to Wigan Pier*

A wealth of literature has improved our comprehension of the root causes, risk factors and symptoms of fuel poverty, yet this has failed to translate into meaningful social change: a significant proportion of English homes (~13%) remain *fuel poor* according to the LILEE definition (DESNZ, 2024a), while the true rate is likely to be much higher. Another crucial aspect of fuel poverty and its quantification in the modern era is the overlap with adjacent political issues, such as housing decarbonisation and energy transitions. Throughout this thesis, it is argued that the LILEE fuel poverty definition lacks modern-day relevance, given its inability to account for the fairness of energy transitions; in fact, it is argued that the LILEE definition contributes to the obfuscation of fuel poverty in homes with relatively high energy efficiency ratings.

The remainder of this chapter provides a review of the literature to understand and distinguish between fuel poverty's root causes, risk factors and symptoms, before also considering the distinction between income poverty and fuel poverty. Following this, a brief history of fuel poverty, from pre-quantifiable conceptualisations to the first quantifiable definition, is discussed and then existing fuel poverty definitions in the UK and Europe are summarised. **Chapter 2** builds on this by providing a more detailed overview of the political evolution of fuel poverty definitions in England. As such, **Chapter 2** is a policy review-based extension to the initial literature review presented in this chapter.

1.1. Root causes, risk factors and symptoms

In simple terms, a fuel poor home is one that lacks the financial means to obtain adequate energy, particularly heating. Although this gives the illusion of a theoretically uncomplicated condition, the root causes, risk factors and symptoms of fuel poverty are numerous, interrelated and frequently confused, which likely contributes to the lack of consensus regarding the most

appropriate fuel poverty definition. To take an illustrative example, homes with older occupants are often identified as a demographic who are particularly vulnerable to the negative health consequences of prolonged exposure to cold living conditions (Rudge & Gilchrist, 2005), which has been linked to excess winter morbidity and mortality among this group (Rudge & Gilchrist, 2007). Despite increased vulnerability to cold living conditions, the state of being old does not necessarily increase the likelihood of being fuel poor. In other words, older people are at an elevated risk of the negative health consequences (or *symptoms*) of fuel poverty, which may qualify this characteristic as a *risk factor* (in the context of fuel poverty's symptoms), yet age is not a *root cause* of fuel poverty. This complex mesh of root causes, risk factors and symptoms can obscure the quantification process; therefore, each of these categories must be clearly delineated. For the purposes of this thesis, the definitions of fuel poverty's *root causes*, *risk factors* and *symptoms* are as follows:

- **Root causes** of fuel poverty are internal (i.e., pertaining to the individual or household) or external (i.e., economic) factors governing the affordability of energy and fuel poverty. These are the primary drivers of fuel poverty: household income, energy prices and household energy efficiency (Boardman, 2009; Hills, 2012)
- **Risk factors** refer to characteristics of a home or the home's occupant(s) that increase the likelihood of fuel poverty or the severity of its symptoms, but *are not considered a root cause* (for example, see Belaïd (2018))
- **Symptoms** refer to the effect of fuel poverty on people's health and quality of life. The most widely understood symptom of fuel poverty is prolonged exposure to cold living conditions and the negative public health consequences that follow (for example, see Hernandez (2016) and Rudge & Gilchrist (2007)).

The remainder of this section consults the literature to better understand fuel poverty's root causes, risk factors and symptoms. A foundational understanding of each and their relevance to the quantification of fuel poverty is an essential precursor to the analyses presented in this thesis.

The root causes of fuel poverty

The literature tends to suggest that a combination of low income, high energy prices and inefficient (or low quality) housing is the root cause of fuel poverty (Boardman, 2009; Bouzarovski, 2014; Lawlor, 2001). This is largely intuitive: *low* income affects the ability of a person or household to afford adequate energy, as do *high* energy prices, while *inefficiency* can also lead to high consumer energy costs. The prioritisation of each of these root causes in the

context of fuel poverty quantifications, however, is hotly contested, while setting meaningful thresholds for *low* income, *high* costs or *inefficiency* is also a complex and often polarising issue (as discussed at length in **Chapter 2**). Moreover, the difference between income poverty and fuel poverty is worthy of further contemplation, given that low income is a primary driver of both; this specific issue is explored in greater detail in Section 1.2.

Though the primary causes of fuel poverty are relatively well-established, Kearns et al. (2019) suggest that occupant behaviour may be a fourth driver of fuel poverty, given that household structure and dynamics, as well as thermal comfort preferences and varying energy consumption behaviours, are bound to have an effect on the affordability of energy. Similarly, Bouzarovski (2014) notes the often understated role of "*specific household needs*" in fuel poverty discourses. Another important theme in the literature is the description of the drivers of poverty as internal (i.e., micro-level drivers at the individual or household level) or external (i.e., macro-level drivers, e.g., structural or economic issues) (Brady, 2009). The description of fuel poverty's root causes as internal or external is also likely to be a highly useful theoretical framework. For example, low income may be attributable to an occupant's inability to work; therefore, the cause of low income and, consequently, fuel poverty is internal; yet in other instances, macroeconomic trends may negatively affect the cost-of-living (i.e., inflation outgrowing income) and individual or household spending power, which would instead have an external cause.

Macro-level economic conditions are especially relevant to modern fuel poverty politics, given that energy prices are generally increasing, and will continue to do so if the UK domestic heating sector remains overly reliant on natural gas (The Oxford Institute for Energy Studies, 2021). If this trend continues, it is highly likely that energy prices will outgrow income (a macro-level phenomenon), resulting in many homes having progressively higher energy expenditure. In such an economic environment, the adoption of fuel poverty definitions that focus on micro-level conditions (e.g., household energy efficiency), as opposed to macro-level fluctuations in energy markets, may become increasingly politically expedient. This argument is made more comprehensively in **Chapter 2** (see Section 2.4).

Fuel poverty risk factors

Beyond the three root causes of fuel poverty—low income, high energy prices, and inefficient housing—a vast range of sociodemographic characteristics are known to increase the risk of experiencing the condition. For example, Mould (2017) found that rural homes were significantly more likely to experience fuel poverty, while Boardman (2009) noted the increased vulnerability

of those living in social housing. Similarly, Kearns et al. (2019) found that poor mental health and unemployment were associated with an increased risk. As studies of this nature are myriad, presenting a truly representative overview of these risk factors is challenging. Furthermore, many of these characteristics are likely to be proxies for root causes; for instance, employment status is strongly correlated with income, while social housing may be a proxy for both occupant deprivation and lower quality housing. Based on this understanding, fuel poverty risk factors are not particularly relevant to this thesis, as data that more directly relate to the root causes are available. As a result, risk factors are not discussed further.

The symptoms of fuel poverty

Fuel poor individuals are exposed to cold living conditions for prolonged periods, which is known to increase the risk of various morbidities and contribute to excess winter deaths (Lawlor, 2001; Rudge & Gilchrist, 2005; Rudge & Gilchrist, 2007; Teller-Elsberg, et al., 2016). While quantitative studies on the relationship between living conditions and health outcomes are limited, those that exist suggest that fuel poverty can worsen respiratory health outcomes and lead to higher rates of depressive symptoms among older people (de Vries & Blane, 2013). Rudge and Gilchrist (2007) also found that inadequate dwelling temperatures contribute to excess winter morbidity more generally.

In contrast, qualitative studies, such as those by Hernandez (2016), Lacroix & Chaton (2015), and Sawyer et al. (2022), are based on relatively small samples but more comprehensively capture the broad range of symptoms experienced by fuel poor individuals. Lacroix & Chanton (2015) and Sawyer et al. (2022) deployed subjective scales to assess the impact of inadequate indoor temperatures on mental and physical health. These subjective assessments are best described as a bottom-up approach to quantifying fuel poverty, as affected populations are queried directly about their experiences. This stands in contrast to top-down quantifications—including the government's official definitions—which rely entirely on monetary or household indicators.

The root causes, risk factors, and symptoms of fuel poverty are all relevant to this thesis; however, the primary focus is on the established root causes, given that the research questions (see Table 0-1) mainly concern the definition and quantification of the condition. Nonetheless, associated factors may be tangentially relevant to the quantification process; for example, a subjective fuel poverty scale is adopted in **Chapter 4**, which shares some similarities with the qualitative studies discussed here. Ultimately, the symptoms of fuel poverty serve as a reminder of why the condition

must be alleviated and, potentially, eradicated, and this hinges on the accurate measurement of the condition itself.

1.2. Distinguishing between income poverty and fuel poverty

As discussed previously, the distinction between income poverty and fuel poverty is occasionally debated, given that low income is arguably the most notable driver of both. This section briefly explores this debate, providing an overview of the main distinguishing factors. There is a wealth of literature on poverty and its various subtypes. Many of these are out of scope; however, a base definition of poverty must be established to describe fuel poverty as a distinct condition. This section relies on two seminal books for generally recognised definitions of poverty and fuel poverty: The Economics of the Welfare State (Barr, 2020) and Fixing Fuel Poverty (Boardman, 2009). Barr (2020, p.103–108) discusses approaches to measuring welfare through an amalgam of poverty and inequality variables, where poverty concerns measurable indicators of financial capacity, such as consumption, expenditure and total money income. Inequality, on the other hand, refers to equal opportunities among individuals or households, specifically those related to employment and income, and their quantification is often more complex.

The poverty indicators, discussed by Barr (2020): consumption, expenditure and income, all have relevance to how fuel poverty is measured. A household's energy expenditure is dependent on consumption, while both are ultimately dependent on income: the ability to consume and expend. Reduced to elementary components, this gives the impression of a theoretically straightforward issue; however, the reality of fuel poverty is that numerous moderating variables affect each of these indicators, creating the distinction between poverty and fuel poverty. For example, energy expenditure also depends on energy market dynamics (Petrova, 2018), and housing characteristics, e.g., energy efficiency and space-heating requirements (Boardman, 2009); energy consumption, too, depends on energy efficiency, but also climatic conditions (i.e., the required amount of heating or cooling), thermal comfort preferences (Xie, et al., 2023) and household composition (Heinrich, et al., 2016); while the value of a household's income is dependent on the wider economic environment, as economic decline and austerity lead to greater levels of precarity, as demonstrated by Peck (2012). In such environments, household spending power contracts, deepening poverty among already low-income groups and driving more into financially precarious situations. This type of financial precarity often manifests as involuntary spending trade-offs between necessities, the obvious example being the heat-or-eat dilemma, in which individuals are compelled to choose between heating their home adequately or decreasing their nutritional expenditure during the winter season (Beatty, et al., 2014; Bhattacharya, et al., 2003).

To summarise, fuel poverty entails all of Barr's indicators of financial capacity; the factors which make fuel poverty a distinct condition include energy market dynamics, household energy efficiency, behavioural variation or thermal preferences, environmental conditions and the broader economic context. The breadth and variety of these factors are a likely cause for the inconsistent and evolving approaches to measuring fuel poverty; however, there is undeniably a political element underpinning the relative importance afforded to each, as discussed at length in **Chapter 2**.

Boardman's Fixing Fuel Poverty supplemented her earlier work, Fuel Poverty: From Cold Homes to Affordable Warmth (Boardman, 1991), and explicated the 10% definition of fuel poverty, which was eventually adopted as the first official definition of fuel poverty in the UK (DEFRA, 2001). Regarding the factors that distinguish fuel poverty from income poverty, Boardman (2009, p.xv) states the following:

> *While fuel prices and low incomes contribute [to fuel poverty], these are also problems for many people who are not fuel poor. With fuel poverty, the real differentiating cause is the energy efficiency of the home as a result of insufficient capital expenditure on improving the calibre of the home.*

It is worth noting that since 2009, there have been near-unprecedented rises in typical energy costs (DESNZ, 2023a) and the cost-of-living (ONS, 2022a), which may increase the relative contributions of energy prices and low income. It remains true that inefficient homes perpetuate cold living conditions and fuel poverty, but this does not necessarily qualify energy efficiency as the sole or principal differentiating cause from income poverty, as discussed previously. Whilst energy prices do negatively impact the prospects of many who are not officially deemed fuel poor, abrupt increases in energy costs will inevitably be felt most acutely by low-income groups, as this expense composes a relatively larger proportion of their total income. It is this trend: the inevitability of higher energy costs affecting already-poor or vulnerable groups that resonates with newer concepts of energy precarity and justice (Petrova, 2018). The following sections elucidate the historical progression of fuel poverty definitions, from pre-quantification to the origins of the first quantifiable definitions. Following this, **Chapter 2** discusses the political history of fuel poverty definitions, encompassing the influence of the austerity era and the shift from absolute to relative fuel poverty metrics in England.

1.3. Pre-quantification

Before the first quantifiable approach to measuring fuel poverty was proposed by Boardman (1991), there was little consensus on how best to measure and treat fuel poverty, or indeed whether it existed as a separate condition from poverty (Bradshaw & Hutton, 1983; Boardman, 1991). Although not referenced by name, fuel poverty and the inability to keep oneself warm was debated as early as the 1930s in literary and political circles; for example, George Orwell's *The Road to Wigan Pier* (published 1937) documented living conditions in Northern England prior to World War II. The day-to-day activities of a single unemployed man are described (Orwell, 1937, p.74):

> *He spends his days loafing in the public library or any other place where he can keep warm. That – keeping warm – is almost the sole preoccupation of a single unemployed man in winter… Even people on the verge of starvation will readily pay twopence to get out of the ghastly cold of a winter afternoon.*

Despite the specificity of this example, it does illustrate that affordable warmth was a matter of public and political consciousness as early as the 1930s. The latter half of the excerpt also expresses early evidence, albeit in an anecdotal manner, of the heat-or-eat dilemma, as still documented in the 21st century (Beatty, et al., 2014). It was not until the 1980s that Bradshaw & Hutton (1983) provided the theoretical foundations for quantifiable fuel poverty definitions:

> *Individuals, families and groups in the population can be said to be in fuel poverty when they lack the resources to obtain the reasonably warm and well-lit homes which are customary, or at least widely encouraged or approved in the societies to which they belong.*

Although the Bradshaw & Hutton definition is unquantifiable, some interesting discrepancies with modern definitions are evident, for example: fuel poverty is considered at individual-, family- and group-level, rather than household-level, as is often the case with modern definitions; further, the term "*in the societies to which they belong*" gives the definition a relative quality and acknowledges that energy requirements and fuel poverty are geographically, climatically and culturally heterogeneous.

1.4. Quantifiable fuel poverty and a summary of existing definitions

In the early 1990s, Boardman (1991) published the first quantifiable, 10% fuel poverty definition, an approach which is still adopted, in varying forms, across many countries. The 10% definition

was adopted as the first UK Government definition of fuel poverty (DEFRA, 2001), which was later succeeded by the LIHC definition (Hills, 2012). Finally, the current English fuel poverty definition (LILEE) was introduced in 2019 (BEIS, 2021). Table 1-1 displays a chronological summary of the fuel poverty definitions that are relevant to the remainder of the thesis: grey fill indicates previous or current English fuel poverty definitions or metrics, and blue fill indicates the current Scottish definition of fuel poverty, which is particularly relevant to later analyses.

Table 1-1. A chronological summary of existing fuel poverty definitions

Name/Author	**Description/Definition**
Fuel Poverty Bradshaw & Hutton (1983)	*Individuals, families and groups in the population can be said to be in fuel poverty when they lack the resources to obtain the reasonably warm and well-lit homes which are customary, or at least widely encouraged or approved in the societies to which they belong.*
10% Definition (Boardman, 1991)	*[A fuel poor household] is unable to have adequate energy services for 10 per cent of its income.*
10% Definition (DEFRA amendment) (DEFRA, 2001)	*A fuel poor household is one which needs to spend more than 10% of its income on all fuel use and to heat its home to an adequate standard of warmth. This is generally defined as 21ºC in the living room and 18ºC in the other occupied rooms - the temperatures recommended by the World Health Organisation.*
Low Income High Costs (LIHC) (Hills, 2012)	*Households should be counted as fuel poor if a) they [have] required fuel costs above the median level; and b) were they to spend that amount they would be left with a residual income below the official poverty line.*
Fuel Poverty Gap (Hills, 2012)	*The [amount] by which the assessed energy needs of fuel poor households exceed the threshold for reasonable costs.*
10% + MIS Scottish Definition (Scottish Parliament, 2019)	*A fuel poor household is one where: [Part A] more than 10% (20% for extreme fuel poverty) of net income is required to pay for their reasonable fuel needs after housing costs have been deducted; [or Part B] the remaining household income is not enough to maintain an acceptable standard of living, defined as at least 90% of the UK Minimum Income Standard (MIS) once childcare costs and disability or care benefits are deducted.*
Low Income Low Energy Efficiency (LILEE) (BEIS, 2021)	*LILEE finds a household to be fuel poor if it 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 below Band C.*
European Parliament (2023) definition of *Energy Poverty*	*'Energy poverty' means a household's lack of access to essential energy services that provide basic levels and decent standards of living and health, including adequate heating, hot water, cooling, lighting, and energy to power appliances, in the relevant national context, existing social policy and other relevant policies, caused by a combination of factors, including but not limited to non-affordability, insufficient disposable income, high energy expenditure and poor energy efficiency of homes.*
EU Energy Poverty Advisory Hub (EPAH) (European Parliament, 2023) (EPOV, 2020)	*Energy poverty is a multi-dimensional issue, and so cannot be measured by a single indicator… The four primary indicators include: i) arrears on utility bills; ii) low absolute energy expenditure; iii) high share of energy expenditure in income; iv) inability to keep home adequately warm… In addition, 19 secondary indicators have been developed. These do not measure energy poverty itself, but are relevant in the wider context, for example: energy prices; being at risk of poverty or social exclusion; energy expenses in different income groups; number of rooms per person; share of dwellings with energy label A; air conditioning facilities; excess winter mortality; and presence of leak, damp or rot in a dwelling*

Subjective Fuel Poverty (Harker Steele & Bergstrom, 2021)	*Subjective fuel poverty is a bottom-up measurement approach based on self-reported data pertaining to energy affordability and household conditions.*

1.5. Conclusions

This chapter provided the necessary background on fuel poverty's root causes, risk factors and symptoms. Following this, the distinction between income poverty and fuel poverty was explored, so as to justify the separate estimation of fuel poverty as a distinct condition, and subsequently the first attempts to define and quantify fuel poverty were summarised. Though the fuel poverty definitions that are most relevant to this thesis were explored briefly, the political context underlying their introduction and repeal (in the case of 10% and LIHC) has not yet been fully explored. To remedy this, **Chapter 2** presents a political history of English fuel poverty politics, which encompasses the evolution of the government's official fuel poverty definition. For this reason, a more complete set of knowledge gaps is presented in **Chapter 2**: Section 2.6, after the academic and political context has been examined in more detail.

Chapter 2: A Political History of Fuel Poverty Definitions in England

> *This new problematisation, fuel poverty as a problem that cannot be eradicated, is reflected in the LIHC indicator, which was chosen partly because of its tendency to show a consistent population of fuel poor households over time.*
>
> Lucie Middlemiss

Fuel poverty is an issue of intense political disputation in England, as demonstrated by the adoption of three fuel poverty definitions (or metrics) during the last decade. The 10% indicator (Boardman, 1991; DEFRA, 2001) was superseded by the Low Income High Costs (LIHC) definition in 2015, following the Hills (2012) review, before the introduction of the Low Income Low Energy Efficiency (LILEE) definition in 2019 (BEIS, 2021)[1]. This chapter provides a timeline of the aforementioned metrics and discusses each regarding their advantages and shortcomings, statistical properties, and the political rationale, in the case of 10% and LIHC, for their succession. Following this, the inadequacies of the LILEE metric are discussed, and knowledge gaps are identified.

Figure 2-1 displays a timeline of English fuel poverty definitions, from the first conceptual definition of fuel poverty in 1983 to the adoption of the LILEE definition in 2019. In summary, Bradshaw and Hutton's (1983) conceptual definition inspired the first quantifiable fuel poverty definition—Boardman's (1991) 10% definition, also referred to as the *fuel poverty ratio*—which was later adopted, in amended form, by the Department for Environment, Food & Rural Affairs (DEFRA, 2001) and constituted the UK Government's first official approach to quantifying fuel poverty. A key aspect of the 10% definition is that fuel poverty is considered to be an *absolute*; that is, in principle, any home can be deemed fuel poor, as the condition of spending >10% of income to maintain sufficient energy is conceivable in any dwelling.

[1] The UK Government's Department for Business, Energy and Industrial Strategy (BEIS) was divided into three sub-departments in 2023, including the Department for Energy Security and Net Zero (DESNZ), which inherited the fuel poverty-related responsibilities of BEIS.

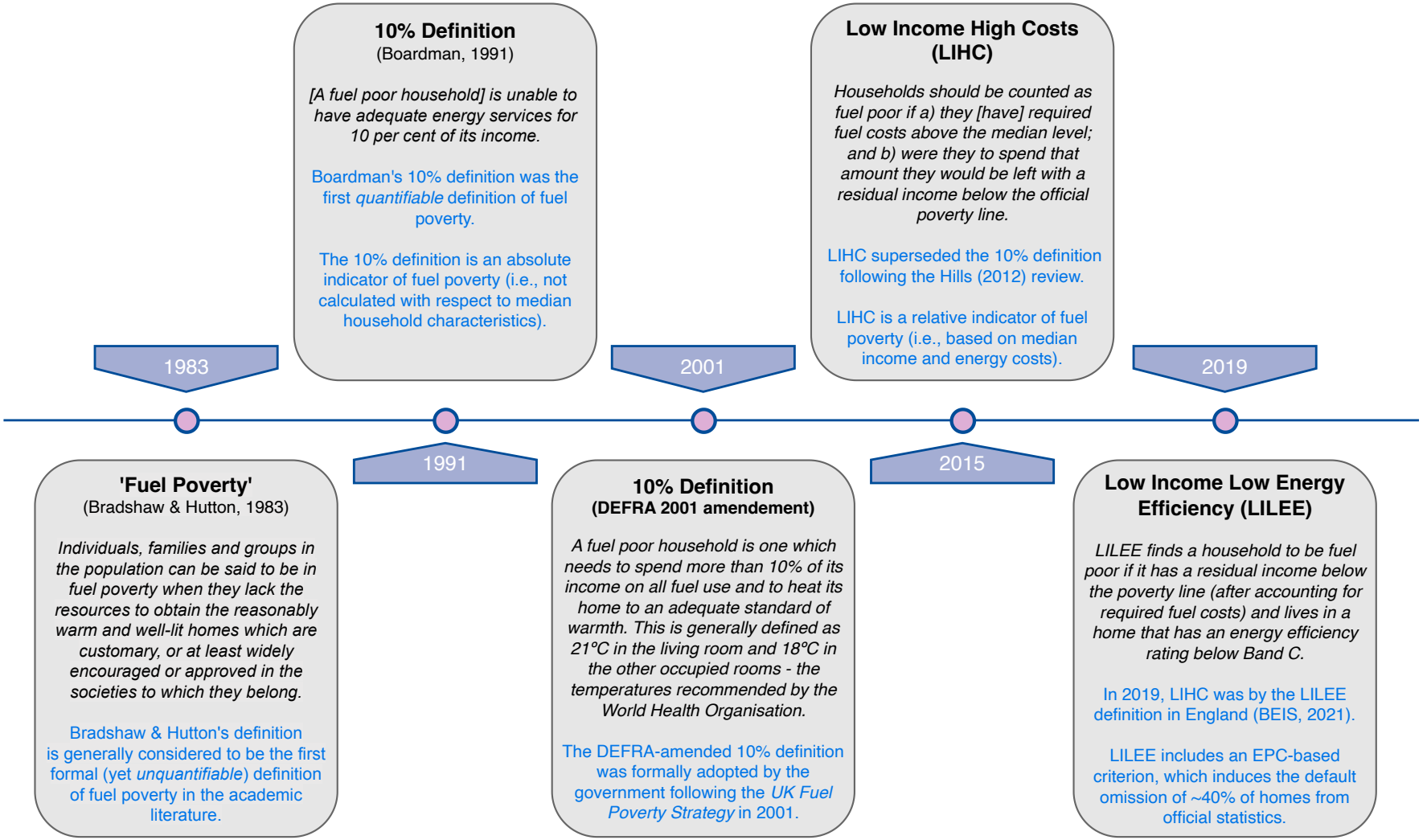


Figure 2-1. A timeline of English fuel poverty definitions (1983–present)

The crucial ideological shift in the Figure 2-1 timeline is signified by the UK Government's adoption of the LIHC definition in 2015 following the Hills (2012) review (commissioned by the Conservative-Liberal Democrat Coalition Government). The LIHC definition reimagined fuel poverty as a relative form of poverty and apportioned fundamental importance to energy-efficiency-induced fuel poverty. This newly established relativity ensures that—according to LIHC—fuel poverty is necessarily capped below the median household, and is therefore measurably ineradicable, while low-income homes with below-median energy costs are universally considered *not fuel poor* by default. This emerging trend in English fuel poverty politics culminated in the adoption of the LILEE definition, another relative fuel poverty metric that suffers similar deficiencies to LIHC. In addition, LILEE includes an EPC-based criterion; specifically, almost all homes with an EPC rating of C or above are omitted from fuel poverty statistics by default, despite the fact that this demonstrably leads to the underestimation of fuel poverty in some low-income homes.

2.1. The 10% definition

In the 1990s, Boardman (1991) devised the first quantifiable definition of fuel poverty. The 10% definition states that fuel poverty occurs when a household is unable "*to have adequate energy services for 10% of income*" (Boardman, 1991, p.277). *Energy services* refer to any energy requirement within the home, the bulk of which is attributable to space heating and cooking, while *income* refers to *full household income* (including housing benefit and income support). The 10% definition is represented by the following equation:

$$fuel\ poor \implies {}^{modelled\ household\ fuel\ costs}/_{full\ household\ income} > 0.1. \qquad (2.1)$$

The UK Government (DEFRA, 2001) adopted an amended version of 10% (including the adequate warmth clause) as the first official fuel poverty definition in the UK:

> *A fuel poor household is one which needs to spend more than 10% of its income on all fuel use and to heat its home to an adequate standard of warmth. This is generally defined as 21ºC in the living room and 18ºC in the other occupied rooms - the temperatures recommended by the World Health Organisation.*

The adequate warmth clause formalised the role of thermal comfort and the detrimental impact cold homes have on public health and excess winter morbidity (Rudge & Gilchrist, 2007).

Although not mentioned explicitly, *an adequate standard of warmth* indicates some recognition of adequate living conditions within the home, which have since been eroded by LIHC and LILEE. Another notable characteristic of 10% fuel poverty is its absolute nature. In practice, this means that fuel poverty rates and the profile of homes deemed fuel poor can vary significantly; for example, the 2021–2022 rise in consumer energy prices would have seen a corresponding rise in fuel poverty if the 10% definition was still used in England. As discussed previously, a particular characteristic of relative indicators (like LIHC and LILEE) is that poverty rates are less sensitive to variable economic conditions. In the context of the broader austerity politics of the 2010s, it is likely that one of the political benefits of reframing fuel poverty as a relative condition was the partial obscuration of fuel poverty in homes that would otherwise be deemed fuel poor according to an absolute definition.

There are, however, several issues with the 10% definition. First, the 10% threshold is based on outdated energy expenditure data from 1988: the justification for the 10% threshold was that the median household typically spent ~5% of income on energy (Boardman, 2009, p.22), so the 10% threshold represents two times the energy expenditure of the median household. This is problematic because unless energy costs and household income have appreciated at the same rate since the initial conceptualisation of the 10% definition, then, from a statistical perspective, the 10% threshold no longer has the same meaning. In fact, this is simply demonstrated by examining time series data for typical household energy costs (DESNZ, 2023a) and household income (ONS, 2023a). Table 2-1 shows changes in the fuel poverty ratio from 2020 to 2022, that is, the value of typical energy costs divided by median household income, as presented in *Equation 2.1*. Table 2-1 shows that the 10% definition is somewhat effective, given that the outgrowth of energy costs relative to household income results in the nearing of the median household to the fuel poverty threshold (10% or 0.1); however, it is also the case that the specificity and fixed nature of the 10% threshold contradict the original reasoning behind its selection. In other words, incommensurate growth in energy costs and income, even during this three-year example period, shows that the 10% threshold has disparate interpretations over time. The 10% definition could be amended so that the critical threshold changes over time to reflect median household conditions; however, this would also effectively deem the metric relative in nature, reintroducing the same shortcomings as LIHC and LILEE (e.g., stabilisation of fuel poverty rates) and losing the advantages of absolute quantification. A further shortcoming of the 10% definition is that there is no clause to discount higher-income homes with high running costs, which could be due to superfluous heating of uninhabited rooms. A simple clause to omit these homes seems sensible from a policy perspective.

Table 2-1. Fuel poverty ratio from 2020 to 2022

Year	Typical household energy costs (£/year)	Median household income (£/year)	Fuel poverty ratio (energy costs/income)
2020	£1,286	£31,883	0.040
2021	£1,333	£32,529	0.041
2022	£2,294	£32,349	0.071

2.2. LILC, LIHC, HILC and HIHC homes

The concept of low income low costs (LILC), low income high costs (LIHC), high income low costs (HILC) and high income high costs (HIHC) homes is the theoretical foundation for most modern fuel poverty definitions, where *costs* refer to household fuel/energy costs. Figure 2-2 elaborates the categorisation of LILC, LIHC, HILC and HIHC homes using synthetically generated data. The data presented in Figure 2-2 were based loosely on the energy costs and household income displayed in Table 2-1. Each data point represents a hypothetical dwelling with household income (X) and corresponding energy costs (Y). If the data were real, a stronger positive linear relationship would be likely, as higher income tends to be associated with larger dwellings and higher energy consumption (Gao, et al., 2024).



Figure 2-2. Example LILC (light pink), LIHC (dark pink), HILC (light blue) and HIHC (dark blue) designations (red lines = approximate thresholds, based on median income and costs)

This designation captures what is meant by the *multidimensional* nature of fuel poverty. For example, each of the categorisations in Figure 2-2 can be described in terms of the specific

dimension of fuel poverty that they refer to, most pertinently: i) income-poverty-induced; and/or ii) energy-costs-induced. For example, LIHC[2] homes may experience income-poverty and energy-costs-induced fuel poverty; hence, direct financial support and measures to reduce energy costs (e.g., retrofitting) may both be appropriate remedial actions in these cases. In the case of LILC homes, however, fuel poverty is most probably induced by limited income; hence, direct financial assistance is likely the most effective form of support in these cases. The inverse is true for HIHC homes: if these homes experience fuel poverty, it is likely the result of energy-costs-induced fuel poverty. Finally, HIHC homes are not at risk of any form of fuel poverty, barring astronomical rises in energy costs.

The dimensions discussed above are generally concurrent with the literature; for example, Burlinson et al. (2018) propose three dimensions of fuel poverty: "*income-poverty-high-cost; housing-cost-induced-poverty-high-cost; and fuel-cost-induced-poverty-high-cost*". Typically, housing costs are deducted from household income prior to fuel poverty classifications; therefore, this dimension of fuel poverty can be accounted for through the correct specification of income variables, for example, after housing costs (AHC), rather than before housing costs (BHC), as recommended by Moore (2012). The finer details of income variables, including adjustments for taxes, housing costs, household composition (equivalisation) and benefits, are all crucial considerations, regardless of the definition in question (Burlinson, et al., 2018; Moore, 2012).

2.3. The LIHC definition and the fuel poverty gap

The Hills review (Hills, 2012) was commissioned during 2011 by the Conservative-Liberal Democrat Coalition Government (2010–2015). The review examined the following matters (Hills, 2012, p.6):

i) Whether 'fuel poverty' is, in fact, a distinct problem, or simply a manifestation of more general problems of poverty.
ii) If it is distinct, how it is best measured and whether the current approach to doing this captures the problems most effectively.
iii) The implications of measurement for the way we understand the effectiveness of the range of policy approaches to reducing it.

In short, the review concluded that fuel poverty "is not synonymous with general poverty" and suggested the crux of the matter is "the overlap between low income and high costs" (Hills, 2012, p.37). Predicated on this and several other objections to the 10% definition, the review

[2] It should be noted that the LIHC portion of Figure 2-2 is not equivalent to LIHC fuel poverty. LIHC fuel poverty is instead calculated with respect to the poverty line, which would lie around 60% of median income (~£20,000); hence, homes below the poverty line with above-typical energy costs are considered *fuel poor* according to the LIHC definition.

recommended the adoption of the LIHC definition (or indicator) in England. The main concerns cited with the 10% definition included a lack of modern applicability, due to the 10% threshold being based on outdated energy data; greater-than-expected fluctuations in fuel poverty rates; the potential to erroneously count some HIHC homes as fuel poor, as well as undercount LIHC homes if energy prices fell relative to income (Hills, 2012, p.8). All of these claims are warranted, perhaps with the exception of fluctuations in the rate of fuel poverty, which is not necessarily a negative trait from a measurement perspective. On this matter, Middlemiss (2017) raises the objection that LIHC was adopted for "*its tendency to show a consistent population of fuel poor households over time.*" Hills (2012, p.9) defined their preferred approach, the LIHC indicator, as follows:

> *Households should be counted as fuel poor if a) they have required fuel costs above the median level; and b) were they to spend that amount they would be left with a residual income below the official poverty line.*

The LIHC definition of fuel poverty (see Figure 2-3) is easily understood visually. Similar to Figure 2-2, high-costs homes are those with above-median energy costs, while *income below threshold* refers to the poverty line. The co-occurrence of these conditions results in fuel poverty, according to LIHC. The Hills review also formulated the *fuel poverty gap* (see Figure 2-4), providing valuable information on the depth of fuel poverty, or more specifically, the amount in monetary terms that a home falls short of affording its modelled energy costs.

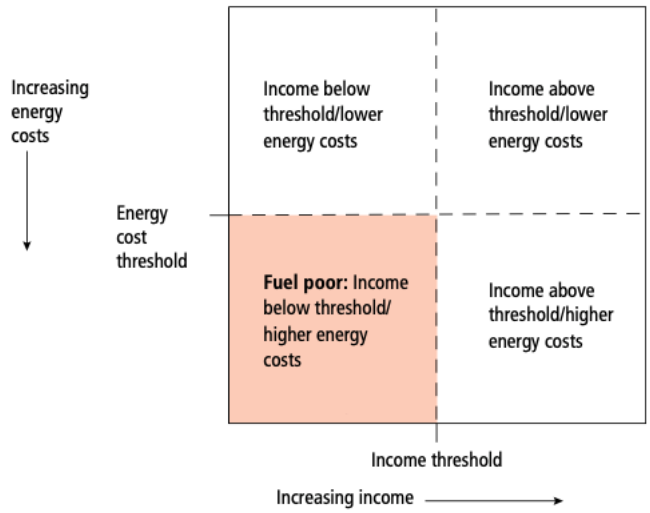


Figure 2-3. The LIHC definition (Hills, 2012, p.33)

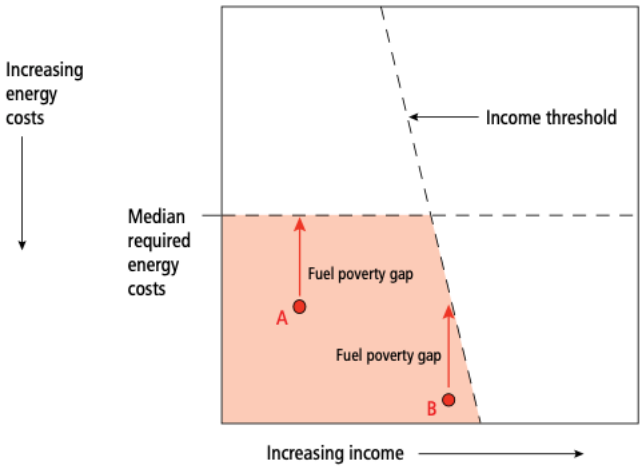


Figure 2-4. The fuel poverty gap (Hills, 2012, p.34)

The LIHC definition and fuel poverty gap were both adopted as the official means of measuring fuel poverty in England in 2015. Despite addressing some of the issues with the 10% definition, the introduction of LIHC was, more importantly, a politically symbolic evolvement, as the LIHC approach embodied a shift in the problematisation of fuel poverty as a condition more distinct from income poverty; the result of this being that a potentially unjust level of focus is apportioned to energy efficiency as the principal solution to fuel poverty, as argued by Middlemiss (2017):

> *… the LIHC definition further entrenches the distinction between poverty and fuel poverty, obfuscating any links between these agendas.* ***This results in a stronger emphasis on energy efficiency as the only possible policy solution to fuel poverty.***

This judgement effectively foreshadowed the LILEE definition, which focuses even more explicitly on the energy efficiency-related dimension of fuel poverty and diminishes the roles of income and energy costs. Besides this, the other more obvious implication of the LIHC definition is that, given its relative nature (in both dimensions: *median energy costs* and the poverty line, *60% of median income*), the rate of LIHC fuel poverty remains within a predictable range (Herrero, 2017; Middlemiss, 2017). This is acknowledged in *Sustainable Warmth* (BEIS, 2021, p.10), the policy paper that justified the succession of LIHC and introduction of LILEE:

> *As LIHC is a relative indicator, the total proportion of fuel poor households remains relatively static at 10-12%, or around 2.5 million homes.*

It is arguable that the adoption of the LIHC definition was a deliberate, preemptive response intended to maintain control of fuel poverty rates, considering the increasing instability of global

gas markets, characterised by increased demand and, consequently, higher consumer costs (International Energy Agency, 2024; The Oxford Institute for Energy Studies, 2021). This is particularly pertinent to fuel poverty, as the vast majority of UK dwellings are reliant on gas boilers (DLUHC, 2024). Increasing uncertainty in global gas markets may have further enhanced the political expedience of LIHC in the short and long term. The most evident short-term political benefit of LIHC, however, was the immediate "reduction" in the English fuel poverty rate from 13.9% under the 10% definition to 10.4% under LIHC—expressed in absolute terms, 770,000 fewer households were considered fuel poor (DECC, 2015). Prior to the formal adoption of LIHC, Moore (2012, p.25) raised similar concerns, suggesting that "*the definition largely obscures the impact of escalating fuel prices on the affordability of fuel*". In other words, using a median energy costs threshold does not do enough to protect lower-income homes from seemingly inevitable rises in energy costs.

To summarise, the LIHC definition caps the proportion of homes that can possibly be deemed fuel poor, a measurement characteristic that renders the quantification of LIHC fuel poverty ineffectual during times of economic volatility. A similar paradox concerns the eradication of fuel poverty, as neither financial support nor energy efficiency upgrades could achieve the eradication of fuel poverty according to LIHC. Most importantly, significant rises in energy costs have little effect on fuel poverty rates under LIHC, as the LIHC classification is tethered to the median home. This supports the theory that LIHC was introduced to control the rate of fuel poverty in the context of broader austerity politics and the inevitable global trajectory of gas prices. This theory resonates with energy precarity discourses (Petrova, 2018), which suggest that an increasing proportion of homes or individuals are becoming exposed to energy price fluctuations. This precarity is likely to be particularly pronounced among LILC homes over periods when typical energy costs outgrow income, an effect that is significantly downplayed by the LIHC definition.

Despite the transience of the LIHC definition in England, it is still used in other countries, emphasising the global influence that the UK has in fuel poverty research (Brabo-Catala, et al., 2024; Herrero, 2017). This highlights the broad and lasting effects that domestic policy decisions can have on other populations and reiterates the importance of objective and nonpartisan approaches to measuring poverty. Despite the UK Government's repeal of LIHC in England, it is arguable that its successor, the LILEE definition, is also politically charged and suffers from many of the same measurement deficiencies as LIHC.

2.4. The LILEE definition

The LILEE definition was introduced in 2019, purportedly to address issues with LIHC. According to the government, the issues with LIHC were the production of an unrealistically stable rate of fuel poverty and that "*fluctuations in the average income and average energy bill can change who is considered to be fuel poor*" (BEIS, 2021, p.10). Surprisingly, the LILEE definition (restated below) fails to address the aforementioned issues in a meaningful way, retaining the LIHC income clause and supplanting "*higher than typical energy costs*" with a similar modelled energy costs criterion based on the Standard Assessment Procedure (SAP) methodology:

> *"a household [is] fuel poor if it 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 below [FPEER] Band C."*

Like LIHC, LILEE is a relative indicator of fuel poverty, calculated with respect to the poverty line (as shown in Figure 2-5). Like the visual representation of LIHC and its counterparts in Figure 2-2, the LILEE definition has Low Income High Energy Efficiency (LIHEE), High Income Low Energy Efficiency (HILEE) and High Income High Energy Efficiency (HIHEE) parts. Mirroring the discussion of LILC homes in the previous section, a concern with the LILEE definition is that the impact of increased energy costs is neglected in LIHEE homes. Figure 2-5 is an example visualisation of the LILEE definition, showing household income, the approximate poverty threshold (adjusted for household energy costs[3]), and Fuel Poverty Energy Efficiency Rating (FPEER) band. There is a trivial distinction to be made between FPEER and EPC bands: both are based on SAP score (modelled fuel costs, on a scale of 0–100+) and are aggregated as bands, from A (most efficient) to G (least efficient), however, FPEER accounts for energy support schemes through directly subtracting rebates, such as the Warm Home Discount, Cold Weather Payment and Winter Fuel Payment, from a home's energy costs (DECC, 2014). In other words, a home with a marginal EPC rating of D may have an FPEER rating of C after energy discounts or rebates are accounted for; however, in most cases, a home's EPC and FPEER are equivalent. For example, recent estimates show that the value of the Warm Home Discount (~£150/year) is relatively modest as a proportion of typical energy costs; as a result, EPC D-rated homes receiving this discount saw an increase of around 3 FPEER points during 2022/2023 (DESNZ, 2023b, p.14), which is unlikely to result in the home moving band. It is also worth noting that SAP is due to be superseded by the *Home Energy Model* (HEM) during 2025 (DESNZ, 2023c), which will have

[3] The poverty line *adjusted for energy costs* creates the characteristically oblique poverty threshold used by the LILEE methodology. In practice, the line is slanted as homes with lower FPEER ratings are expected to have higher corresponding energy costs.

implications for the EPC rating system and, consequently, fuel poverty definitions that are based on SAP-derived criteria.

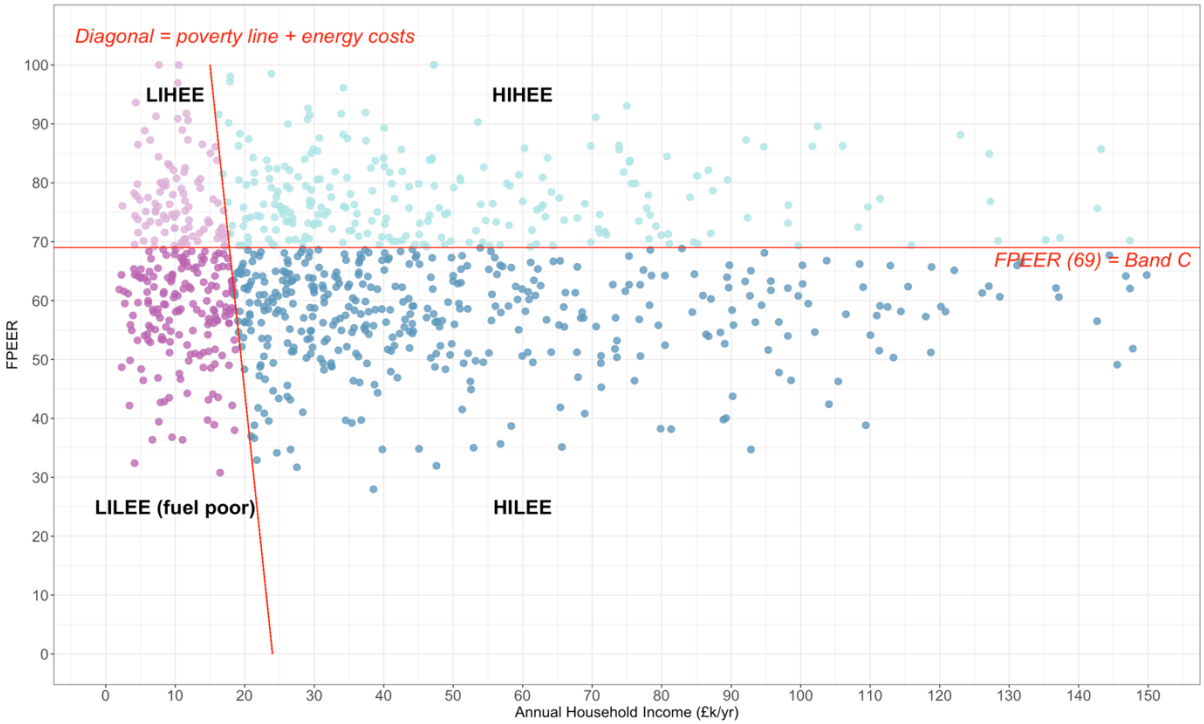


Figure 2-5. An example of the LILEE methodology, based on DESNZ (2023b, p.12)

Further to the general omission of homes in FPEER bands A–C, previous studies have evidenced significant disparities between modelled EPCs and actual energy use (Coyne & Denny, 2021; Few, et al., 2023; Nagarajah & Davis, 2019); therefore, secondary poverty classifications using SAP scores are bound to contain inaccuracies. The general oversight of LIHEE homes, as well as the LILEE definition's median-tethered classification process, is likely to omit many people living in low-income homes from fuel poverty statistics, who, in many cases, will still struggle to afford sufficient energy. This apparent shortcoming of the LILEE definition is analysed in more detail in **Chapters 3** and **4**. The government acknowledges this significant deficiency in the LILEE methodology (BEIS, 2021, p.10):

> *Whilst we recognise that there are households living in energy efficiency Band A, B or C homes* ***who are unable to afford sufficient energy to keep warm, due to a very low income****, most will not significantly benefit from energy efficiency measures.*

This logic is entirely incongruent with the academic literature and previous fuel poverty policy. Homes "*who are unable to afford sufficient energy to keep warm*" are precisely the demographic that fuel poverty metrics attempt to identify (EPOV, 2020; DEFRA, 2001; Hills, 2012) and are those

whose occupants suffer cold living conditions and the negative health consequences of fuel poverty (Rudge & Gilchrist, 2007). Potentially overlooking cases of fuel poverty among this demographic based on a home's energy efficiency rating alone is hard to justify. Moreover, the government's suggestion that these homes are omitted because "*most will not significantly benefit from energy efficiency measure*s" vindicates the arguments of Middlemiss (2017) and Herrero (2017) that fuel poverty has been redefined to the point where the English approach is irrationally fixated on energy efficiency. The critiques of Middlemiss (2017) and Herrero (2017), which were originally in reference to the LIHC definition, are equally applicable to LILEE.

LIHC and LILEE were introduced under Coalition (Conservative-Liberal Democrat) and Conservative rule, respectively. This is an important consideration as LIHC is widely believed to be the product of an era of austerity, as alluded to previously, where the fuel poverty agenda shifted from the absolute, income-centric 10% definition to a relative, energy-efficiency-focused indicator. The significance of this is that relative indicators (like LIHC and LILEE) cap the number of homes that can possibly be deemed fuel poor and tend to overstate the role of energy efficiency as the cause and solution to fuel poverty (Herrero, 2017; Middlemiss, 2017). As a result, the government's responsibility to address fuel poverty is, to a degree, diminished. For example, seemingly lower rates of fuel poverty draw less attention and less pressure to act; a greater focus on household energy efficiency diverts responsibility to the property owner; and the subtext of relative indicators—that fuel poverty cannot be eradicated—contributes to its normalisation.

2.5. Fuel poverty definitions across the UK and Ireland

Examining the fuel poverty definitions used in other UK nations (Scotland, Wales, and Northern Ireland) and the Republic of Ireland is a necessary step to contextualise the LILEE approach. The executive powers (Scottish Government, Welsh Government, and the Northern Ireland Executive) continue to utilise versions of the 10% fuel poverty definition, yet finer details of the measurement criteria vary quite considerably. Nevertheless, this reiterates how extreme an outlier England is, particularly given that the other UK nations are the most comparable in terms of climate and housing stock (Piddington, et al., 2020). Table 2-2 presents the current definitions of fuel poverty used in Scotland, Wales, Northern Ireland and the Republic of Ireland.

Table 2-2. Fuel poverty definitions in Scotland, Wales, Northern Ireland and the Republic of Ireland

Nation and approach	Definition
Scotland *10% + MIS definition* (Scottish Parliament, 2019)	*A fuel poor household is one where:* *[Part A] more than 10% (20% for extreme fuel poverty) of net income is required to pay for their reasonable fuel needs after housing costs have been deducted;* *Or* *[Part B] the remaining household income is not enough to maintain an acceptable standard of living, defined as at least 90% of the UK Minimum Income Standard (MIS) once childcare costs and disability or care benefits are deducted.*
Wales *10% definition* (National Assembly for Wales, 2020, p.13)	*Having to spend more than 10 per cent of income (including housing benefit) on all household fuel used to maintain a satisfactory heating regime.*
Republic of Ireland *10% definition* (Irish Government, 2016, p.8)	*[Energy poverty] is quantified in Ireland using what is known as the expenditure method of measuring energy poverty, whereby a household that spends more than 10% of their income on energy is considered to be in energy poverty.*
Northern Ireland *10% definition* (Northern Ireland Executive, n.d.)	*A household is said to be in fuel poverty if it needs to spend more than 10 per cent of its income on energy costs.*

The official fuel poverty definitions in Wales, Ireland and Northern Ireland are all versions of the fuel poverty ratio, and, barring some minor terminological differences, are equivalent to the DEFRA (2001) version of 10%. The Scottish Government's (2019) approach, which was informed by an earlier review of evidence—*a new definition of fuel poverty in Scotland* (Scottish Government, 2017)—is particularly noteworthy. First, varying degrees of fuel poverty are captured through the 10% (fuel poverty) and 20% (extreme fuel poverty) thresholds, while a five-fold indicator was also considered as follows (proportional energy expenditure threshold in parentheses) (Scottish Government, 2017, p.59): *not fuel poor* (<8%), *marginal fuel poverty* (8% < x > 10%), *fuel poverty* (10% < x > 13%), *severe fuel poverty* (13% < x > 20%) and *extreme fuel poverty* (>20%). Additional detail regarding the depth of fuel poverty, of which the five-level version of 10% is an example, is highly valuable and can be used to prioritise the most extreme cases of fuel poverty. This approach is broadly similar to the *fuel poverty gap*, which describes the depth of fuel poverty in monetary terms (Hills, 2012) and the five-fold scale proposed by Bridgen & Robinson (2023): *entrenched energy deprivation, fluctuating energy deprivation, changeable middle, fluctuating energy affluence and sustained energy affluence*, which is used to demonstrate the spatiotemporal entrenchment and degree of fuel poverty.

Yet, the most notable characteristic of the Scottish approach is the two-clause definition; Part A refers to the Scottish amendment to the 10% definition, as discussed above, and Part B includes a household's adherence to the UK Minimum Income Standard (MIS) (Scottish Government, 2017). Thus, a home is considered fuel poor in Scotland if it meets *either of these criteria*. MIS is the most common type of budget standard in the UK and is used to gauge the minimum expenditure that is required for a household to maintain a given living standard. Hirsch, et al. (2016, p.5) define budget standards as follows:

> *Typically, budget standards aim to show what is the minimum needed to reach an acceptable living standard, allowing people to meet their material needs and participate in society.*

A budget standard differs from a poverty threshold in the sense that it captures living standards information based on a "*basket of goods and services*" (e.g., food, shelter and clothing) required by a household (Hirsch, et al., 2016), rather than the more generic calculation of the poverty line, which assumes a distinct income threshold. In the context of fuel poverty definitions, Moore (2012) advocated for a budget standard approach, which also underpins much of the Scottish Government's rationale. The MIS-based fuel poverty approach is written as follows (Moore, 2012, p.22):

$$MIS\ based\ fuel\ poverty \implies$$
$$Fuel\ costs > net\ household\ income - housing\ costs - minimum\ living\ costs\ (MIS) \quad (2.2)$$

In other words, a household is considered fuel poor if required fuel costs exceed net household income, after deducting housing and minimum living costs. A slight variation of this method was adopted as Part B of the Scottish definition and arguably resolves many of the weaknesses identified in previous definitions. For example, given the potential for LIHC and LILEE to underestimate the proportion of LILC homes, the Scottish Government (2017, p.156) instead acknowledges that *"people living in very energy efficient homes (SAPs of A to C) can often [still] be classified as fuel poor, given the extent to which even the most basic energy bill (based on standing charges) constitutes a significant financial burden*. This position, which stands in stark contrast to post-2012 English fuel poverty policy, refocuses the measurement of fuel poverty on the interaction between household income, energy costs and living standards. As argued further in the following sections, the MIS-based definition has the most in common with recent European Parliament (2023) measurement guidance and is able to facilitate a fair energy transition, in the

sense that it accurately measures fuel poverty despite changing external circumstances, as discussed in greater detail in **Chapter 5**.

In summary, the measurement of fuel poverty is undoubtedly affected by competing political philosophies. There are surprisingly broad discrepancies in fuel poverty definitions across the UK and Ireland, despite comparable environmental conditions and housing stocks. The English and Scottish approaches are particularly polarised. The most recent English definitions (LIHC and LILEE) focus on energy efficiency as the primary cause and solution to fuel poverty. Conversely, the Scottish approach is more holistic, addressing the likelihood that relative indicators undercount fuel poverty in LILC homes, rejecting the single-indicator approach and acknowledging the overlap with living standards. In addition, the MIS-based approach constitutes far greater alignment with the prevailing academic (Herrero, 2017; Hirsch, et al., 2016; Middlemiss, 2017; Moore, 2012) and political consensus (EPOV, 2020; European Parliament, 2023).

2.6. Conclusions and knowledge gaps

In this chapter, the evolution of English fuel poverty politics was scrutinised to better contextualise significant changes to the official fuel poverty definition throughout the 2010s. Theoretical issues concerning all previously adopted English definitions (10%, LIHC and LILEE) were discussed at length. Specifically, the 10% definition uses an outmoded fuel poverty threshold based on dated energy costs and income data; the LIHC definition frames fuel poverty as an ineradicable and relative form of poverty, contributing to its normalisation and likely undercounting instances of fuel poverty in low-income, low-costs homes; and the LILEE definition, which suffers many of the same deficiencies to LIHC given its quantification of fuel poverty as a relative issue, contains a further SAP-based criterion that likely leads to the continued underrepresentation of low-income, low-costs (or low-income, high energy efficiency) homes in England's fuel poverty statistics.

Despite the seemingly conspicuous deficiencies of the currently used LILEE definition, there is little empirical evidence suggesting that the approach leads to an underestimation of fuel poverty in low-income homes. To address this knowledge gap and to substantiate the theoretical supposition that the LILEE definition unduly undercounts fuel poverty in some low-income homes, **Chapters 3** and **4** provide independent empirical critiques of England's fuel poverty definition.

Chapter 3: An Empirical Critique of the LILEE Definition (Case Study I): Geography and Energy Performance Certificates

> *There is a common tendency to ignore the poor or to develop some rationalisation for the good fortune of the fortunate.*
>
> John Kenneth Galbraith

As discussed in the opening chapters, it is likely that the LILEE approach obscures the true nature of fuel poverty in England. In this chapter, two analyses of the LILEE definition are conducted in Nottingham and London[4] to address *Research Question A*:

> *Given the LILEE definition's universal omission of energy-efficient households, is fuel poverty (i.e., the actual ability of occupant(s) to afford adequate energy) currently underestimated in England, and if so, to what extent?*

First, a spatial analysis is conducted to analyse discrepancies between rates of LILEE fuel poverty and deprivation, using the Index of Multiple Deprivation (IMD), in Lower Super Output Areas (LSOAs)[5]. Previous research (Marchand, et al., 2019) analysed the relationship between IMD and fuel poverty across England, according to the previously adopted 10% fuel poverty definition; however, a similar analysis of the LILEE definition was yet to be done. Second, the number of low-income, high-efficiency homes that are omitted from LILEE statistics by default is estimated in both case cities by analysing a combination of publicly available datasets, including the Energy Performance Certificate (EPC) database and the English Housing Survey (EHS)[6].

[4] It should be noted that when referring to London as the study area, reference is being made to Greater London, which includes the City of London and surrounding boroughs

[5] The ONS (2021a) define LSOAs as areas with between 400 and 1,200 households and resident populations of 1,000–3,000; e.g., the average number of households per LSOA in London is 725.

[6] The findings of **Chapter 3** contributed to the following article: An Empirical Critique of the Low Income Low Energy Efficiency Approach to Measuring Fuel Poverty. *Energy Policy*.

3.1. Data, methods and assumptions

The analyses in this chapter require the integration of publicly available datasets for LILEE fuel poverty (BEIS, 2023), EPC ratings (DLUHC, 2023a), employment status (DLUHC, 2023b) and IMD (DLUHC, 2020). The data and methods used in the spatial analysis (Part 1) and estimation of financially vulnerable homes that are omitted from LILEE statistics (Part 2) are discussed in succession below.

Part 1: Spatial analysis

For the spatial analysis, LILEE fuel poverty (BEIS, 2023) and IMD (DLUHC, 2020) data were integrated to provide combined LSOA-level statistics for London and Nottingham. IMD is a composite metric developed by the UK's ONS that accounts for various aspects of deprivation and is used to rank LSOAs from least to most deprived. In this context, city-specific indices were generated for LILEE fuel poverty (i_{FP}) and IMD (i_{IMD}) to rank LSOAs according to both; thus, the spatial analyses of both cities are useful for comparing discrepancies between fuel poverty and IMD *within* each city, rather than between cities. *Equation 3.1* and *Equation 3.2* show the calculation of the LILEE fuel poverty rank ($\mathrm{i_{FP}}$) and IMD ($\mathrm{i_{IMD}}$) rank for London, respectively:

$$i_{FP,London} = {\text{LSOA FP rank}}/{Median\ London\ FP\ rate\ (\%)} \tag{3.1}$$

$$i_{IMD,London} = {LSOA\ IMD\ rank}/{Median\ London\ \text{IMD}\ LSOA\ rank} \tag{3.2}$$

Following this, bivariate maps of LILEE fuel poverty and IMD indices are generated using geographical information system (GIS) software (QGIS, 2002) to visualise LSOA-level disparities between LILEE fuel poverty and deprivation indices.

Part 2: Estimating the number of financially vulnerable homes omitted from LILEE statistics

The estimation of financially vulnerable homes omitted from LILEE statistics required housing and energy performance data for England, namely the EPC database (DLUHC, 2023a), and employment information, which was retrieved from the English Housing Survey (EHS) (DLUHC, 2023b). The estimation process is visualised in Figure 3-1, where the use of EPC and EHS data is denoted by red and blue boxes, respectively. The estimation process is theoretically straightforward: three *yes* responses per *choice* (i.e., rhombus node) result in a proportion of homes being categorised as *likely to be fuel poor*, in spite of their omission from LILEE statistics. The assumption that these homes are likely to be fuel poor is based primarily on tenure status

and economic activity of the household reference person (HRP), i.e., the household's main earner. Hence, the term *likely to be fuel poor* effectively means *likely unable to afford adequate warmth/energy services*.

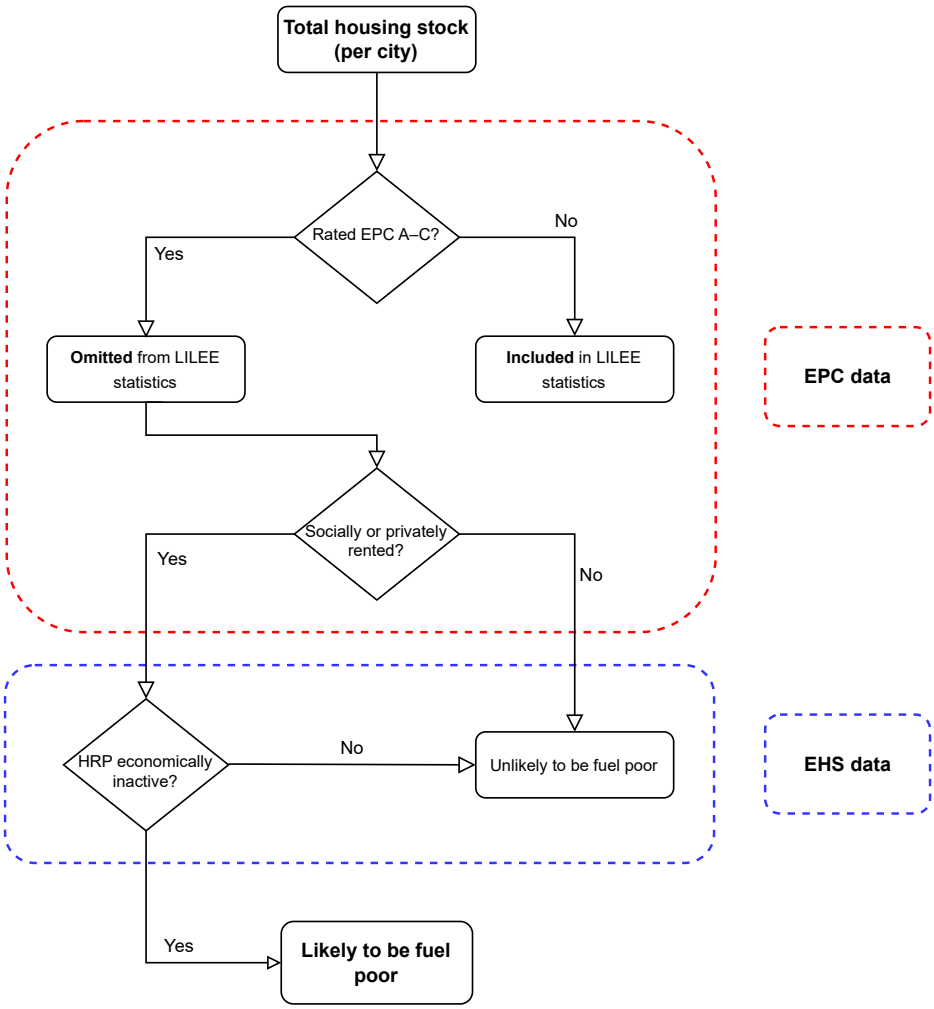


Figure 3-1. Estimation process: The number of financially vulnerable homes omitted from LILEE statistics

Several assumptions and limitations of the proposed estimation process should be noted. First, only socially and privately rented properties are considered in the estimation process, as people who rent tend to have lower incomes than those with mortgages or those who own property outright (DLUHC, 2023b); it is, however, worth noting that in reality a proportion of owner-occupied homes also struggle to afford adequate warmth. Second, EHS data for economic activity is extrapolated to provide rough estimates of the proportion of socially and privately rented homes with economically inactive occupants (i.e., unemployed or unable to work) per city. Given that the EHS is nationwide, a certain degree of inaccuracy is induced for the economic activity of Nottingham and London households. Finally, it is also worth noting the assumption that EPC and

FPEER are essentially equivalent in this analysis. As previously discussed, FPEER considers government energy support schemes through directly subtracting rebates from a home's fuel costs (DECC, 2014). In other words, a home with a marginal EPC rating of D may have an FPEER rating of C after energy discounts or rebates are accounted for; however, in the vast majority of cases a home's EPC and FPEER ratings are equivalent. Despite these limitations, the city-level estimations can still be used to demonstrate the shortcomings of the LILEE definition's measurement criteria.

3.2. Results, Part I: A spatial analysis of LILEE fuel poverty

The rate of LILEE fuel poverty is estimated to be 11.9% in London and 20.6% in Nottingham (BEIS, 2023). Figure 3-2 and Figure 3-3 display bivariate choropleth maps of Greater London and Nottingham, respectively, showing fuel poverty (according to LILEE) versus IMD. Each of the areas in these figures represents an LSOA (neighbourhood) in Nottingham or London. There are a total of 4,835 LSOAs in London; surprisingly, 220 of these LSOAs (around 4.7%) have IMD scores that rank them amongst the most deprived in London, but lower-than-average rates of fuel poverty. Given that IMD utilises a ranking system, i.e., LSOAs are ranked from most to least deprived, the LSOAs analysed here were also ranked in terms of fuel poverty prevalence, as previously specified in the methods. In Nottingham, 5 out of 182 LSOAs have higher-than-average IMD scores (i.e., high deprivation) but lower-than-average rates of fuel poverty.

In order to help interpret the bivariate legend, consider cell A3 (dark pink) in Figure 3-2: these LSOAs have a fuel poverty rate higher than the London average (fuel poverty index=1.34–2.00, i.e., these LSOAs are in top ~33% of fuel poor areas in London), however, the corresponding IMD index is 0.00–0.67, which means the LSOA is in the least deprived ~33% of areas in London. Table 3-1 provides a detailed numerical interpretation of each of the corresponding legend cells. The bivariate maps and associated indices refer to intracity variation only, as per *Equations 3.1* and *3.2*. This is a particularly important point, as London is a distinctive UK city with the largest municipal population and area, while median household income also tends to be higher than in other regions (ONS, 2022b); Nottingham, conversely, is one of the most deprived cities in England. The selection of a citywide or nationwide IMD baseline, therefore, significantly warps the impression given by this type of map; for example, see Appendix: Chapter 3, Figure 1 for the varying impressions created by the use of a Nottingham-specific or England-specific IMD baseline in another project.

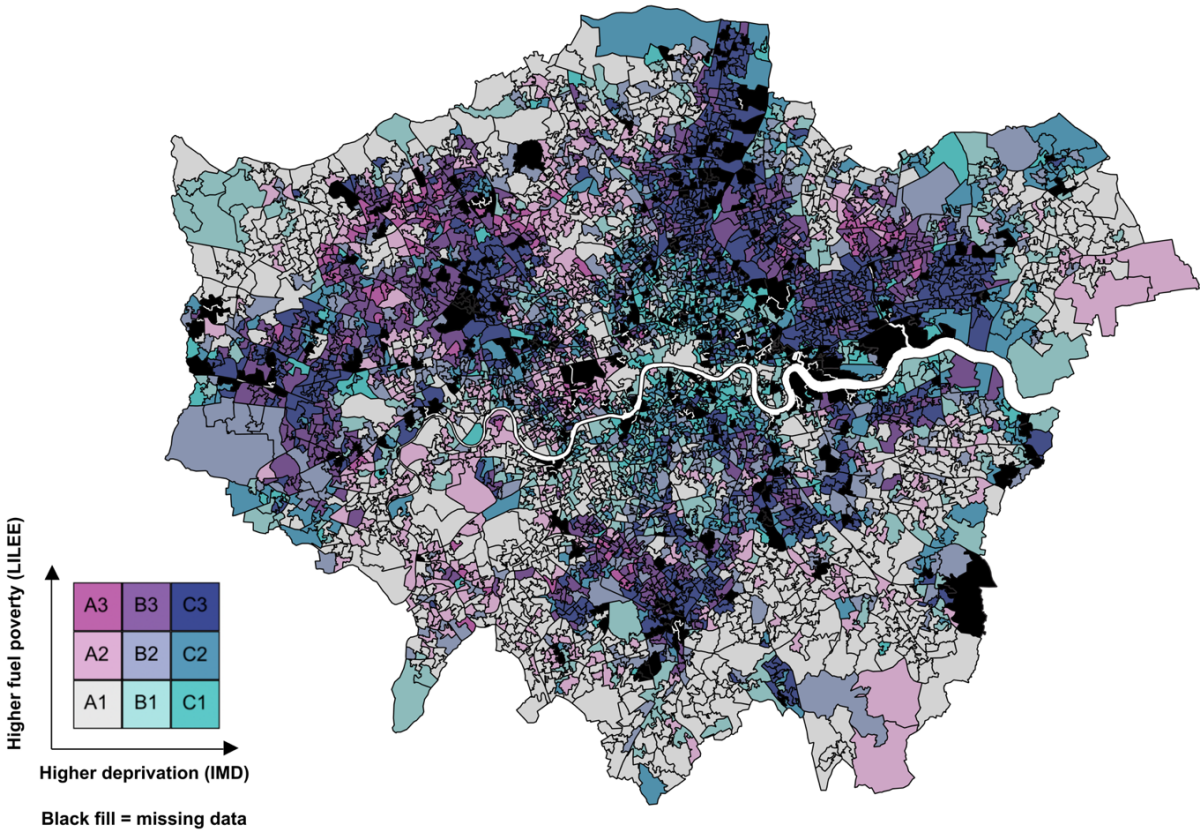


Figure 3-2. Bivariate choropleth map of Greater London: fuel poverty (LILEE) and IMD per LSOA

Table 3-1. Corresponding A, B and C legend codes for fuel poverty and IMD

Legend code	Fuel poverty index (i_{FP})	IMD index (i_{IMD})
A1	0.00–0.67	0.00–0.67
A2	>0.67 & <1.34	0.00–0.67
A3	1.34–2.00	0.00–0.67
B1	0.00–0.67	>0.67 & <1.34
B2	>0.67 & <1.34	>0.67 & <1.34
B3	1.34–2.00	>0.67 & <1.34
C1	0.00–0.67	1.34–2.00
C2	>0.67 & <1.34	1.34–2.00
C3	1.34–2.00	1.34–2.00

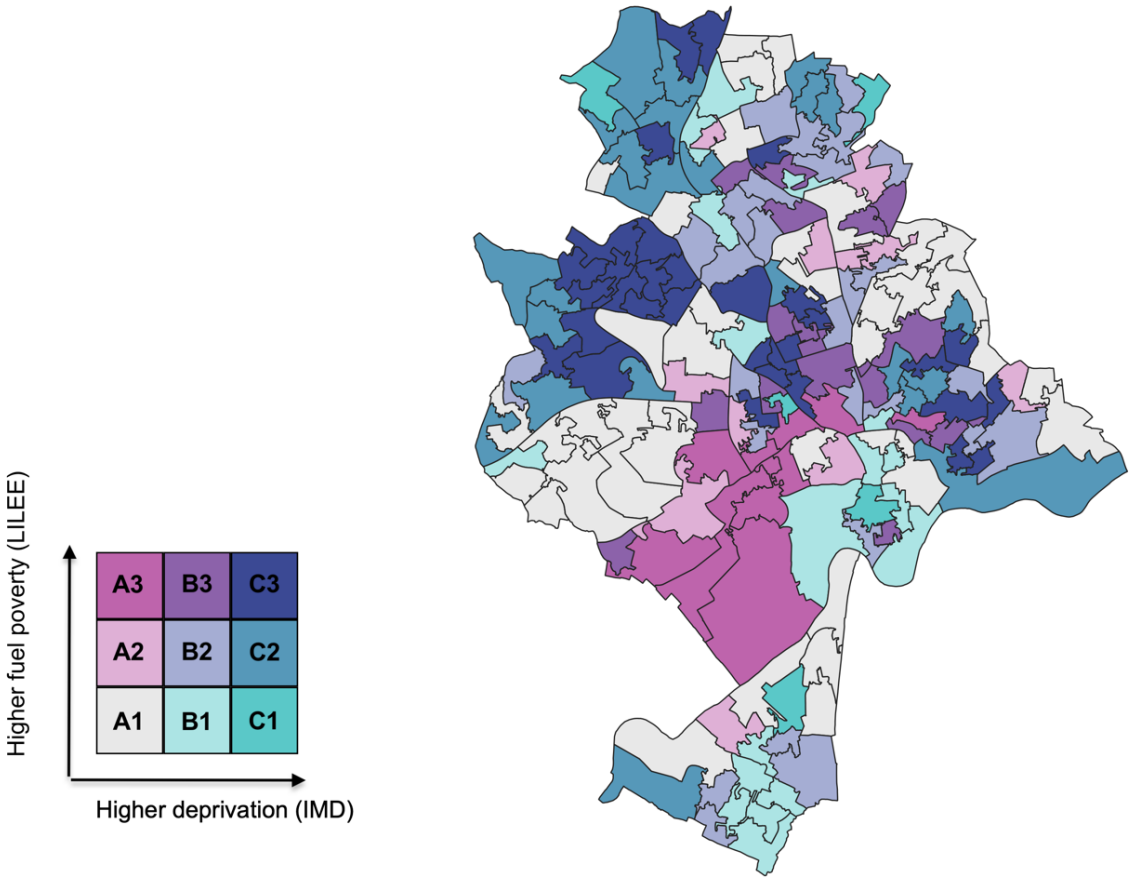


Figure 3-3. Bivariate choropleth map of Nottingham: fuel poverty (LILEE) and IMD per LSOA

The Nottingham map is relatively simple to interpret, given the city's smaller size and, as a consequence, the increased granularity of LSOA boundaries. As a result, it is also more straightforward to examine the geographical clustering of LSOAs; for example, there are distinct clusters of A1 (low fuel poverty, low deprivation), A3 (high fuel poverty, low deprivation) and C3 (high fuel poverty, high deprivation) LSOAs in southwest Nottingham. The reason for this clustering is mostly dependent on deprivation: the northwest of Nottingham is relatively deprived, whereas the southwest tends to be more affluent (ONS, 2022b). Interestingly, the cell C1 LSOAs are dispersed across Nottingham, signalling weak geographical clustering of these cases.

As previously mentioned, the most intriguing LSOAs are those that have unexpectedly disparate levels of fuel poverty and deprivation, i.e., cells A3 (high fuel poverty, low deprivation) and C1 (low fuel poverty, high deprivation). A further analysis of these cases is presented below in an attempt to explain why these outlying LSOAs might exist. Figure 3-4 displays the LSOA IMD index plotted against the LILEE fuel poverty index. Fitting a simple linear regression model (R^2=0.26) to the data shows that there is a moderately positive relationship between the IMD and LILEE fuel

poverty indices. However, there are a considerable number of outlying LSOAs, which can be seen in the top left and bottom right sections of Figure 3-4 (highlighted by red polygons), corresponding to cells A3 and C1 of the bivariate legend, respectively.

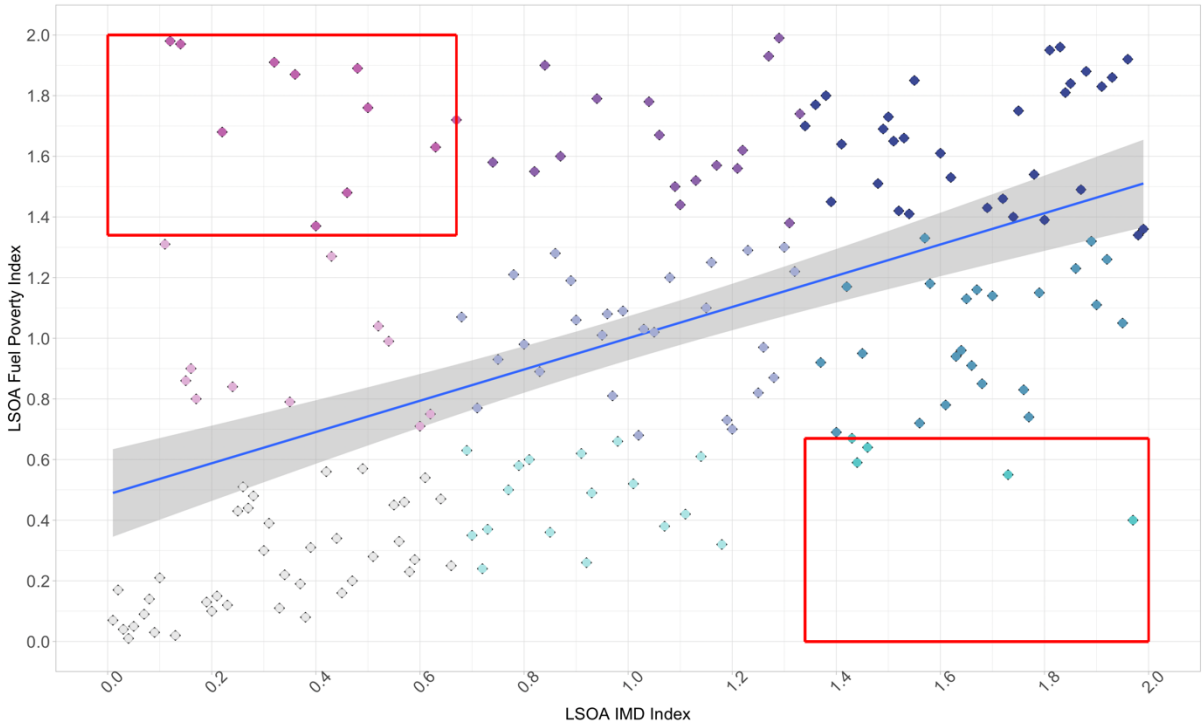


Figure 3-4. IMD plotted against fuel poverty (LILEE) per LSOA in Nottingham (n=182 LSOAs)

A linear model was also fitted to the London LSOAs, producing an R^2 of 0.27. This suggests that IMD is a marginally stronger predictor of LILEE fuel poverty in London; for the equivalent London scatter plot, see Appendix: Chapter 3, Figure 2. The cell C1 (low fuel poverty, high deprivation) outlying LSOAs may well be attributable to the LILEE definition's indiscriminate omission of households with EPC ratings of A–C, constituting ~40% of Nottingham homes, without having considered household or occupant characteristics. It is worth noting, however, that in the context of the 10% fuel poverty indicator, Marchand et al. (2019) also comment on the surprisingly disparate distribution of fuel poverty and IMD in English LSOAs, suggesting that this may in fact be a common trend between various fuel poverty metrics and IMD. Regardless, it may be informative to characterise outlying LSOAs further, to provide potential explanations for the disparity between LILEE fuel poverty and deprivation in these cases[7].

[7] Note: Further notes on outlying LSOAs are only provided for Nottingham, given that the equivalent analysis of London would be far more complex due to the higher absolute number of LSOAs.

Further notes on outlying LSOAs in Nottingham

Outlying LSOAs in Nottingham (i.e., those with unexpectedly disparate LILEE and deprivation scores: cells A3 and C1) are characterised in greater detail here, allowing several potential explanations for these cases to be explored. Specifically, the outlying LSOAs are evaluated in terms of demographic composition, energy efficiency and tenure status. Table 3-2 displays a complete list of outlying LSOAs in Nottingham, as well as their corresponding council ward, which may be of use for the formulation of local authority-level fuel poverty strategies. In the context of the current work, however, LSOA-level and council ward-level data are used to understand the pronounced discrepancy between LILEE fuel poverty and IMD.

All cell A3 outliers (high fuel poverty, low deprivation) are located in council wards with particularly high student populations. Census data (ONS, 2022c) provided in Table 3-3, shows that the student populations in Lenton and Wollaton East (~61%), Radford (~63%), Hyson Green and Arboretum (~42%) and St. Ann's (~28%) are among the highest in Nottingham (see highlighted rows in Table 3-3), whilst they are also higher than the citywide average (~19%). A possible explanation may be that high student populations are skewing IMD statistics in these areas, in the sense that many students are likely in income poverty but only transitorily; hence, these areas may score as highly deprived according to the income poverty component of IMD, but less deprived according to other IMD components (e.g., education and crime).

Table 3-2. List of LSOA outliers in Nottingham (i.e., cells A3 or C1)

Legend code & description	LSOA name	Nottingham council ward
Cell A3	E01033410	Lenton & Wollaton East
	E01033408	Lenton & Wollaton East
High fuel poverty, low deprivation	E01013973	Lenton & Wollaton East
	E01013974	Lenton & Wollaton East
	E01013928	Lenton & Wollaton East
	E01013926	Lenton & Wollaton East
	E01013924	Lenton & Wollaton East
	E01013816	Hyson Green & Arboretum
	E01013953	Radford
	E01033404	Radford
	E01033401	St. Ann's
Cell C1	E01032621	Bestwood
	E01013883	Bulwell
Low fuel poverty, high deprivation	E01013896	Clifton West
	E01013871	Meadows
	E01013948	Radford

Table 3-3. Student population per Nottingham council ward, according to Census 2021 data (ONS, 2022c)

Ward	Residents	Students (n)	Students (%)
Aspley	18792	1402	7.46
Basford	16368	1147	7.01
Berridge	17912	1848	10.32
Bestwood	17067	933	5.47
Bilborough	16924	1204	7.11
Bulwell	16216	797	4.91
Bulwell Forest	13995	680	4.86
Castle	10866	4439	40.85
Clifton East	17041	964	5.66
Clifton West	10743	1774	16.51
Dales	16889	1375	8.14
Hyson Green & Arboretum	23337	9867	42.28
Leen Valley	9913	783	7.90
Lenton & Wollaton East	21826	13275	60.82
Mapperley	16402	1680	10.24
Meadows	11016	1394	12.65
Radford	16652	10527	63.22
Sherwood	15822	996	6.30
St. Ann's	20690	5850	28.27
Wollaton West	15168	1031	6.80
Total (Nottingham)	323639	61966	19.15

It is also likely that the quality and energy efficiency of housing in each LSOA contributes to outlying cases, particularly given the role of EPCs as a central LILEE fuel poverty criterion. Table 3-4 shows the aggregate distribution of EPC ratings for cell A3 (n=14,197 homes) and cell C1 (n=5,141 homes) outliers. A higher proportion of cell C1 outliers (low LILEE fuel poverty and high deprivation) have EPC ratings of A–C (60.22%) than among cell A3 outliers (43.57%). In practice, this means that only ~40% of homes belonging to cell C1 LSOAs are considered in LILEE fuel poverty estimations.

Table 3-4. Aggregate EPC ratings for households in outlying LSOAs, compared to Nottingham average (DLUHC, 2023a)

Legend Code	EPC rating					
	A	B	C	D	E	F–G
Cell A3 (n=14,197)	0.40%	11.78%	31.39%	33.85%	17.91%	4.68%
Cell C1 (n=5,141)	0.14%	6.98%	53.10%	31.76%	7.39%	0.62%
Nottingham (n=169,786)	0.26%	7.34%	31.66%	38.45%	17.55%	4.74%

Further context is provided in Figure 3-5, which shows the distribution of SAP scores (i.e., the antecedent score to EPC bands) per LSOA. This type of LSOA-level disaggregation is particularly useful for targeting remedial efforts, or in this case, to identify the profile of areas where the LILEE definition's undercounting of fuel poverty is likely to be most pronounced. Considering the cell C1 LSOA *E01013948* (see also Table 3-2), for example, the distribution of SAP scores in this LSOA indicates a high level of household energy efficiency, which is likely attributable to previous targeted interventions in this area. However, somewhat paradoxically, the high energy efficiency

of homes in this LSOA precludes their inclusion in LILEE fuel poverty statistics, despite high deprivation. This type of example is particularly useful for demonstrating the fundamental ideological flaw in the LILEE approach; high household energy efficiency alone does not necessarily mean a home's essential energy needs can be met. This is simply demonstrated by considering *at-risk* groups, for example, single-occupancy or single-parent homes, who are particularly prone to fuel poverty (Belaïd, 2018). It is logical to suppose that single-occupancy and single-parent homes belonging to cell C1 LSOAs still struggle to afford adequate energy, despite the *relatively* high level of energy efficiency present in these cases. This calls the ideology and motivations of *Sustainable Warmth*—the policy that formally introduced the LILEE methodology—into question. BEIS (2021) state that homes with FPEER bands of C or above are not considered in fuel poverty statistics as "*most [of these homes] will not significantly benefit from energy efficiency measures*"; however, as demonstrated via the bivariate mapping of LILEE fuel poverty and IMD, this likely leads to a considerable underestimation of fuel poverty in low-income, high energy efficiency homes.

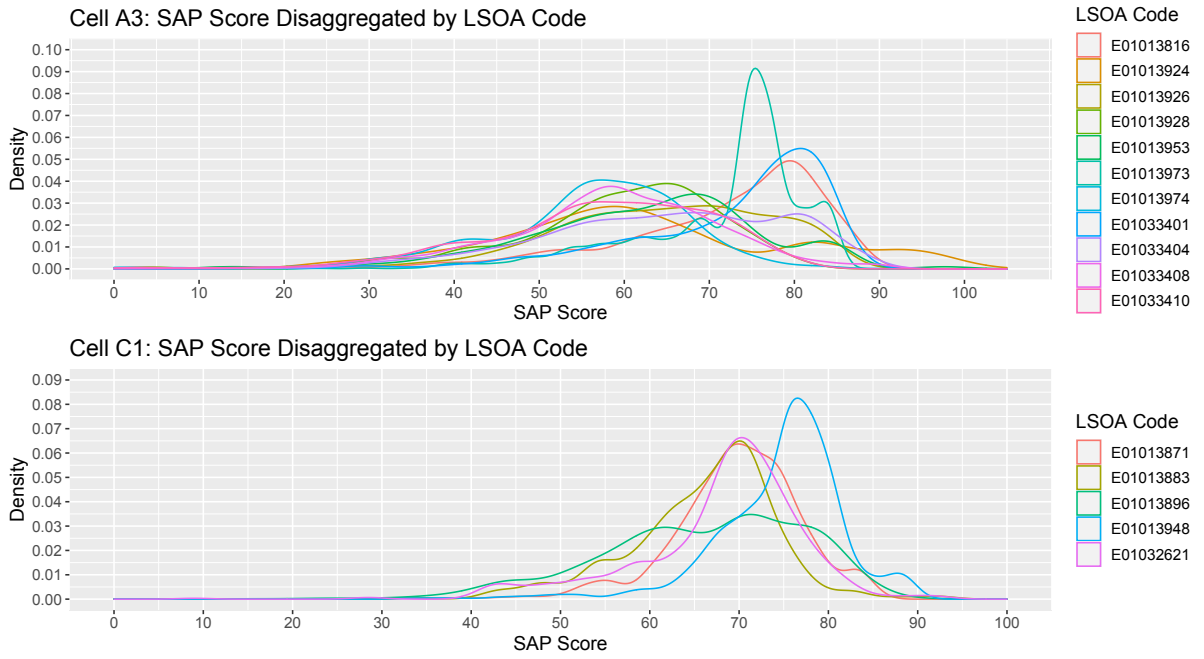


Figure 3-5. Density plots showing distribution of SAP scores in outlying Nottingham LSOAs (DLUHC, 2023a)

Another potentially relevant consideration is the tenure status of homes in outlying LSOAs. Tenure status is of interest, given that it is often a strong indicator of occupants' financial security. Owner-occupied homes tend to be relatively financially secure and at lower risk of fuel poverty, whereas the opposite is true for socially and privately rented properties (Boardman, 2009; ONS, 2023b). Table 3-5 shows tenure status for homes in the outlying Nottingham LSOAs. Strikingly, the rate of socially rented properties is very high in cell C1 LSOAs (66.45%). This is potentially cause for

concern, since a sizeable majority of homes designated as cell C1 (low fuel poverty, high deprivation) are also socially rented, which is essentially a proxy for financial insecurity. As also shown in Figure 3-5, it seems probable that the LILEE definition undercounts fuel poverty in cell C1 LSOAs due to the relatively high energy efficiency of homes in these areas; however, the evident financial insecurity and high rate of social housing in these LSOAs are largely overlooked in fuel poverty statistics. This is an especially counterproductive quality of the LILEE approach, particularly as various local authorities in England have justifiably focused on upgrading the energy efficiency of their social housing stocks in recent years (REFS). As a result, housing decarbonisation at the local government level and national fuel poverty policy seem to contradict one another. Paradoxically, the drive to upgrade social housing to an EPC rating of C or above means that these homes are no longer represented in LILEE data, regardless of crucial occupant (e.g., income) and household (e.g., composition and energy costs) characteristics.

Table 3-5. Aggregate household tenure status in outlying LSOAs (DLUHC, 2023a)

Legend Code	Tenure status			
	Owner-occupied	**Privately rented**	**Socially rented**	**Unknown**
Cell A3 (n=14,197)	17.43%	59.27%	15.28%	8.02%
Cell C1 (n=5,141)	22.54%	7.45%	66.45%	3.56%
Nottingham (n=169,786)	31.18%	27.82%	35.45%	5.55%

Another notable trend in Table 3-5 is the pronounced rate of privately rented properties in cell A3 (high fuel poverty, low deprivation). This potentially corroborates the earlier claim that cell A3 LSOAs are those with relatively high student populations and contradictory deprivation scores, due to the component-based approach of IMD. It is also the case that students are less likely to own property or be eligible for social housing.

3.3. Results, Part II: The estimation of financially vulnerable homes omitted from LILEE statistics

This section estimates the number of financially vulnerable, EPC A–C rated homes in Nottingham and London that are omitted from LILEE statistics by default. This exercise demonstrates the potential scale at which LILEE underestimates cases of fuel poverty in low-income homes with relatively high energy efficiency. The estimation process, as previously defined in Figure 3-1, is based on EPC, tenure status and the economic activity of the household reference person (HRP), i.e., the household's highest earner (DLUHC, 2023b). First, the number of EPC A–C rated properties in London and Nottingham was calculated. There is a total of 3,864,247 lodged EPCs

in London, and 1,819,012 (47.1%) have an EPC rating of A–C, meaning the vast majority of these homes are considered *not fuel poor* by default under LILEE[8]. In Nottingham, the smaller of the two cities, there are 169,786 lodged EPCs, 66,651 (39.3%) of which are rated A–C. Second, the proportion of EPC A–C rated properties that are socially or privately rented was calculated (see Table 3-6). These homes typically have lower incomes (ONS, 2022d) and are more likely to experience energy insecurity than other tenures (ONS, 2023b); hence, they are of primary interest in this section. Interestingly, a higher proportion of socially rented homes had EPC ratings A–C (20.2% in London and 44.8% in Nottingham) than among EPC D–G properties (15.6% and 30.1% in London and Nottingham, respectively). This highlights a further potential oversight of the LILEE approach, as living in a socially or privately rented property is a well-established fuel poverty risk factor (Boardman, 2009; ONS, 2023b). The third step of the estimation utilises EHS data (DLUHC, 2023b) to determine the typical economic activity of HRPs in socially and privately rented properties (see Table 3-7). This step focuses exclusively on households where HRPs are *unemployed* or *economically inactive*[9], as many of these households are likely to be heavily dependent on benefits as their main source of income (ONS, 2022d). *Economically inactive* is defined as "*people not in employment who have not been seeking work within the last 4 weeks and/or are unable to start work within the next 2 weeks*". This distinction versus being *unemployed* (i.e., not employed but actively seeking work) is important, as a significant proportion of those who are economically inactive have a disability or long-term illness preventing them from working, a risk factor which has also been associated with fuel poverty and energy insecurity (Boardman, 2009; Hernandez, 2016; Snell, et al., 2015).

Table 3-6. Tenure status among EPC A–C rated properties in London and Nottingham (DLUHC, 2023a)

Tenure	London A–C subset (n=1,819,012)	Nottingham A–C subset (n=66,651)
Owner-occupied	494,394 (27.2%)	12,461 (18.7%)
Privately rented	516,731 (28.4%)	17,372 (26.1%)
Socially rented	367,786 (20.2%)	29,833 (44.8%)
Unknown	440,101 (24.2%)	6,985 (10.5%)

Table 3-7. Typical economic status of HRP per tenure type, according to EHS (DLUHC, 2023b)

Economic status of HRP	Proportion of tenure type (%)	
	Socially rented	Privately rented
Full-time work	28.5%	66.1%
Part-time work	14.8%	11.4%

[8] Note: as previously discussed, the LILEE definition strictly uses an FPEER criterion; however, EPC ratings are equivalent in the majority of cases, and household-level FPEER ratings are not publicly available and cannot be accounted for in these estimations.
[9] In reality, a proportion of people in each economic status category in *Table 3* are likely to be in receipt of some form of benefits; however, a lack of granular income data makes these proportions hard to calculate. As a result, we do not focus on those who work part- or full-time, are retired or are in full-time education.

Retired	25.5%	6.8%
Unemployed	7.9%	3.6%
Full-time education	1.3%	3.8%
Economically inactive	21.9%	8.3%

In London, there were an estimated 29,055 HRPs[10] who were unemployed and a further 80,545 who were economically inactive in EPC A–C rated social homes. Among privately rented properties, 18,602 HRPs were unemployed and 42,889 were economically inactive. Collectively, 171,091 households in London have an EPC rating of A–C, where the HRP is either unemployed or inactive. This accounts for 9.4% of London's EPC A–C rated properties and 4.4% of the city's entire stock. The equivalent figures for Nottingham were as follows: approximately 2,357 and 6,533 HRPs were unemployed or economically active, respectively, and living in a home with an EPC rating of A–C; among privately rented, EPC A–C-rated homes, it was estimated that 625 HRPs were unemployed and 1,442 were inactive. The sum of Nottingham homes fitting the description of EPC A–C rated, socially or privately rented and with an unemployed or economically inactive HRP was 10,957, or around 6.5% of the city's total stock. It is highly likely that the majority of these instances, ~171,000 homes in London and ~11,000 in Nottingham, if not more, are currently deemed *not fuel poor* by default, given the LILEE definition's questionable measurement criteria.

These estimations provide some level of insight into the LILEE definition's underestimation of fuel poverty in low-income, high energy efficiency homes; however, the findings should be interpreted with a degree of caution. It is possible, for example, that some of the omitted households are able to rely on savings or external income sources to afford energy, whilst the estimation process suffers several unavoidable limitations, as acknowledged in the methods. Nevertheless, living in a privately or socially rented property, and having a low income, has consistently been linked to both a higher risk of fuel poverty (Belaïd, 2018; Boardman, 2009) and energy insecurity (ONS, 2023b).

3.4. Discussion of results

The findings presented in this chapter provide initial evidence of the LILEE definition's measurement deficiencies. The bivariate spatial analysis visualised and contextualised cases where LSOA-level fuel poverty and deprivation statistics were surprisingly disparate. Moreover, the nature of these outlying cases—with high fuel poverty and low deprivation (cell A3), and low

[10] Calculated as follows: $\left({}^{No.\ socially\ rented\ EPC\ A-C\ homes}/_{100}\right) * Proportion\ of\ tenure\ unemployed$

fuel poverty and high deprivation (cell C1)—was explored in greater detail through the post hoc analysis of sociodemographic and EPC data. The findings of this analysis point to a fundamental flaw in the LILEE approach, one that appears to assign cardinal importance to household energy efficiency, while neglecting other relevant occupant and household characteristics. The spatial analysis is caveated such that Marchand et al. (2019) have previously found disparities between 10% fuel poverty and IMD, suggesting that this type of disparity is not necessarily specific to LILEE.

To reinforce the findings of the bivariate mapping analysis, a rough estimation of the financially vulnerable, EPC C-rated (or higher) properties that are omitted by LILEE statistics by default was also provided in the case cities. Specifically, homes that were socially or privately rented with unemployed or economically inactive HRPs were considered to be financially vulnerable in this instance. A considerable number of households across Nottingham (n=10,957, 6.5%) and London (n=171,091, 4.4%) were found to meet this description (i.e., omitted from LILEE statistics, an EPC rating of C or above, socially or privately rented, and with unemployed or economically inactive occupants). The omission of these homes is further evidence that the LILEE fuel poverty definition cannot accurately quantify fuel poverty in all low-income homes, corroborating the findings of the spatial analysis. The estimations produced by this analysis are also likely to be conservative, given that many households whose main earner is retired or in full-time education are also likely to be economically precarious in reality.

3.5. Conclusions, policy implications and limitations

This chapter evidenced potential shortcomings of the LILEE fuel poverty definition via spatial and estimation-based analyses. The findings of both analyses indicated that some low-income homes are likely to be overlooked by the LILEE fuel poverty definition, as a result of the EPC/FPEER criterion. The findings of both analyses were consistent in terms of showing that the LILEE definition is likely to underestimate fuel poverty in low-income homes with relatively high energy efficiency. However, the granularity of the data used in both analyses (i.e., LSOA-level data) meant that a more precise estimation of the homes deemed *not fuel poor* by LILEE, who, based on the findings in this chapter, are likely to be *fuel poor* according to other definitions, was not possible. To address the limitations of the results presented in this chapter, **Chapter 4** critiques the LILEE definition via the analysis of survey data, providing a more complete analysis of the homes that may be wrongly omitted from fuel poverty statistics.

Chapter 4: An Empirical Critique of the LILEE Definition (Case Study II): Household Energy Security Survey

> *Poverty is not a character failing or a lack of motivation. Poverty is a shortage of money.*
>
> Barbara Ehrenreich

The purpose of this chapter is to provide further empirical evidence of the LILEE definition's measurement deficiencies via the collection and statistical analysis of survey data. The survey, which was deployed among London residents during the winter of 2022, gauged subjective fuel poverty (also referred to as *household energy security*) through a standardised scale: the *Residential Energy Consumption Survey* (RECS). The analysis of subjective fuel poverty rates elucidated the degree to which fuel poverty is currently underestimated by the LILEE definition and also provided insights into the sociodemographic features of London residents that were associated with energy insecurity (i.e., the self-reported inability to afford sufficient energy services in the home)[11]. As such, the primary aim of this chapter was to provide further evidence that the LILEE definition underestimates fuel poverty in low-income, high efficiency homes, as also demonstrated in **Chapter 3,** and, crucially, to allow a more accurate estimate of the LILEE definition's underestimation of fuel poverty based on primary survey data. In terms of the thesis's research questions, this chapter contributes further evidence to *Research Question A*:

Given the LILEE definition's universal omission of energy-efficient households, is fuel poverty (i.e., the actual ability of occupant(s) to afford adequate energy) currently underestimated in England, and if so, to what extent?

And *Research Question B*:

What are the salient determinants of subjective fuel poverty during a cost-of-living crisis?

[11] The findings of **Chapter 4** contributed to the following article: An Empirical Critique of the Low Income Low Energy Efficiency Approach to Measuring Fuel Poverty. *Energy Policy*.

R code describing the statistical analysis of the survey data, in particular the development of a random parameters ordered probit model, is included in the thesis's associated GitHub repository (see: https://github.com/torransemple/thesis_supplementary_material/tree/main/Chapter_4).

4.1. Data and methods

A survey was disseminated among London-based users of OLIO (a mobile app where users share food and household items) and was active from 22nd November 2022 to 5th December 2022. The household energy security (or subjective fuel poverty) scores of respondents were collected using the 2015 Residential Energy Consumption Survey (RECS) scale, which was originally developed by the *US Energy Information Administration* (EIA); see EIA (2015). The RECS 2015 survey questions, which are displayed in full in Table 4-1 (Harker Steele & Bergstrom, 2021), capture a broad range of experiential data that describe various aspects of domestic energy affordability, housing quality, arrears on utility bills and trade-offs between energy and other necessities (i.e., food).

Table 4-1. RECS questions contributing to household energy security score (Harker Steele & Bergstrom, 2021)[12]

Question No.	Question text	Response scale	
1	In the past year, how frequently did your household reduce or forego expenses for basic household necessities, such as medicine or food, in order to pay an energy bill?	i. ii. iii. iv.	Never (0) 1 or 2 months (0) Some months but not every month (1) Almost every month (1)
2	In the past year, how frequently did your household keep your home at a cold temperature that you felt was unsafe or unhealthy?	i. ii. iii. iv.	Never (0) 1 or 2 months (0) Some months but not every month (1) Almost every month (1)
3	In the past year, how frequently did your household run behind on payments for energy bills, or receive a notice to disconnect?	i. ii. iii. iv.	Never (0) 1 or 2 months (0) Some months but not every month (1) Almost every month (1)
4	In the last year, was there ever a time your household was unable to use your main source of heat because you could not afford to pay for gas or electricity?	i. ii.	Yes (1) No (0)
5	About how many days over the past year has your household gone without heat because you could not afford to pay for gas or electricity?	i.	No. of days (1 if >=36, 0 if otherwise)
6	In the last year, was there ever a time your household was unable to use your main source of heat because the equipment was broken, and you couldn't afford to pay to repair or replace the equipment?	i. ii.	Yes (1) No (0)
7	In the past year, did anyone in your household need medical attention because your home was too cold?	i. ii.	Yes (1) No (0)

[12] Note: numerical values in parentheses in the *response scale* column correspond to assumed value in Equation 4.1.

Each of the questions in Table 4-1 contributed to a composite household energy security (CHES) score per respondent, i, which can be written in mathematical notation as follows:

$$CHES_i = \sum_{j=1}^{7} Q_{j,i} \tag{4.1}$$

Where $Q_{j,i}$ is a numerical value of 0 or 1 based on the *response scale* column in Table 4-1, and CHES is the score achieved by the responses of each individual to the RECS questionnaire. In simple terms, a higher CHES score indicates higher energy *insecurity* (or subjective fuel poverty), whereas a zero or low score indicates relative security. Although it would be informative to analyse the RECS questions independently, the goal of this analysis is to compare LILEE fuel poverty (which is binary: 1 = *fuel poor*, 0 = *not fuel poor*) and household energy security in the surveyed sample. As a result, the CHES score was aggregated further, initially to four qualitative levels: very low energy security (Y=1); low energy security (Y=2); marginal energy security (Y=3); and high energy security (Y=4), which was deemed the optimal format for the subsequent statistical analysis. Further, household energy security was also aggregated further to a binary outcome to facilitate comparisons with LILEE statistics. Considering the four-level version of household energy security (HES) per individual, i, the assignment of respondents to each level (Y=1 to Y=4), based on the CHES score in *Equation 4.1*, can be written as:

$$HES_i = \begin{cases} High\ energy\ security\ (Y = 4) \quad if\ CHES_i = 0 \\ Marginal\ energy\ security\ (Y = 3) \quad if\ CHES_i = 1 \\ Low\ energy\ security\ (Y = 2) \quad if\ 2 \leq CHES_i \leq 4 \\ Very\ low\ energy\ security\ (Y = 1) \quad if\ 5 \leq CHES_i \leq 7 \end{cases} \tag{4.2}$$

The binary version of household security was achieved by simply aggregating *marginal* and *high* HES outcomes as *energy secure* and *low* and *very low* HES outcomes as *insecure*. As well as gauging energy security, the survey also collected sociodemographic (e.g., age, gender, household income and household characteristics), behavioural (e.g., food and energy consumption habits, and reliance on family, friends or charities) and perceptual characteristics (e.g., life satisfaction and financial anxiety) of the respondents. As discussed in the literature (Dutwin & Buskirk, 2023; Chambers, et al., 2022), the deployment of the survey via a mobile app could lead to certain demographics being excluded. Chambers et al. (2022), for example, raise the potential digital exclusion of certain individuals or households given the growing digitalisation of the energy market (e.g., smart meters and other internet-dependent services). Similarly, it is possible that households with no internet access, or simply those who are late adopters of digital technologies, were not able to be reached in the current survey. In any case, the survey sample was highly

representative of London in terms of socioeconomic status, as discussed further below; therefore, the degree of digital exclusion related to affordability is at least partially controlled for in the survey sample.

In total, the survey received 2,886 responses; however, the number of complete observations (those that could be used in the statistical analysis) was 2,170. The survey sampling strategy involved the application of quota restraints for socioeconomic status (informed by the IMD score of respondents' home area, according to Lower Super Output Areas (LSOAs)). Figure 4-1 shows the distribution of LSOA IMD deciles for the survey sample versus London, indicating that the survey sample was highly representative in terms of LSOA IMD deciles (1=most deprived; 10=most affluent). It is worth commenting on the slight right skew present in the survey sample and across London, with the exception of the first decile. The high proportion (>10%) of London LSOAs in the second, third and fourth deciles suggests that many London residents live in LSOAs with higher-than-average IMD scores; however, the significant underrepresentation of decile one shows that, despite this, London residents rarely live in LSOAs that are in the most deprived 10% of English LSOAs. This reiterates the socioeconomic heterogeneity that London is known for.

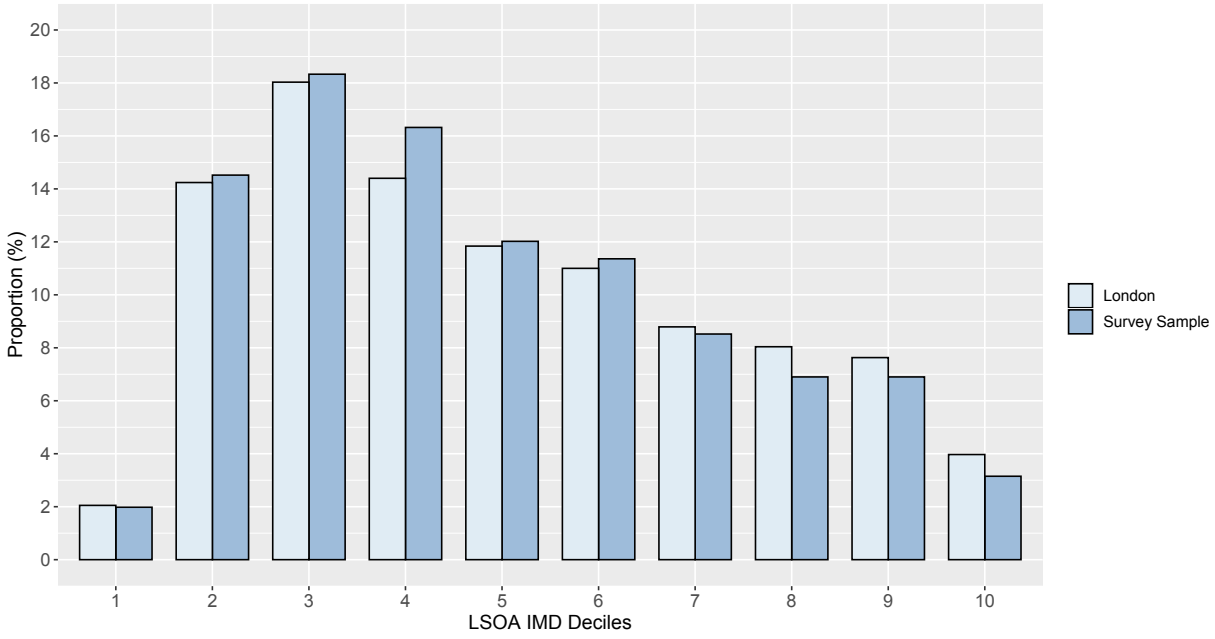


Figure 4-1. Proportion of London and survey sample respondents' LSOA IMD deciles (where 1=most deprived decile and 10=most affluent) (n=2,886)

Methods: Statistical modelling approach

A discrete outcome modelling framework was adopted to investigate the factors influencing household energy security (i.e., HES, as previously defined in *Equation 4.2*) in London[13]. Discrete outcome models are used when the dependent variable in question is discrete (i.e., not continuous) (Washington, et al., 2020). In this case, the dependent variable (Y) had four discrete, ordered outcomes: (Y=1) very low energy security; (Y=2) low energy security; (Y=3) marginal energy security; and (Y=4) high energy security. For ordinal dependent variables, the Fixed Parameters Ordered Probit (FPOP) framework was deemed most appropriate. Random parameters, which allow for the potential effects of unobserved heterogeneity (i.e., unobserved characteristics of the respondents not recorded in the survey) to be accounted for, were also trialled in the modelling framework; hence, the modelling framework is referred to as the Random Parameters Ordered Probit (RPOP) from hereon. Previous studies have shown that accounting for unobserved heterogeneity in discrete outcome models can achieve significantly higher explanatory power than fixed parameters approaches (Fountas, et al., 2021; Mannering, et al., 2016). The modelling framework employed echoes the approach in Washington et al. (2020). An ordered probit model is derived by defining a latent variable (z), typically specified as a linear function per observation (z_n), as follows:

$$z_n = \boldsymbol{\beta}\mathbf{X}_n + \varepsilon\,, \tag{4.3}$$

Where $\boldsymbol{\beta}$ is a vector of estimable parameters, $\mathbf{X}$ denotes a vector of independent variables dictating the discrete ordering per observation, n, and ε is a random disturbance term, which is assumed to be normally distributed across observations (with mean = 0 and variance = 1). The ordered outcomes, y, for each observation are defined as:

$$\begin{aligned} &y = 1 \text{ if } z \leq \boldsymbol{\mu}_0 \\ &y = 2 \text{ if } \boldsymbol{\mu}_0 < z \leq \boldsymbol{\mu}_1 \\ &y = \text{" ..."} \\ &y = I \text{ if } z \geq \boldsymbol{\mu}_{I-1}\,, \end{aligned} \tag{4.4}$$

Where $\boldsymbol{\mu}_I$ are estimable parameters (i.e., thresholds) that explain y, which correspond to levels of the ordered dependent variable (i.e., household energy security outcomes). The thresholds, $\boldsymbol{\mu}_I$, are estimated in conjunction with model parameters, $\boldsymbol{\beta}$. The main objective of model estimation then becomes determining the probability of I for each observation, n. Given the previously assumed distribution of ε, and that $\boldsymbol{\Phi}$ denotes the cumulative normal distribution, the resulting ordered selection probabilities are as follows:

[13] Note: R code to reproduce the energy security model is in 'CH4_energy_security_model.Rmd' of the thesis's associated GitHub repository (see **Chapter 4** folder).

$$
\begin{aligned}
P(y=1) &= \boldsymbol{\Phi}(-\boldsymbol{\beta}\mathbf{X}) \\
P(y=2) &= \boldsymbol{\Phi}\left(\boldsymbol{\mu}_1 - \boldsymbol{\beta}\mathbf{X}\right) - \boldsymbol{\Phi}(-\boldsymbol{\beta}\mathbf{X}) \\
P(y=3) &= \boldsymbol{\Phi}\left(\boldsymbol{\mu}_2 - \boldsymbol{\beta}\mathbf{X}\right) - \boldsymbol{\Phi}(\boldsymbol{\mu}_1 - \boldsymbol{\beta}\mathbf{X}) \\
P(y=4) &= 1 - \boldsymbol{\Phi}\left(\boldsymbol{\mu}_2 - \boldsymbol{\beta}\mathbf{X}\right), \qquad (4.5)
\end{aligned}
$$

To allow for random parameters within the ordered probit framework, the estimable parameters are written as follows:

$$\boldsymbol{\beta}_n = \boldsymbol{\beta} + \boldsymbol{\omega}_n, \qquad (4.6)$$

Where, $\boldsymbol{\beta}_n$ is a vector of estimable parameters that may vary across observations, *n*, $\boldsymbol{\beta}$ is the vector of mean parameter estimates across the dataset and $\boldsymbol{\omega}_n$ is a vector of randomly distributed terms (normally distributed with mean = 0 and variance = σ^2). Due to the complexity of calculating the ordered selection probabilities (*Equation 4.5*), a simulation-based maximum likelihood is used for model estimation (Washington, et al., 2020). Halton draws are often considered a more effective alternative to random draws (Halton, 1960) and are thus employed here. The selection of independent variables in the final model was justified via the Akaike Information Criterion (AIC). A lower AIC is indicative of relatively superior model performance and is used in this case to justify the assumption that the inclusion of random parameters in the ordered modelling framework provides higher explanatory power.

Following the RPOP model estimation, average marginal effects are calculated for each independent variable. Average marginal effects quantify the change in the probability of each household energy security outcome given a unit change in the independent variable. In simple terms, the computation of average marginal effects makes the model estimation results more interpretable and provides more information concerning the interior categories (Y=2 and Y=3) of household energy security.

4.2. London survey data: An exploratory data analysis

Initially, an exploratory analysis of the London survey data was conducted. As previously defined in Table 4-1, the dependent variable for this analysis (household energy security—*HES*) was determined by a range of questions, including trade-offs with other essential expenses (e.g., food and medicine); the inability to maintain adequate household temperature because of affordability or lack of access to heating equipment; and how often the respondent has fallen behind on energy bill payments. The distribution of household energy security disaggregated by the IMD score of the respondents' residence is displayed in Figure 4-2. To simplify this visualisation, IMD deciles

have been aggregated to *deprived* (deciles 1–3), *middling* (4–7) and *affluent* (8–10). Among the survey respondents, household energy security was *very low* for 3.6%, *low* for 24.6%, *marginal* for 18.9% and *high* for 52.9%. Interestingly, several respondents who reside in middling or affluent LSOAs were still deemed to have very low or low energy security. This may be the result of income heterogeneity within LSOAs, as some low-income households are likely still present in middling and affluent areas; alternatively, this trend may indicate that rising energy costs are affecting many households regardless of socioeconomic status. To explore the relationship between household energy efficiency and energy security, Figure 4-3 shows the distribution of respondents' household EPC ratings disaggregated by household energy security. 915 respondents (approximately a third of the sample) reported their home's EPC rating. As discussed throughout, the LILEE fuel poverty definition omits EPC A–C rated households on the basis that they are too energy efficient to be considered fuel poor. However, Figure 4-3 highlights that there is still a considerable likelihood of the occupant(s) experiencing low or very low energy security, even in EPC A–C-rated homes, which casts doubt on the logic underpinning LILEE's energy efficiency-based criterion.

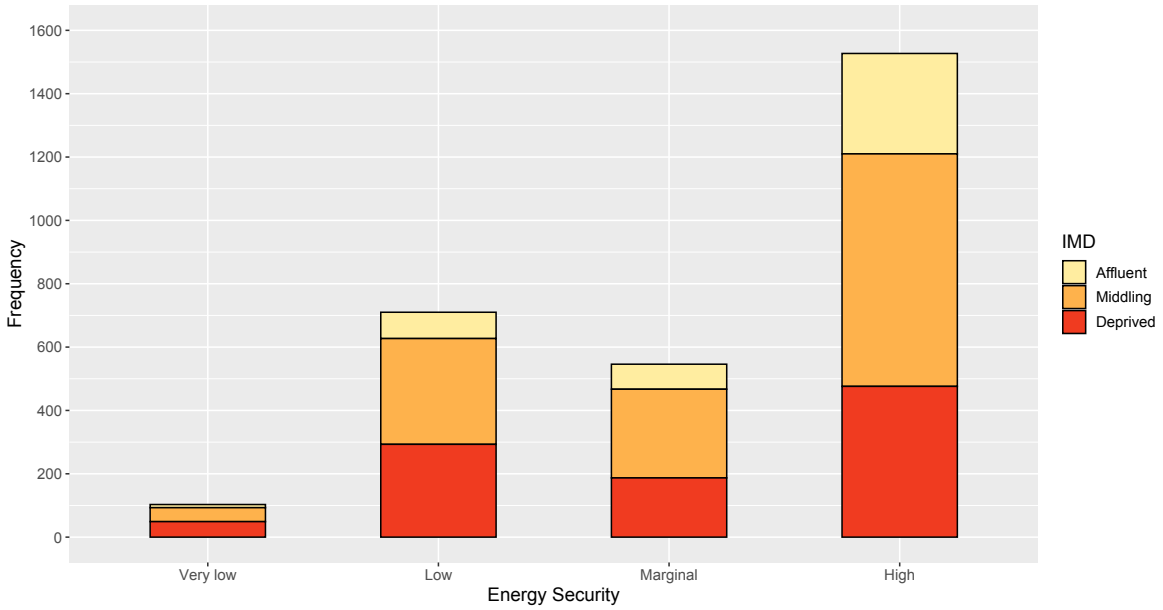


Figure 4-2. Distribution of survey respondents' household energy security disaggregated by LSOA IMD (n=2,886)

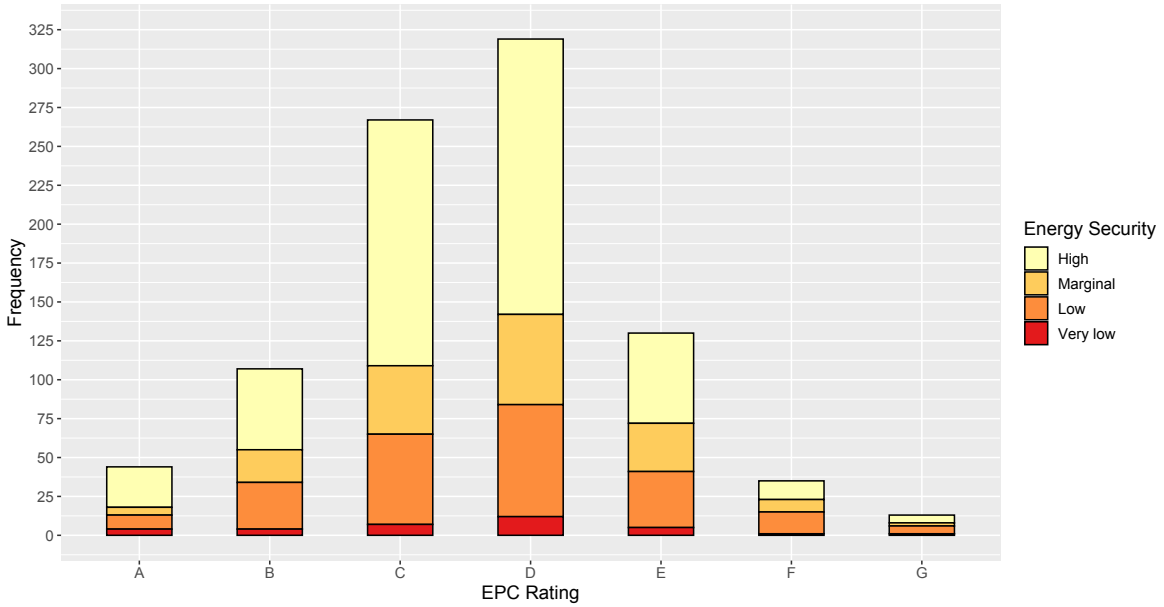


Figure 4-3. Distribution of EPC-known survey respondents' household EPC rating disaggregated by household energy security (n=915)

To facilitate comparisons between household energy security scores in the survey sample and LILEE fuel poverty statistics, Table 4-2 displays the proportion of respondents deemed to be *energy secure* or *energy insecure* per EPC rating. The binarization of household energy security is less detailed than the original four-level scale and is likely to induce a degree of aggregation bias; however, in this case, this was a necessary step in enabling comparisons with LILEE fuel poverty statistics, which are also binary (*fuel poor* or *not fuel poor*). Amongst respondents who live in an EPC A–C rated property, 26.8% were energy insecure (very low or low), which is slightly lower than the equivalent figure for EPC D–G rated properties (29.4%). This suggests that energy efficiency may play a modest role in decreasing the likelihood of household energy insecurity.

Critically, a two-sample t-test was performed to test whether the rate of binary energy security differed significantly between EPC A–C and D–G properties. The test produced a statistically insignificant p-value of 0.39 (critical value=0.05); therefore, there was not sufficient evidence to reject the null hypothesis (H_0)—that the population means (i.e., rate of energy insecurity) are equal in EPC A–C and D–G-rated homes (H_0: $\mu_1=\mu_2$). In simple terms, the rate of household energy security in EPC A–C and D–G households was not dissimilar. This amounts to further evidence that the LILEE definition overstates the influence of household energy efficiency on fuel poverty.

Table 4-2. Binary household energy security versus EPC rating among EPC-known survey respondents (n=915)

EPC rating	Energy insecure		Energy secure	
	Frequency	% of group	Frequency	% of group
A (n=44)	13	29.55%	31	70.45%
B (n=107)	34	31.78%	73	68.22%
C (n=267)	65	24.34%	202	75.66%
D (n=319)	84	26.33%	235	73.67%
E (n=130)	41	31.54%	89	68.46%
F (n=35)	15	42.86%	20	57.14%
G (n=13)	6	46.15%	7	53.85%
Total (n=915)	258	28.20%	657	71.80%

Moreover, the combined prevalence of *very low* and *low* energy security across the sample (28.2%) was around two and a half times higher than the LILEE fuel poverty rate in London (11.5%) (DESNZ, 2023b). Initially, this finding may seem surprising, given that research has previously found fuel poverty estimates to be higher than the actual rate of those struggling to afford energy (Kearns, et al., 2019). While a conflict with previous results is possible, another plausible explanation is that the LILEE definition significantly underestimates the true rate of fuel poverty due to its omission of EPC A–C rated properties; thus, an artificial gap between the fuel poverty rate in London and the rate of household energy insecurity among the respondents is produced. The following section (4.3) builds on this evidence by statistically analysing the survey data and exploring the sociodemographic, behavioural and perceptual factors impacting the energy security of survey respondents.

4.3. Results: A statistical analysis of household energy security in London

This section presents the RPOP model estimation results for the exploration of factors affecting household energy security among the London survey respondents. Table 4-3 lists the independent variables that were included in the final model[14]. Each independent variable was structured as a binary indicator, as per the parenthetical comments in the *variable description* column, while the *descriptive statistics* column describes the proportion of the indicator group (1) with respect to the remaining control group (0). An example interpretation is as follows: for the variable 'physical or mental health condition (1 if yes, 0 if no)', 18.39% of the survey respondents have a physical or mental health condition (i.e., the indicator group), while the remaining 81.61% (the control group) do not.

[14] Although the final model contains the most influential combination of independent variables, some relevant variables were omitted to control for multicollinearity (i.e., a strong linear relationship between two or more independent variables). To account for collinearity, no independent variables with paired correlation coefficients > 0.3 (or less than –0.3) were included in the same model.

Table 4-3. Descriptive statistics for influential independent variables

Variable Description	Descriptive statistics (%)
Sociodemographic characteristics	
Physical or mental health condition (1 if yes, 0 if no)	18.39%
Household income (1 if less than £14,900 per year, 0 otherwise)	20.05%
Age (1 if under 25, 0 otherwise)	9.08%
Age (1 if 25 to 34, 0 otherwise)	31.00%
Energy payment method (1 if prepayment meter, 0 if otherwise)	25.81%
Behavioural & perceptual characteristics	
Social connection (1 if relied on neighbours for food in the last year, 0 otherwise)	11.15%
Social connection (1 if relied on a community/faith group for food in the last year, 0 otherwise)	11.43%
Social connection (1 if relied on family and friends for food in the last year, 0 otherwise)	23.59%
Social reliance (1 if relies on family and friends to a large extent for help, 0 otherwise)	41.24%
Foodbank use (1 if used in the last 12 months, 0 otherwise)	11.57%
Food purchasing habits (1 if never avoids raw food, 0 otherwise)	57.05%
Financial anxiety (1 if worries about housing payments almost every month, 0 otherwise)	15.12%
Life satisfaction (1 if high/very high satisfaction, 0 otherwise)	45.20%

Table 4-4 displays the RPOP model estimation results, accompanied by average marginal effects. The results show that five sociodemographic and eight behavioural or perceptual characteristics significantly influenced respondents' likelihood of experiencing household energy security. The independent variables presented in the final model were selected using an iterative, forward stepwise selection algorithm (based on minimisation of AIC) capability of the *MASS* package in R (Venables & Ripley, 2002), while the final model was estimated using the *Rchoice* package (Sarrias, 2020). Model coefficients in Table 4-4 can be interpreted as follows: an independent variable with a significantly positive coefficient indicates that the variable significantly increased the likelihood of the highest level of energy security (i.e., Y=4). Conversely, a significantly negative coefficient indicates increased likelihood of very low energy security (Y=1). The 't-stat' column indicates the level of statistical significance associated with each independent variable (where a t-stat>1.96 corresponds to p-value<0.05 and >95% level of confidence (l.o.c.)), in line with standard practice (Fountas, et al., 2021; Washington, et al., 2020).

A particularly beneficial aspect of the RPOP framework is that the potential effects of unobserved heterogeneity can be accounted for through the specification of certain independent variables as

random parameters. Three independent variables produced statistically significant random parameters (indicated by grey fill in Table 4-4): 'physical or mental health condition (yes)', 'age (under 25)' and 'social connection (relied on community/faith group)'. An example interpretation of the 'physical or mental health (yes)' variable is as follows: overall, those who have a physical or mental health condition are significantly more likely to have very low energy security when compared to those who do not have a health condition. However, this variable's specification as a random parameter suggests that household energy security levels are highly heterogeneous among those who do have a health problem, despite the overall negative direction of the variable's effect. A possible explanation may be that the variable erroneously combines respondents with different types of health conditions, when in reality, there are likely subgroups of distinct health conditions within the variable, some of which may have opposing effects on energy security.

Table 4-4 also presents the average marginal effects associated with each independent variable. In the case of binary independent variables, the marginal effects describe the change in the dependent variable (Y=1 to Y=4) given a one-unit change in the independent variable (i.e., from 0 to 1). Considering the 'physical and mental health condition' variable for example, the interpretation of this variable's average marginal effects is as follows: the presence of a health condition means the probability of very low energy security is 0.070 higher (on average), the probability of low security is 0.035 lower, the probability of marginal security is 0.023 lower, and the probability of high security is 0.012 lower. The magnitude of the average marginal effects can also provide insights into the relative importance of each variable.

Table 4-4. RPOP model estimation results: Factors affecting energy security

Variable Description	**RPOP model**		**Average marginal effects**			
	Coefficient	**t-stat**	**Y = 1**	**Y = 2**	**Y = 3**	**Y = 4**
Constant	2.570	21.251	–	–	–	–
Physical or mental health condition (1 if yes, 0 if no)	-0.266	- 3.511	0.070	-0.035	-0.023	-0.012
Standard deviation of parameter density function	*0.364*	*1.807*	–	–	–	–
Household income (1 if less than £14,900 per year, 0 otherwise)	-0.433	-5.948	0.118	-0.064	-0.036	-0.018
Age (1 if under 25, 0 otherwise)	-0.251	-2.152	0.066	-0.033	-0.022	-0.012
Standard deviation of parameter density function	*0.523*	*2.210*	–	–	–	–
Age (1 if 25 to 34, 0 otherwise)	-0.122	-1.977	0.031	-0.014	-0.011	-0.007
Energy payment method (1 if prepayment meter, 0 if otherwise)	-0.334	-5.192	0.089	-0.045	-0.029	-0.015

Social connection (1 if relied on neighbours for food in the last year, 0 otherwise)	-0.220	-2.455	0.058	-0.028	-0.019	-0.011
Social connection (1 if relied on a community/faith group for food in the last year, 0 otherwise)	-0.200	-2.156	0.053	-0.025	-0.018	-0.010
Standard deviation of parameter density function	*0.451*	*2.168*	–	–	–	–
Social connection (1 if relied on family and friends for food in the last year, 0 otherwise)	-0.272	-4.047	0.072	-0.035	-0.024	-0.013
Social reliance (1 if relies on family and friends to a large extent for help, 0 otherwise)	0.468	7.545	-0.124	0.055	0.045	0.024
Foodbank use (1 if used in the last 12 months, 0 otherwise)	-0.520	-5.489	0.142	-0.082	-0.041	-0.019
Food purchasing habits (1 if never avoids raw food, 0 otherwise)	0.895	14.665	-0.268	0.163	0.074	0.032
Financial anxiety (1 if worries about housing payments almost every month, 0 otherwise)	-0.923	-11.025	0.265	-0.178	-0.061	-0.026
Life satisfaction (1 if high/very high satisfaction, 0 otherwise)	0.267	4.499	-0.070	0.031	0.025	0.014
Threshold 1	2.010	20.218	_	_	_	_
Threshold 2	2.802	25.232	_	_	_	_
Observations	2170		_	_	_	_
Log-likelihood with constant only (LLc)	-2430		_	_	_	_
Log-likelihood at convergence (LL0)	-1805		_	_	_	_
$AIC_{CONSTANT}$	4866		_	_	_	_
AIC at convergence (AIC_{RPOP})	3648		_	_	_	_

Energy security model: Sociodemographic factors

The model estimation results showed that five sociodemographic variables significantly influenced energy security. The presence of a prepayment meter within the home was treated as a sociodemographic variable, given that use is often not the choice of the occupant and rather a consequence of household characteristics or low income (Burlinson, et al., 2022). Respondents with prepayment meters were significantly more likely to have very low energy security than those who pay in other ways. Prepayment customers are often charged a higher rate per unit of fuel in comparison to households that pay monthly (Boardman, 2009; Burlinson, et al., 2022), further increasing the likelihood that these households are unable to afford energy. It is also well

documented that prepayment customers are more likely to be fuel poor than non-prepayment households, regardless of the fuel poverty definition in question (Boardman, 2009).

Two age-related variables were also influential; those aged under 25 and 25–34 were significantly more likely to have very low energy security than their respective control groups (all other ages). A likely explanation is that younger adults tend to have lower household income and are more likely to live in privately rented accommodation than older adults (DLUHC, 2023b). Relatedly, the ONS (2023b) recently found that renters are several times more likely to suffer energy insecurity than those who own their home outright. Significant heterogeneity was discovered among "under 25" respondents, suggesting that although the overall effect of this variable was negative (increased likelihood of energy *insecurity*), in some cases, the variable has the opposite effect (increasing energy *security*). This is likely due to the misclassification of under 25s as a homogeneous group, as there are likely various exogenous factors (e.g., demographic or behavioural characteristics not recorded in the survey) that create subgroups of under 25 respondents and their experiences of energy security in practice. One such subgroup might be delineable via employment status. Among under 25 respondents, 40.8% were students, and the rate of energy insecurity (very low or low) among this group was 29.9%; conversely, a larger proportion of non-student under 25s were energy insecure (40.0%). The rate of energy insecurity among students aged under 25 is not considerably higher than the rate across the whole sample (28.2%), which suggests that heterogeneity within the under 25 variable could be a result of the student contingent. Past research has shown that young adults who grow up in affluent areas are more likely to participate in higher education (Richardson, et al., 2020), with some under 25 students potentially more able to rely on familial wealth and subsequently less likely to suffer energy insecurity than non-student under 25s.

Respondents with a physical or mental health condition were significantly more likely to experience very low energy security than those with no health conditions, further evidencing prior observation of this relationship (Boardman, 2009; Kearns, et al., 2019; ONS, 2023b). The heterogeneous effects associated with this variable, however, are more novel and may be due to the conflation of physical and mental health conditions; for example, Kearns et al. (2019) previously found that those with mental health problems are particularly prone to fuel poverty. Care must be taken to consider the potential for reverse causality between physical or mental health conditions and energy insecurity, particularly since qualitative studies have evidenced that experiencing energy insecurity can exacerbate mental health problems (Hernandez, 2016). Finally, respondents with a household income of less than £14,900 per year were also significantly more likely to have very low energy security compared to other income groups. Given that the

RECS scale contains several questions related to respondents' actual ability to afford sufficient energy and spending trade-offs with other necessities, it is unsurprising that respondents from lower-income households are significantly more likely to have very low energy security. The link between income and energy security is a consistent theme in the literature (Belaïd, 2018; Memmott, et al., 2021; ONS, 2023b).

Energy security model: Behavioural and perceptual factors

Four independent variables gauging aspects of respondents' social connection or social reliance were found to significantly affect energy security. All three social connection variables—those who relied on either neighbours, a community/faith group, or family and friends for food—significantly increased the probability of very low energy security in comparison to their respective control groups (i.e., those who did not rely on these groups for food). This finding illustrates the complex and intertwined reality of poverty, as those who struggle to afford food at certain times throughout the year are also more likely to experience energy insecurity. Although general deprivation is a potential confounding factor, this is at least partially controlled for through the inclusion of the household income variable. The presence and directional effects of the social connection variables provide tentative evidence that many of the respondents are likely to have made involuntary food and energy trade-offs during the winter of 2022. Previous studies (Beatty, et al., 2014; Bhattacharya, et al., 2003) indicate that a substantial proportion of those relying on others for food have done so to afford energy during cold-weather shocks. However, due to the formulation of the variable in this case (gauging behaviour over 12 months), it remains uncertain whether seasonal trade-offs were being made by the respondents here. The final social variable ('social reliance') had the opposite effect, with respondents who "rely on family to a large extent for help" significantly more likely to have higher energy security than those who did not. A possible explanation is that those with the ability to rely on family to a large extent may also be more likely to receive financial assistance from family members to pay for necessities. The subjective nature of this variable should be noted, as respondents were asked to state the level of general "help" they receive from family members, which was likely interpreted in different ways.

Two variables describing food acquisition also proved influential. Intuitively, those who used a foodbank in the last 12 months were significantly more likely to have very low energy security. In contrast, respondents who never avoid raw food when shopping were significantly more likely to have high energy security. The foodbank variable follows a similar interpretation to the social connection variables, as those who rely on others for food are more likely to have limited disposable income, leading to trade-offs between necessities (Beatty, et al., 2014). The "never

avoids raw food" variable provides insight into the link between the energy costs associated with cooking food and energy insecurity. For example, the contingent that "never avoids raw food" may be relatively less concerned about the energy cost associated with cooking than those who avoid raw food sometimes or often; in other words, this variable may be a proxy for energy-saving habits that were not captured by other survey questions.

The remaining variables that were found to significantly influence the likelihood of household energy security were related to the wellbeing of respondents. The first measured financial anxiety, with those who worry about housing payments every month (i.e., most frequently compared to other outcomes) being significantly more likely to have very low energy security than those who worry less frequently. This finding reiterates the commonly observed relationship between poor mental health and energy insecurity (Boardman, 2009; Kearns, et al., 2019; ONS, 2023b). In this case, the financial anxiety variable likely serves as a proxy for financial vulnerability and precarity (Petrova, 2018). Similarly, those with high or very high perceived life satisfaction were significantly more likely to have high energy security than those with middling (neutral) or low life satisfaction. Both of these findings concur with recent research (ONS, 2023b) showing that those suffering depressive symptoms are significantly more likely to experience energy and food insecurity.

4.4. Discussion of results

The analysis of survey data in this chapter provides a more detailed assessment of the LILEE definition's shortcomings. First, an exploratory analysis of the survey data showed that ~27% of respondents in EPC A–C rated households were energy insecure—a figure only marginally less than among EPC D–G rated properties (~29%). The considerable proportion of EPC A–C rated properties experiencing energy insecurity indicates that improving building efficiency is not synonymous with eradicating energy insecurity or fuel poverty, as is tacitly implied by the LILEE definition's energy efficiency-centric measurement criteria. This finding demonstrates that omitting properties from fuel poverty statistics on the basis of household energy efficiency is unjustifiable from a household energy security perspective. Although the current analysis is generally framed in terms of the English approach to measuring fuel poverty, the finding that EPCs have little effect on household energy security is likely transferable to other countries with similar housing profiles and environmental conditions. Simply put, the findings suggest that measures of building energy efficiency should not be used as central criteria in fuel poverty classifications.

The prevalence of household energy insecurity among the London-based survey sample (~28%) was 145% higher than the London LILEE fuel poverty rate, highlighting the likelihood that LILEE is considerably underestimating the proportion of households struggling to afford energy. It is worth noting the recency of the survey data (collected in winter 2022) and the particular context of the data collection window. UK residents suffered rapid rises in inflation and energy prices, dwarfing price increases of recent times therefore it is likely that the rate of energy insecurity observed among the sample is likely to be higher than previous years. Following the exploratory data analysis, an RPOP model was estimated to show the sociodemographic, behavioural and perceptual characteristics of respondents that significantly increased the likelihood of energy security (or subjective fuel poverty). These included: being under the age of 34; the presence of a physical or mental health problem; low household income; and the use of a prepayment meter in the home. The remaining influential variables mostly concerned characteristics derived from food insecurity, social connection and mental wellbeing-related survey questions, and provided further understanding of the food versus energy trade-offs that financially vulnerable households are likely to make, as well as the mental toll associated with energy insecurity.

In summary, the exploratory and statistical analyses of the London survey data contributed several important findings concerning the validity of the LILEE definition. First, the gap between household energy security and LILEE fuel poverty statistics was quantified; second, the rate of household energy security was shown not to be significantly affected by EPC rating (i.e., considering A–C versus D–G-rated properties); and third, the RPOP model estimation results showed the respondent characteristics that increased or decreased energy security.

4.5. A further analysis of household energy security: The case of Broxtowe

The analysis of household energy security in London supported the thesis that the LILEE approach erroneously prioritises energy-efficiency-induced fuel poverty, leading to the underestimation of some low-income homes in fuel poverty statistics; however, the survey data may have been skewed by events in 2022, most notably, the cost-of-living crisis and rapidly rising consumer energy costs. To test this theory, this section presents a brief complementary analysis of household energy security survey data gathered in the UK borough of Broxtowe during the winter of 2024/2025. The main aim of this exercise was to reproduce the exploratory data analysis of household energy security using 2024/2025 data; specifically, this analysis facilitates the comparison of energy security and LILEE fuel poverty rates in a different region during a more recent period.

The Broxtowe *Household Energy Survey*, which also utilised the RECS scale (see Table 4-1), was disseminated among residents from 1st December 2024 to 1st February 2025, receiving 322 responses. The distribution of household energy security (as previously defined in *Equation 4.2*) is shown in Table 4-5. The distribution bears some resemblance to that previously observed in London (see Figure 4-2)[15]. In terms of binary household energy security, 79 respondents (approximately 24.5%) were energy insecure, which is around 80% higher than the rate of LILEE fuel poverty in Broxtowe (13.6%) (DESNZ, 2024a). Although the gap between LILEE fuel poverty and household energy security appears to be more modest in Broxtowe than in London, where household energy insecurity was 145% higher than the rate of fuel poverty, the general thesis is consolidated: the rate of LILEE fuel poverty tends to be considerably less than the rate of household energy insecurity or subjective fuel poverty.

Table 4-5. Distribution of household energy security in Broxtowe (n=322)

	Household Energy Security			
	Very low (Y=1)	**Low (Y=2)**	**Marginal (Y=3)**	**High (Y=4)**
Frequency (% in parentheses)	8 (2.5%)	71 (22.0%)	70 (21.7%)	173 (53.7%)

It should be noted that the Broxtowe survey did not follow the same LSOA-level IMD constraints as the London survey and is likely less representative of the broader population as a result. Regardless, the Broxtowe survey provides further evidence, albeit less rigorous than the London survey, of how household energy security rates compare to LILEE statistics.

4.6. Conclusions, policy implications, limitations and further research

This chapter presents further empirical evidence of the LILEE fuel poverty definition's likely measurement deficiencies, including the underestimation of fuel poverty in low-income homes with relatively low energy costs. The findings of the household energy security analysis in London raise serious concerns with the LILEE approach to measuring fuel poverty. Most notably, levels of household energy insecurity in the survey sample were considerably higher than the LILEE fuel poverty rate in London, begging the question as to why the LILEE definition does not accurately capture all households that are unable to afford energy. Further, energy security was not found to differ significantly between EPC A–C and EPC D–G-rated properties, casting substantial doubt on the rationale underpinning the omission of EPC A–C-rated households from fuel poverty statistics.

[15] Note: the precise distribution of household energy security in London was *very low* = 3.6%, *low* = 24.6%, *marginal* = 18.9% and *high* = 52.9%.

The way in which fuel poverty is measured has often been a politically contentious issue in England, as illustrated by the evolution of the fuel poverty metric—from 10%, to LIHC and, most recently, to LILEE. In *Sustainable Warmth*, the government acknowledges that the LILEE definition omits some "*homes who are unable to afford sufficient energy to keep warm*" (BEIS, 2021). This contradicts most other official definitions of fuel poverty (European Parliament, 2023; Scottish Parliament, 2019) and prompts questions over whether the primary function of LILEE is to accurately measure fuel poverty or incentivise energy efficiency upgrades. Although upgrading the energy efficiency of the English housing stock constitutes a vital step towards decarbonising the housing sector and reducing the burden of energy bills to some extent, it is evidently not equivalent to eradicating fuel poverty. The analysis presented in this chapter demonstrates that household energy insecurity is still experienced by a considerable proportion of EPC A–C households, indicating that the eventual successor to the LILEE definition should also capture the vulnerabilities that perpetuate energy insecurity in these cases. This could be achieved by ensuring that future definitions have a mechanism to *directly* account for fluctuations in energy prices; in other words, it is necessary that energy price increases and higher consumer energy costs affect fuel poverty estimates, as also suggested by Middlemiss (2017) in the context of the LIHC definition.

The analysis presented in this chapter, and also in **Chapter 3**, clearly demonstrated that the LILEE definition does not consistently identify all households that are unable to afford energy. As a result, policy recommendations were formulated based on the assumption that the LILEE definition will eventually be succeeded by a more accurate and fairer alternative. The statistical analysis of household energy security, which involved modelling the current determinants (i.e., sociodemographic characteristics) of energy insecurity during the winter of 2022 in London, might profitably be used to guide criteria for future fuel poverty definitions. One potential amendment to the LILEE approach, which could be implemented immediately, is to complement official fuel poverty statistics with household energy security estimates for those living in EPC A–C rated properties (i.e., those who are currently considered not *fuel poor* by default). This would provide an extra safety net for those in EPC A–C-rated properties generally, but would be especially beneficial for capturing missed cases of fuel poverty in properties whose occupants are likely to be at an increased risk of energy insecurity based on sociodemographic factors, which, according to the current analysis, include the presence of a health condition, being aged under 35, and very low (<£14.9k) household income.

More straightforwardly, there was no statistical evidence that the energy insecurity rates experienced by EPC A–C and D–G-rated households varied significantly. This finding suggests that

the inclusion of EPC ratings (or, specifically, FPEER rating) as an essential fuel poverty criterion is unwarranted. As discussed throughout, this finding reiterates that fuel poverty definitions should directly capture changes in energy unit prices and, consequently, changing consumer energy costs, as opposed to focusing on household energy efficiency. Future fuel poverty definitions may also benefit from non-binary categorisations; the complex nature of fuel poverty is not wholly recognised by simple designations of *fuel poor* and *not fuel poor*, as is generally the case for all traditional definitions, including 10%, LIHC and LILEE. The four-level scale used in the survey, for example, usefully delineates between those who are energy secure and insecure, whilst also expressing further intermediate degrees of energy security. There is no reason why this scale could not be further disaggregated to express a higher resolution understanding of fuel poverty or energy security in a similar manner to the EPC banding system. This would undoubtedly enhance the granularity of fuel poverty data with likely benefits for local and national fuel poverty strategies.

Several limitations pertaining to the analysis reported in this chapter should be noted. First, London-related bias should be considered, given that sociodemographic strata are able to vary considerably between UK cities. Nonetheless, the application of the LILEE indicator and energy prices are practically consistent across English regions; therefore, results are expected to be transferrable. Further, the replication of the central finding in Broxtowe in 2024—that the rate of household energy insecurity tends to exceed that of LILEE fuel poverty in a given area—minimises this potential limitation and suggests that the findings are likely to be geographically and temporally transferable. The representativeness of survey respondents, i.e., those who chose to use a community sharing app (OLIO), was a further potential limitation considered. The IMD deciles of respondents' home area, however, proved highly representative of the wider London population (as per *Figure 1*). A final notable limitation concerns the modelling framework. To mitigate against multicollinear effects in the modelling framework, independent variables with pairwise correlation coefficients greater than 0.3 were omitted from the final model. For example, a variable gauging whether respondents were currently students was positively correlated with the 'age (under 25)' variable. As a result, only the under 25 variable was retained in the final model, as the inclusion of the student variable led to a lower final model AIC. Analyses that are able to consider variable interactions might prove a valuable extension.

Several further research opportunities are as follows. First, further investigation of the LSOA outliers discovered in the exploratory spatial analysis, which could provide a better understanding of the geographical features leading to LILEE fuel poverty as well as the geographical clustering of fuel poor households, as observed in previous studies (Pérez-Fargallo,

et al., 2020; Robinson, et al., 2018). Second, the allowance for random parameters in the modelling framework led to the discovery of significantly heterogeneous levels of energy security among under 25s and those with a physical or mental health condition. Further investigation as to the cause of this heterogeneity would be productive, as there may be different types of health problems generating different experiences of energy insecurity.

In summary, the findings of **Chapter 3** and **Chapter 4** comprehensively demonstrate that the LILLE definition prioritises building characteristics (EPC/FPEER) over occupant characteristics and the self-reported affordability of energy (i.e., household energy security), which inevitably leads to fuel poverty being underestimated across England. The LILEE definition's misrepresentation of fuel poverty in England risks counterproductive results, as policies that are based on the UK Government's official fuel poverty statistics are likely to place unjust focus on EPC upgrades, rather than directly assisting households through other means (e.g., energy support payments) or attempting to regulate wholesale and consumer energy markets more effectively. Until the LILEE definition is amended to reflect on-the-ground fuel poverty experiences, mitigating policies will be based on misleading information, and financially vulnerable households will continue to be overlooked in the government's fuel poverty statistics.

Chapter 5: A Critical Review of Existing Fuel Poverty Definitions

> *Overcoming poverty is not a gesture of charity. It is an act of justice. It is the protection of a fundamental human right, the right to dignity and a decent life.*
>
> Nelson Mandela

The findings of **Chapter 3** and **Chapter 4** reiterated that the LILEE definition suffers from various measurement deficiencies and underestimates fuel poverty in low-income homes. As a result, the LILEE definition was deemed unfit for use. Given the recommended succession of LILEE, the purpose of the current chapter is to explore whether other existing fuel poverty definitions, most of which were introduced in **Chapter 2**, are able to provide a fairer and more accurate impression of fuel poverty in England. This exercise also allows greater scrutiny of other traditional definitions (e.g., 10% and LIHC) and newer alternatives (e.g., the MIS-based approach), given the overwhelming focus on the LILEE approach to this point. Specifically, this chapter critically reviews competing fuel poverty definitions via the application of a novel evaluation framework, with the ultimate aim of summarising the pros and cons associated with each existing definition. The pros and cons generated by this process are then used to inform future fuel poverty measurement criteria and further experimental work[16].

In terms of the thesis's research questions (as defined in Table 0-1), this chapter contributes evidence towards *Research Question C*:

> *Are existing fuel poverty definitions compatible with parallel political agendas, including the decarbonisation of housing and a just energy transition?*

The quantification of fuel poverty and the evaluability of transitional fairness (or the equity of energy transitions) are intrinsically linked. While rhetoric regarding transitional fairness is occasionally confined to labour market displacement within the fossil fuel industry, the concept of a 'just transition' increasingly encompasses the broader societal impacts of decarbonisation

[16] The findings of **Chapter 5** contributed to the following article: A Critical Review of Existing Fuel Poverty Definitions: Problematisation, Obfuscation and Compatibility with a Just Energy Transition. *Energy Research & Social Science*.

and electrification, as evidenced by the European Commission's (n.d.) Social Climate Fund. In the context of fuel poverty, this necessitates that the decarbonisation of domestic energy does not adversely affect affordability, particularly among vulnerable populations (Abbasi et al., 2022; Sovacool et al., 2019). Consequently, the (in)compatibility between fuel poverty definitions and the assessment of transitional fairness is a central focus of *Research Question C* and the remainder of this thesis.

5.1. Methods

To ensure a rigorous evaluation process, we propose a *Fuel Poverty Definition Evaluation Framework* (FPDEF), informed by various standard evaluation criteria in the public policy and social sciences literature. The FPDEF facilitates the comparison of competing definitions according to three primary categories: i) the *conceptualisation of poverty* (Adcock & Collier, 2001; Babbie, et al., 2015), ii) *methodological operationalisation* (Adcock & Collier, 2001; Babbie, et al., 2015) and iii) *policy utility and implications* (Dunn, 2018). As defined by Babbie (Babbie, et al., 2015), conceptualisation is *"the refinement and specification of abstract concepts"*; thus, the conceptualisation in the current context refers to how the concept of fuel poverty is understood and defined. The closely related category of methodological operationalisation describes the development of specific procedures (operations) that allow empirical observation of a given concept (Adcock & Collier, 2001; Babbie, et al., 2015), which, in this context, concerns the translation of fuel poverty as a concept into measurable variables. Methodological operationalisation is closely related to measurement validity, which refers to the accuracy of the chosen operationalisation of a given concept (Adcock & Collier, 2001). The final primary category, policy utility and implications, concerns the practical implications of a policy, including whether it serves its intended purpose (Dunn, 2018) and, in the context of fuel poverty, whether the data produced by a particular measurement approach are interpretable and usable by relevant stakeholders (e.g., academics and policymakers). A visual representation of the proposed FPDEF approach is provided in Figure 5-1.

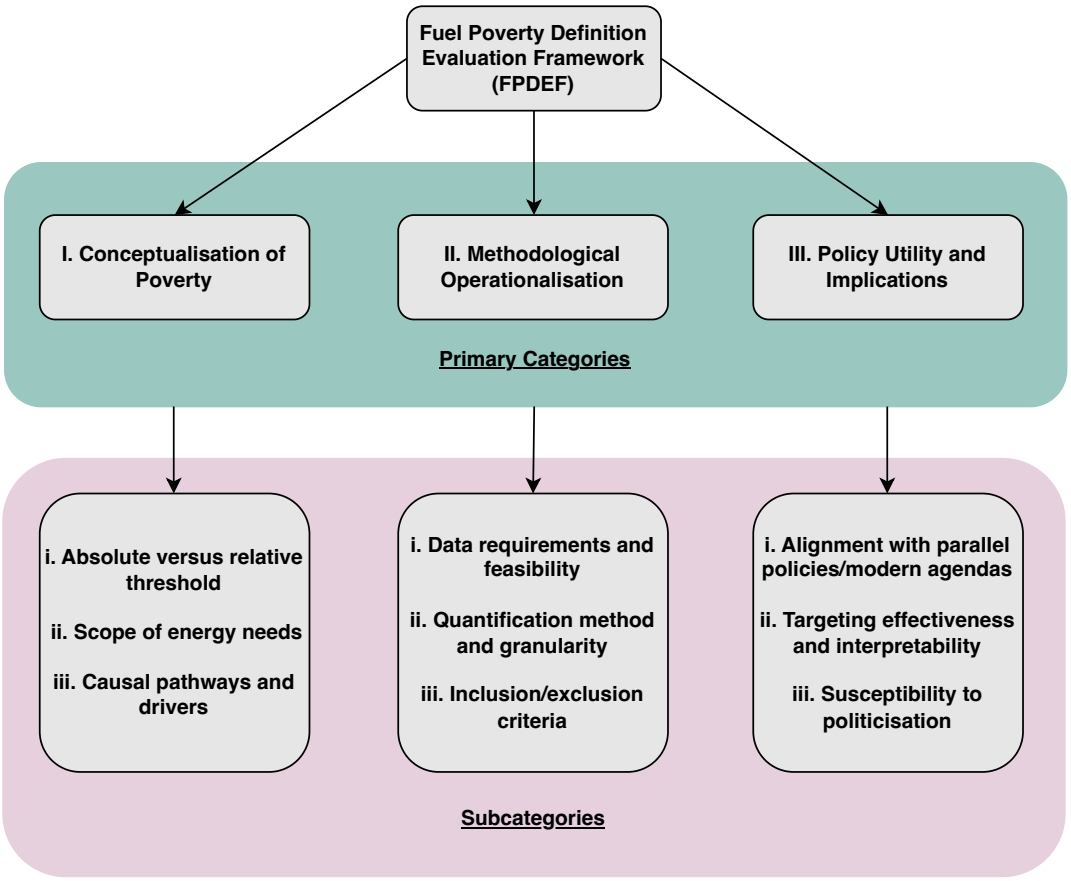


Figure 5-1. Fuel Poverty Definition Evaluation Framework (FPDEF)

The primary categories described were disaggregated into several key subcategories that relate more tangibly to fuel poverty definitions and measurement criteria. The subcategories were selected according to common themes in the literature (as specified below). Namely, the **conceptualisation of fuel poverty** includes the following considerations:

i. The utilisation of an absolute (i.e., fixed) or relative (i.e., dynamic) threshold (Hills, 2012; Moore, 2012);
ii. The scope of energy needs, for example, the energy services (e.g., heating, lighting, cooking) that are considered essential in the home (Boardman, 2009; Bouzarovski & Petrova, 2015);
iii. The causal pathways and drivers (i.e. variables) that are prioritised in a definition's measurement criteria (e.g., a direct or indirect energy costs variable) (Hills, 2012; Middlemiss, 2017).

Methodological operationalisation includes the following subcategories:

i. The practical feasibility of collecting the data that are required to estimate fuel poverty (Boardman, 2009; Scottish Government, 2017);
ii. The mathematical approach chosen to model or quantify fuel poverty and the granularity of the outputted data (e.g., binary, ordinal or continuous scale) (Bouzarovski & Petrova, 2015; Scottish Government, 2017);
iii. The effectiveness of a given definition to rightfully or wrongfully include or exclude certain homes, for example, the exclusion of LILC homes from LIHC fuel poverty (Middlemiss, 2017) and LIHEE according to the LILEE definition.

The **policy utility and implications** category was disaggregated into the following key components:

i. The level of alignment with parallel policies and modern agendas; for example, does the definition provide insights into energy precarity (Petrova, 2018) and is the impact of energy transitions on fuel poverty measurable?
ii. The interpretability and usability of outputted statistics (Boardman, 2009) and, consequently, whether outputted data are usable/useful for the targeting of resources or interventions?
iii. The susceptibility to politicisation or political bias affecting the problematisation of fuel poverty and the subsequent ordering of measurement criteria (Middlemiss & Gillard, 2015; Herrero, 2017).

It should be noted that some of the subcategories presented in the FPDEF are inherently overlapping (e.g., 'causal pathways and drivers' and 'susceptibility to politicisation' both capture aspects of political bias affecting measurement criteria). In such cases, evaluations can simultaneously be relevant to two primary categories, as demonstrated later in Table 5-1.

5.2. A review of adjacent concepts: Energy security, vulnerability, precarity and justice

A number of adjacent concepts, namely, energy security, precarity, vulnerability and justice, have gained prominence in the last decade and are increasingly tethered to fuel poverty discourses. Household energy security and vulnerability are often bottom-up approaches to quantifying fuel poverty via direct measurement of its symptoms in the home. These methods are increasingly important gauges of fuel poverty, especially since relative indicators like LIHC and LILEE underestimate fuel poverty in some financially vulnerable homes (Middlemiss, 2017), as also

demonstrated in **Chapters 3–4**. Conversely, energy precarity and justice tend to focus on external (i.e., outside of the home) macroeconomic and political factors that contribute to the systematisation and perpetuation of fuel poverty. Accounting for these external factors is particularly pertinent to modern fuel poverty definitions, which should be able to account for modern levels of volatility in energy prices, as well as being able to assess the effects of energy transitions on fuel poverty and living standards.

Household energy security and subjective fuel poverty both gauge aspects of self-reported energy affordability (Brabo-Catala, et al., 2024; Harker Steele & Bergstrom, 2021). In contrast, national energy security refers to higher-level (national or international) themes, including energy availability, infrastructure, energy prices, societal effects, environment, governance, and energy efficiency (Ang, et al., 2015), all of which have complex and intertwined implications for fuel poverty rates; however, the quantification or evaluation of national energy security is a convoluted process. The quantification of household energy security, however, is more practicable and has been deployed in England by the ONS (2023b), as well as in **Chapter 4**, to evidence disparities between rates of energy insecurity and LILEE fuel poverty. The related condition of energy vulnerability is captured in a similar way. One of the main distinctions is that energy vulnerability also considers the temporality and entrenchment of fuel poverty "*according to [a household's] exposure, sensitivity and adaptive capacity*" (Middlemiss & Gillard, 2015). Hihetah et al. (2024) provide a competing definition of energy vulnerability that prioritises people's ability to access the energy required "*for a dignified life and for meeting their human capabilities within their communities*", based on a budget standards methodology, in this case, the Minimum Essential Standard of Living (MESL). In summary, an important core tenet of the energy vulnerability literature is volatility, which, in the current context, means the profile of homes deemed fuel poor, as well as the entrenchment and deepening of fuel poverty, is something that is inherently temporal and liable to change depending on external factors. According to Bouzarovski & Petrova (2015), people or homes experience vulnerability depending on a range of temporally-influenced internal and external factors that go beyond the typical tripartite composition (prices, income and efficiency) of most fuel poverty definitions. Specifically, flexibility (e.g., the ability to move to a form of energy provision that matches household needs), needs (e.g., a mismatch between household energy requirements and available energy services) and practices (e.g. lack of knowledge concerning support programmes or ways of using energy efficiently in the home) are important constituents of energy vulnerability that are bound to have an impact on the way in which a person or home experiences fuel poverty.

Energy precarity can be understood as a subtype of economic (or financial) precarity. The term economic precarity is used to describe conditions of uncertainty and instability (e.g., declining employment opportunities or other forms of income volatility) (Waite, 2009), which are further exacerbated by economic decline; hence, economic precarity may describe those who already experience poverty as well as those who are on the brink of poverty, contingent on external economic factors. Economic precarity was, and continues to be, applicable to recent economic strife and a prolonged era of austerity in the UK, as the average person was often compelled to "*do the same with less*" (Peck, 2012). The academic evolution of economic precarity has resulted in the disaggregation of its effects to specific sectors, including housing (Debrunner, et al., 2024) and energy (Petrova, 2018). Energy precarity , according to Petrova's definition, crystallises the political, structural and market mechanisms that contribute to the normalisation and perpetuation of fuel poverty. Although energy precarity is decidedly abstract and challenging to quantify as a result, there is a definite relationship between fuel poverty and higher-level issues of governance and market regulation. In this context, the embedding of energy precarity principles within future fuel poverty definitions can provide greater protection for homes that are on the brink of poverty, instead of focusing only on those below a fixed threshold. Specifically, future definitions should be able to identify perpetual and entrenched cases of fuel poverty and should recognise energy markets as a potential root cause of energy unaffordability.

In contrast, the theory of energy justice strives for fairer, equitable and democratised energy systems (Jenkins, et al., 2016; Sovacool, et al., 2017), posited on the existence of current injustices. This is increasingly salient to the modern context, as many of the benefits of renewables are likely to be harnessed by already prosperous nations, which is likely to perpetuate and widen existing injustice in global energy systems (Sovacool, et al., 2017). Energy justice frameworks have since been applied more specifically to evaluate the fairness of fuel poverty policies in the UK (Gillard, et al., 2017; Sovacool, 2015) and evidence existing household-level injustices (Reames, 2016). Although these concerns are tangential to the quantification of fuel poverty, it is imperative that there be a degree of compatibility between modern fuel poverty definitions and energy justice.

The concomitant concept of a just energy transition is becoming increasingly pivotal to domestic and international climate strategies (European Parliament, 2021; Scottish Government, 2023). A just transition refers to many facets of the energy system, from extraction to final use, yet the implications for fuel poverty mostly concern the effect that energy transitions may have on the economy (e.g., employment and household spending power) and energy markets, more specifically. For example, within the domain of energy markets, renewable energies are cheaper to produce than fossil fuel-based alternatives, in theory (Christophers, 2024); however, the

transition to renewables itself does not necessitate the resolution of existing injustices in energy systems nor guarantee that reduced energy production costs will transfer to the consumer. This reasserts the need for a fairer fuel poverty definition that is able to account for all homes whose situations may be adversely affected by energy transitions. This point is further demonstrated by the fact that switching to renewable heating systems can increase household energy costs, excepting sizeable government subsidies and appropriate build configurations (Liu & Mauzerall, 2020), and increase the risk of financially vulnerable homes experiencing fuel poverty.

All of the aforementioned concepts have implications for the way that fuel poverty is problematised, measured and combatted. Household energy security and vulnerability are an indictment of traditional fuel poverty definitions, demonstrating that the nuanced experiences of those suffering fuel poverty cannot always be captured by singular monetary indicators. Energy precarity and justice, conversely, are guiding principles used to scrutinise inequality and unjustness at various levels of domestic and international energy systems. In relation to fuel poverty, the most relevant consideration is the effect that the reorganisation of energy systems might have on energy affordability. More specifically, modern quantifications of fuel poverty must be able to account for changes at various levels of energy systems, including macroeconomic shifts induced by the phasing out of fossil fuel-based energies. As consolidated in the following section, traditional and current fuel poverty definitions (10%, LIHC and LILEE) do not account for the potentially adverse effects of energy transitions sufficiently.

5.3. A critical review of existing fuel poverty definitions

To this point, it has been argued that a new or amended fuel poverty definition should be considered in England. The reasons for this are as follows: i) the LILEE definition is short-sighted, politically charged, and undercounts fuel poverty in some low-income homes, and as a consequence, is unable to gauge the fairness of energy transitions. ii) Readopting previous definitions (10% or LIHC) may lack political appeal, given that previous administrations comprehensively repealed each definition; namely, the Conservative-Liberal Democrat Government commissioned the Hills (2012) review, which suggested the 10% definition was unfit for modern use, and Sustainable Warmth (BEIS, 2021) recommended the succession of the LIHC definition, citing fundamental issues with the definition's responsiveness to changing energy prices. iii) Single-indicator approaches (like 10%, LIHC and LILEE) are outmoded when compared to more sophisticated multiple-indicator approaches; and iv) LIHC and LILEE's lack of consideration for living standards and overstatement of energy-efficiency-induced fuel poverty is detached from the emerging European (European Parliament, 2023) and academic consensus

(Bouzarovski & Petrova, 2015; Middlemiss, 2017), which is also corroborated by the findings of **Chapters 3–4**.

To systematically evaluate the competing characteristics of existing fuel poverty definitions, Table 5-1 provides a detailed summary of pros and cons pertaining to the three English definitions (10%, LIHC and LILEE) and other approaches covered throughout—MIS-based (see Scottish Parliament (2019) and Moore (2012)), subjective (see Harker Steele et al. (2021) and Lawlor & Visser (2022)) and EPOV (2020) (i.e., objective) fuel poverty—via the application of the FPDEF approach. Each observation in Table 5-1 is categorised according to the primary evaluation category it falls under (see Figure 5-1). Further, the specific subcategory that the observation refers to is displayed in parenthesis; for example, the first observation in the pros column for the 10% definition is categorised as "conceptualisation of poverty (i & iii)"; therefore, this comment refers to two conceptual subcategories: "i. absolute versus relative threshold" and "causal pathways and drivers" (see Figure 5-1 for full explanation). It should be borne in mind that the "positive" and "negative" traits of any definition are largely dependent on underlying political and ideological leanings. For example, relative fuel poverty definitions are criticised for their tendency to identify a consistent population of fuel poor homes despite changing external conditions; therefore, the authors consider this relativity to be a negative trait.

Table 5-1. Applying the FPDEF framework to evaluate existing fuel poverty definitions in terms of perceived pros and cons

Definition	Pros	Cons
10% See Boardman (Boardman, 1991) and DEFRA (DEFRA, 2001)	**Conceptualisation of poverty (i & iii)** – The 10% definition is an absolute indicator of fuel poverty; therefore, increased energy costs (relative to income) result in a higher rate of fuel poverty **Conceptualisation of poverty (ii)** – The 10% definition (specifically, the DEFRA (2001) version) includes an "adequate warmth" clause, reifying the importance of in-home conditions **Policy utility and implications (i & ii)** – The 10% definition is relatively straightforward to calculate and is still used in many countries, enabling international comparisons; further, the 10% definition can be used to gauge the impact of energy transitions, because energy prices are directly accounted for	**Methodological operationalisation (iii)** – 10% can erroneously classify HIHC homes as fuel poor, given the lack of an upper income threshold **Policy utility and implications (i)** – The arbitrary and obsolete 10% threshold is based on data from 1988, amounting to a lack of modern applicability **Methodological operationalisation (ii)** and **Policy utility and implications (ii)** – 10% lacks information about the depth of fuel poverty (i.e., it is a binary classification: *fuel poor* or *not fuel poor*)[17], which also limits the specificity of remedial interventions (e.g., identification of entrenched cases)
LIHC See Hills (Hills, 2012)	**Methodological operationalisation (ii)** – The *fuel poverty gap*, introduced alongside LIHC, is a useful gauge of the depth of fuel poverty in monetary terms; however, LIHC fuel poverty is binary (*fuel poor* or *not fuel poor*)	**Conceptualisation of poverty (i & iii)** – LIHC is a relative fuel poverty definition; therefore, the rate of fuel poverty remains relatively stable despite increased energy costs **Conceptualisation of poverty (i)** and **Policy utility and implications (iii)** – Symbolised a change in the problematisation of fuel poverty, such that energy efficiency was considered the principal cause and solution to fuel poverty **Methodological operationalisation (iii)** – LIHC's reordering of causal pathways and drivers ultimately leads to the underestimation of fuel poverty in LILC homes **Policy utility and implications (iii)** – The eradication of fuel poverty is not quantifiably possible according to LIHC, i.e., fuel poverty is problematised as an issue that cannot be resolved, potentially contributing to political inaction **Policy utility and implications (i)** – Ultimately, LIHC is incompatible with a just energy transition due to measurement inaccuracies, i.e., changes in energy costs do not necessarily affect fuel poverty incidence

[17] Note: this is easily remedied by also reporting the fuel poverty gap and/or adopting the graduated (e.g., five-category) version of 10%.

LILEE See BEIS (BEIS, 2021)	**Policy utility and implications (iii)** – The LILEE approach potentially has a secondary function as an incentivisation tool, i.e., LILEE could theoretically contribute to the acceleration of household energy efficiency upgrades, given the EPC/FPEER clause and narrative thrust of Sustainable Warmth (BEIS, 2021) **Methodological operationalisation (ii)** – The LILEE approach retained the fuel poverty gap; however, LILEE fuel poverty is binary (*fuel poor* or *not fuel poor*)	**Conceptualisation of poverty (i & iii)** – LILEE is a relative fuel poverty definition (following the same rationale as provided for LIHC) **Methodological operationalisation (iii)** and **Policy utility and implications (iii)** – The LILEE definition furthered the notion that energy efficiency is the primary cause and solution to fuel poverty, culminating in the adoption of the EPC/FPEER clause, which demonstrably omits many LILC homes from fuel poverty statistics. This also leads to significant deviations between LILEE and subjective fuel poverty rates during periods of economic hardship (e.g., consumer energy costs outgrowing income) **Policy utility and implications (iii)** – The eradication of fuel poverty is not quantifiably possible, barring widespread improvements to the housing stock. Regardless, fuel poverty will continue to occur in overlooked LILC (or LIHEE) homes **Policy utility and implications (i)** – Like LIHC, LILEE is incompatible with a just energy transition due to measurement inaccuracies, i.e., changes in energy costs do not necessarily affect fuel poverty incidence, particularly in LILC homes
MIS-based & **10% + MIS-based** See Scottish Government (Scottish Parliament, 2019)	**Policy utility and implications (i)** – The MIS-based approach considers minimum living standards in fuel poverty measurement criteria (as recommended by the most recent European Parliament guidance) **Policy utility and implications (i)** and **Conceptualisation of poverty (ii)** – Has more in common with qualitative measurements of fuel poverty, like subjective fuel poverty and energy vulnerability, and acknowledges that fuel poverty can be experienced by any low-income homes, regardless of building characteristics **Methodological operationalisation (ii)** – When calculated alongside 10% fuel poverty, the MIS-based approach effectively captures relative and absolute fuel poverty, albeit in binary form: *fuel poor* or *not fuel poor*	**Conceptualisation of poverty (i)** – MIS-based fuel poverty is essentially a relative indicator due to the "typical" basket (i.e., median) baseline; this is not necessarily a disadvantage when attempting to gauge equality or social participation, but it does mean that the rate of MIS-based fuel poverty (like all relative definitions discussed) is necessarily capped below the median household[18] **Methodological operationalisation (ii)** – There is a degree of subjective assessment involved in the derivation of "a [typical] basket of goods and services" (a component of the MIS method), which may affect measurement validity

[18] In the case of the Scottish formulation (10% + MIS-based fuel poverty), this is not strictly the case, as homes can be deemed fuel poor according to the absolute (10%) or relative (MIS) clauses.

	Policy utility and implications (i) – Has greater compatibility with energy transitions, given the relative and absolute calculation of fuel poverty (i.e., the 10% + MIS formulation), as well as considering living standards; hence, the effect of energy transitions on fuel poverty and living standards can be tracked by 10% + MIS	
Subjective approaches For example, see Harker Steele et al. (Harker Steele & Bergstrom, 2021)	**Conceptualisation of poverty (ii & iii)** – Subjective fuel poverty approaches directly capture multiple dimensions of fuel poverty via self-reported scales, and are likely the most accurate depiction of lived experiences in fuel poor homes **Methodological operationalisation (i)** – Overcomes data limitations associated with other approaches (e.g., monetary approaches, which often rely on the availability of extensive income and household composition data)	**Methodological operationalisation (i)** – Subjective fuel poverty is prone to various forms of bias inherent to self-reported data (social desirability, recency, interpretative) **Conceptualisation of poverty (iii)** and **Methodological operationalisation (ii)** – There is a continued lack of standardisation regarding survey formats (i.e., the scales, questions, and thresholds utilised), which hinders the comparability of results **Methodological operationalisation (i)** – Subjective fuel poverty quantifications require large-scale surveys, which are often costly and may lessen the feasibility of high-quality and regularised data collection
EPOV objective indicators See EPOV (EPOV, 2020)	**Conceptualisation of poverty (ii & iii)** – EPOV indicators provide extensive coverage of the causes and consequences of fuel poverty: arrears on utility bills; low absolute energy expenditure; high share of energy expenditure in income; inability to keep home warm **Methodological operationalisation (i)** – Objective measures, such as actual measurement of indoor temperatures, can directly measure cold or unsafe living conditions; however, the scalability of such methods remains doubtful	**Conceptualisation of poverty (iii)** and **Methodological operationalisation (ii)** – Many of the terms in the EPOV guidance lack clarity regarding specific thresholds, e.g., *low* absolute energy expenditure and a *high* share of energy expenditure in income, and, as previously mentioned, the scalability of in-home measurement of fuel poverty (i.e., inadequate temperature) is doubtful.

It is arguable that none of the English definitions (10%, LIHC and LILEE) are fit for modern use, as evidenced by multiple conceptualisation-, operationalisation- and policy utility-related issues in Table 5-1. The 10% definition is based on obsolete energy and income data; hence, the 10% threshold is hard to justify given temporal shifts in the median fuel poverty ratio. In addition, the 10% definition does not measure the depth of fuel poverty. The five-fold formulation of the 10% definition is a more attractive prospect, particularly in terms of exploring entrenched fuel poverty and fostering greater alignment with the energy precarity literature (Petrova, 2018). The LIHC and LILEE approaches epitomise the inherent short-termism of modern fuel poverty definitions in England. Both approaches fail to capture the full extent of fuel poverty in low-income households and place arguably unjust focus on energy efficiency as the central cause and solution to fuel poverty. The rate of LIHC fuel poverty remains unrealistically stable because the measurement criteria (income and energy costs) utilise dynamic median thresholds. Similarly, the rate of LILEE fuel poverty remains reasonably stable due to the EPC/FPEER clause, which omits ~40% of English homes from statistics by default. These characteristics of LIHC and LILEE induce the systematic undercounting of fuel poverty in LILC homes. This is a patent instance of existing energy injustice, as these definitions imply that all homes above a certain energy efficiency threshold cannot experience fuel poverty, regardless of living conditions or occupant characteristics. A just energy transition is incompatible with the LIHC and LILEE measurement approaches, as neither quantify existing levels of fuel poverty accurately. One redeemable characteristic of the LIHC methodology is the complementary fuel poverty gap, which is a valuable monetary measure of the depth of fuel poverty.

The MIS-based approach used in Scotland is a highly promising alternative, particularly if it were to be applied in combination with the five-fold version of 10%. Many of the disadvantages pertaining to the English definitions (10%, LIHC and LILEE) are resolved by this formulation. First, the arbitrariness of the 10% threshold is not as crucial to the five-fold configuration, as information is also provided for intervals above and below the main poverty threshold. In practice, this may prove useful for categorising and treating cases of marginal fuel poverty (e.g., 8–10% of income spent on energy) before they become more severe and is, in essence, a means to identifying and managing energy precarity. Second, budget standard approaches like MIS provide insights into minimum living standards at a particular point in time. Integrating energy costs into this calculation accounts for price changes directly; in addition, the frequent recalculation of MIS allows minimum acceptable living costs to be known during specific periods and is less rigid than the 60% poverty line used by relative fuel poverty definitions. These characteristics of the MIS-based approach are likely to minimise the risk of underestimating fuel poverty in LILC homes. The consideration of minimum living standards also aligns with the

European Parliament's most recent definition of fuel poverty: "a household's lack of access to essential energy services that provide basic levels and decent standards of living and health", as well as the energy justice literature, given that a fair transition should "consider the effects of both the transformation through climate action, and the impacts of climate inaction on all vulnerable communities and sectors" (E3G, 2018). As a result, we recommend that future fuel poverty definitions should contain a living standards criterion to align with European trends in the problematisation of fuel poverty and to ensure living standards are not affected by energy transitions.

The subjective approach (e.g., see the household energy security scale used by Harker Steele et al. (2021) and EPOV (objective) indicators (see EPOV (2020)) are direct measurements of fuel poverty at the household- or individual-level. Both have merits for this reason and could be used to complement other definitions. The deficiencies of relative fuel poverty definitions, for example, could be mitigated by supplementary surveys of subjective fuel poverty and/or objective housing conditions. The subjective approach and EPOV indicators are also prone to some biases and ethical issues, respectively, which further limit the feasibility of their adoption and application in a political context. Subjective fuel poverty is prone to biases that are inherent to any self-reported data, e.g., recency, social desirability and interpretative, while two of the EPOV indicators—arrears on utility bills and low absolute energy expenditure—require access to intimate personal data and the participant's home, which are arguably unjust invasions of privacy. The remaining EPOV indicators (a high share of energy expenditure in income and the inability to keep the home adequately warm) are essentially a rewording of the DEFRA (2001) 10% definition; hence, they are not particularly novel.

5.4. Policy recommendations for modern fuel poverty measurement approaches

The remainder of this article reframes the observations made in Table 5-1 in the form of practicable recommendations for future fuel poverty definitions in England and other comparable contexts. The recommendations are presented according to the FPDEF's primary categories: I) *Conceptualisation of Poverty, II) Methodological Operationalisation* and II) *Policy Utility and Implications*. As noted throughout, there is inevitably a degree of overlap between conceptualisation, methodological operationalisation and policy utility (Babbie, et al., 2015). In such cases, footnotes provide extra clarification.

Recommendations I: Conceptualisation of Poverty

A. Measuring multiple dimensions of fuel poverty

The prevailing academic and political consensus is that fuel poverty cannot be accurately measured by a single indicator (Sareen, et al., 2020; European Parliament, 2023; Herrero, 2017; Scottish Government, 2017). As a result, future definitions should capture the most well-known fuel poverty mechanisms: income-, costs- and energy-efficiency-induced fuel poverty, as well as the overlap between fuel poverty and living standards. The latter point is especially crucial given the increasing burden of essential expenditure (i.e., energy and other necessities) in financially vulnerable homes. In terms of actionable recommendations, further work should explore the degree of overlap between monetary fuel poverty definitions (e.g., 10%, LIHC and LILEE) and living standards-based definitions (e.g., MIS or similar). This exercise would more comprehensively demonstrate the shortcomings of 10%, LIHC and LILEE fuel poverty presented in Table 5-1.

B. Producing relative and absolute quantifications of fuel poverty

Relative and absolute poverty definitions capture fundamentally different conditions. There are merits and disadvantages to both approaches: relative fuel poverty definitions are known to undercount fuel poverty inf low-income homes (see **Chapter 4** and Middlemiss (2017)), which is particularly concerning given generally increasing energy costs and impending systemic changes in the energy sector. Although we argue that the LIHC and LILEE definitions are highly politicised and flawed, the relative poverty they capture is still a potentially valuable gauge of inequality. To remedy the current overreliance of English fuel poverty statistics on relative definitions, further work may explore the design of a fairer measure of *relative* (changing thresholds) fuel poverty, complemented by an *absolute* (fixed threshold) fuel poverty metric. The Scottish Government recently achieved this in the form of MIS-based + 10% fuel poverty, yet there is considerable room for improvement in terms of how the 10% threshold is decided; for example, disaggregation to a graduated five-level (or continuous) scale would reduce the criticality of the outmoded 10% threshold.

C. Reframing fuel poverty as an eradicable issue

A further limitation of relative poverty definitions is the implicit belief that poverty cannot be eradicated, which is likely a contributor to its normalisation and perpetuation (Middlemiss, 2017). In contrast, absolute poverty definitions offer a viable route to eradication. As proposed in

Recommendation B, the joint measurement of absolute and relative fuel poverty ensures that eradication is at least quantifiably possible. Future definitions of fuel poverty should acknowledge and promote the notion of eradication, a concept that gained traction in the political mainstream during the 2000s (UK Parliament, 2009). Ultimately, access to adequate energy services in all homes is an attainable objective; therefore, fuel poverty definitions should reflect this possibility.

D. Reprioritising primary fuel poverty measurement criteria: energy costs first[19]

The LIHC and LILEE definitions diminish the roles of market conditions and national energy security in perpetuating fuel poverty, instead diverting attention to household-level energy efficiency. This evidently leads to many LILC homes being overlooked and is likely the leading cause of current disparities between subjective and LILEE fuel poverty rates (see **Chapter 4:** Section 4.6). There is an important distinction to be made between an effective energy costs criterion, which encompasses a home's actual running costs and volatile energy prices, and the LILEE energy efficiency clause, which is equivalent to *modelled running costs*. The issues with the latter are i) EPC ratings are static, so a C-rated property remains C-rated even if energy costs increase significantly, and ii) modelled running costs do not always accurately reflect *actual* costs. Both of these cases apply to LILC homes omitted by the LILEE definition, whose occupants, in many cases, would likely be categorised as subjectively fuel poor. Although the disentanglement of energy costs and household energy efficiency is complex, future fuel poverty definitions should continue to recognise that increasing energy costs, relative to income, is the main driver of fuel poverty, while household energy efficiency has a lesser moderating effect.

Recommendations II: Methodological Operationalisation

E. Measuring the depth, entrenchment and temporal stability of fuel poverty

The fuel poverty gap devised by Hills (Hills, 2012) was the UK Government's first attempt to quantify the depth of fuel poverty in monetary terms. We recommend that future approaches continue to measure the depth of fuel poverty, as this is a particularly relevant and interpretable method for evaluating the household-specific impact of energy transitions on fuel poverty. There are opportunities to extend the fuel poverty gap to encompass more subtle phenomena, such as the temporal stability of fuel poor homes and their distance from a given fuel poverty threshold. For example, Bridgen & Robinson (Bridgen & Robinson, 2023) suggest a five-point scale to

[19] Recommendation D also has considerable relevance to other FPDEF categories: for example, the prioritisation of an energy costs variable should lead to greater inclusion of LILC homes in fuel poverty statistics (i.e., this is a relevant methodological operationalisation consideration); further, the prioritisation (or diminishment) of energy costs in fuel poverty measurement criteria can be seen as an issue of problematisation that could be politically contentious (i.e., policy utility: susceptibility to politicisation).

measure temporal (i.e., entrenched) fuel poverty. The temporal stability of fuel poverty (as well as economic insecurity) is an increasingly crucial condition amid transitional periods in which already-poor and precarious populations may require further protection.

F. Notes on the technical specification of fuel poverty measurement criteria

The specification of measurement criteria significantly influences fuel poverty classifications. The principal measurement criteria for monetary definitions (e.g., 10%, LIHC and LILEE) are household income, energy costs and household energy efficiency. Household income tends to be equivalised (i.e., adjusted for household composition) following direct tax deductions (e.g., income tax); this category of income is referred to as *equivalised net household income*. A further consideration is whether to deduct housing costs (e.g., rent or mortgage payments) prior to poverty classifications. Previous research has shown that not considering housing costs adjustments can lead to misleading fuel poverty estimates (Moore, 2012); hence, we recommend that income variables are equivalised and taken after housing costs, in the context of fuel poverty classifications. A further consideration is whether energy costs are derived through required (modelled based on household characteristics) or actual energy usage. Required energy costs are based on static energy efficiency data; therefore, people/homes who alter their energy consumption to reduce costs are not particularly well represented. Actual energy use, conversely, is hard to measure at scale, as access to the home or financial records is required. Finally, household energy efficiency—if included as a distinct criterion from energy costs—is likely best gauged by FPEER (EPC rating with energy support payments deducted); however, alternative approaches may be facilitated by the UK Government's impending Home Energy Model (DESNZ, 2023c).

Recommendations III: Policy Utility and Implications

G. Embedding principles of energy security, vulnerability and precarity in fuel poverty measurement criteria

Household energy security (or subjective fuel poverty) and vulnerability are qualitative approaches to quantifying fuel poverty. Their merits include the vast breadth of experiences they capture; however, the feasibility of gathering these data at scale is doubtful. Moreover, the range of symptoms experienced by fuel poor homes is difficult to incorporate within a quantifiable definition. A promising future approach may be to complement the official fuel poverty definition with large-scale surveys of household energy security, as trialled by the ONS (2023b), illuminating deviations between self-reported and quantifiable fuel poverty. Energy precarity is a particularly

useful framework for contextualising the macropolitical shifts of the 2010s. During this period, the responsibility for addressing fuel poverty was seemingly diverted to individuals, prioritising consumer-led solutions (e.g., home retrofits) rather than tackling broader external factors (e.g., rising consumer energy costs). In this context, we recommend that future definitions should be able to account for perpetual and entrenched cases of fuel poverty, as well as marginal "not fuel poor" cases (i.e., homes at risk of becoming fuel poor). In a similar sense to *Recommendation E*, this again refers to the ability of a fuel poverty definition to capture changing external circumstances over time.

H. Aligning the measurement of fuel poverty with energy justice principles to ensure a fair transition

The basis of a fair energy transition is that fossil fuels can be replaced by renewables without exacerbating existing social inequalities. In the context of fuel poverty, the most tangible impact of energy transitions is likely to be felt in energy markets and end-user costs. Given the current uncertainty regarding the distributional effects of energy transitions, it is imperative that modern fuel poverty definitions are able to accurately measure all relevant variables, especially the increasing strain of high energy costs in low-income homes. In England, the LILEE definition already penalises low-income groups by underestimating fuel poverty in LILC homes. As the energy transition progresses, the LILEE definition would continue to underplay the effects of volatile energy costs or other external factors in LILC homes, leading to an obscuration of the potentially adverse effects of energy transitions on fuel poverty in England. As a result, we suggest that the LILEE definition is incompatible with the evaluation of a just energy transition. Future definitions of fuel poverty must be able to accurately gauge living standards in already-fuel poor or financially precarious homes, thus allowing the impact of energy transitions to be evaluated in these cases. In practice, future fuel poverty definitions should be able to account for living standards via the incorporation of an MIS or MESL-based clause (or similar), enabling the *justness* of energy transitions to be evaluated.

5.5. Conclusions, limitations and recommendations for further work

The first half of this article provides a chronological history of English fuel poverty definitions (10%, LIHC and LILEE) and also discusses alternative approaches in other UK nations, for example, the Scottish Government's MIS-based definition. The second part presents a critical review of existing fuel poverty definitions, focusing specifically on the English context, via the application of a novel fuel poverty definition evaluation framework. Our findings suggest that all of the English definitions have limited modern-day applicability: the threshold used for the 10%

definition is obsolete, and varying degrees of fuel poverty are not distinguishable, while the LIHC and LILEE definitions show an unrealistically consistent rate of fuel poverty, penalise LILC homes and do not accurately reflect the financial burden of volatile and, generally, rising energy costs. In the context of modern needs, which are defined via reference to principles of energy precarity and justice, the binary classification method of the 10% definition fails to represent perpetual and entrenched fuel poverty (i.e., the depth of fuel poverty), while neither LIHC nor LILEE can be used to fairly measure the impact of energy transitions on fuel poverty. The most promising approaches are those that directly account for volatile energy costs and living standards; for example, the two-clause Scottish Government definition, which includes a 10% fuel poverty and budget standard-based (MIS) clause. We argue that the adoption of a similar definition in England would significantly reconcile the current incongruity between fuel poverty and energy transitions policy.

The findings presented in this chapter may also be relevant to the broader European and international context, as many countries still quantify fuel poverty via the outmoded 10% definition. Moreover, the energy transition is dependent on myriad international-level political and economic factors; therefore, the establishment of a pan-European definition of fuel poverty, which also accounts for living standards—in line with the European Parliament's Directive on Energy Efficiency—could significantly enhance continental evaluations of the energy transition's effects on fuel poverty. The critical review approach presented in this chapter suffers from a notable limitation, given the inherently subjective nature of the perceived pros and cons of existing fuel poverty definitions. As discussed throughout, perceptions of fuel poverty definitions are likely to be affected by political leanings, so this is, to a large extent, unavoidable. Despite this, considerable efforts were made to systematise the evaluation of competing fuel poverty definitions via the application of the fuel poverty definition evaluation framework.

Recommendations for further work: Fuel poverty measurement experiments

Recommendations for further work mirror those presented more extensively in Section 5.4, however, those presented here are a more specific set of measurement experiments that can be conducted on English household data to better understand the modern appropriateness of competing fuel poverty definitions. Following the measurement experiments, a sensitivity analysis is conducted to show how the impending acceleration of energy transitions (e.g., if all homes were to achieve their *potential energy efficiency*) might affect fuel poverty and how the chosen definition in England might contribute to further obfuscation. This is reducible to the simple fact that the justness of the energy transition is not evaluable without fair and accurate measures of fuel poverty.

Table 5-2. Further work: Fuel poverty measurement experiments

Further work: fuel poverty measurement experiments

A. Estimate the current rate of fuel poverty according to the 10%, LIHC and LILEE definitions, and determine the degree of overlap between all approaches

B. Estimate relative and absolute fuel poverty (not necessarily according to existing definitions) and compare how the profile of fuel poor homes varies spatially and demographically

C. Apply a five-level (or more), temporal version of the 10% definition to simultaneously measure the depth and entrenchment of fuel poverty

D. Estimate the current level of MIS-based fuel poverty, i.e., apply the Scottish methodology (or similar) to English households

E. Where possible, attempt to estimate EPOV fuel poverty indicators (arrears; low absolute energy expenditure; high share of energy expenditure in income; inability to keep home adequately warm) and compare findings with subjective, existing and new fuel poverty definitions

F. Apply various combinations of existing definitions: a) MIS-based + five-fold 10%; MIS-based + LIHC; MIS-based + LILEE. Each scenario can be used to show the degree of overlap between MIS-based fuel poverty and other approaches, or, inversely, to show the number of homes with inadequate living standards that are omitted by existing definitions

G. Conduct further analysis of subjective poverty, ideally integrating responses with EPC data

Chapter 6: Exploring the Utility of Financial Data for Fuel Poverty Classifications

> *A wealth of information creates a poverty of attention.*
>
> Herbert A. Simon

As has been demonstrated, the LIHC and LILEE measurement approaches lack modern appeal as they cannot fully account for changing energy costs in low-income, low-costs homes, which consequently means they are unable to measure the fairness of energy transitions. The 10% definition, on the other hand, more directly accounts for external factors (e.g. energy costs), but lacks modern applicability due to the outdated and arbitrary logic underlying the 10% threshold. Given these findings, the remaining chapters explore alternative approaches to measuring fuel poverty via the analysis of real-world and synthetic datasets, with the overarching aim of remedying the measurement deficiencies of the 10%, LIHC and LILEE approaches. Specifically, **Chapter 6**[20] explores alternative approaches to measuring fuel poverty via the analysis of large financial data (n=1,111,357 customers), retrieved via an industrial collaboration with *Smart Data Foundry*, who provided a curated set of NatWest Group customer data. Although the financial data are large and potentially highly useful for fuel poverty classifications, they refer to individual-level records, meaning that *household* income and expenditure variables were discernible. As such, **Chapter 6** explores the utility of financial data for non-traditional fuel poverty classifications; in other words, the current chapter considers how individual-level financial records might be used to aid the estimation of fuel poverty proxies (e.g., general financial security), before **Chapter 7** refocuses on traditional fuel poverty measurement approaches at the household level and addresses the fuel poverty measurement questions presented in **Chapter 5** more comprehensively.

The analysis presented in this chapter concerns three individual-level indicators that capture aspects of financial security and the affordability of energy: 1) *financial security*, which is the percentage of income that is spent on essential (i.e., food and energy) and committed goods (i.e.,

[20] The findings of **Chapter 6** contributed to the following conference abstract submission: Exploring the Use of Financial Data for Fuel Poverty Classifications. *Digital Footprints 2025*

fixed financial payments, e.g., childcare costs or loan repayments); 2) *potential fuel stress*, which refers to the percentage of essential expenditure spent on energy; and 3) the *fuel poverty ratio*, which, at the individual level, refers to the ratio of median area-level energy costs divided by total income. These three indicators, which are defined in greater detail in Section 6.2, are used to provide insights into how modern data streams, such as donated banking data, could be used to enhance fuel poverty quantifications. A specific benefit of this approach is that financial data could be used to produce more instantaneous insights into financial security and fuel poverty, particularly given that official fuel poverty statistics have regularly been criticised for their delayed publication (Boardman, 2009); for example, LILEE statistics published in 2024 (DESNZ, 2024a) are based on data from 2023. Moreover, the financial data are large, covering in excess of one million people, and tend to contain more detailed income and expenditure variables than comparable datasets. The English Housing Survey, for example, provides no expenditure information and covers a relatively small sample of homes (usually around 10,000–13,000 homes).

6.1. Background: Defining individual-level financial security, potential fuel stress and fuel poverty ratio indicators

This section briefly defines the fuel poverty indicators of interest—financial security, potential fuel stress and individual-level fuel poverty ratio—in relation to similar metrics in the literature, while the mathematical formulation of each indicator is presented in Section 6.2.

Financial security

Financial security can be understood as the inverse condition of financial precarity. Financial precarity, as described by Peck (2012), Standing (2011), and Waite (2009), denotes the economic uncertainty and instability (e.g., declining job security and income volatility) that can affect the financial wellbeing of individuals or households. Financial precarity, like energy precarity (Petrova, 2018), may describe those who already experience poverty as well as those who are on the brink of poverty, depending on a range of external economic factors. In this analysis, *financial security* is defined as the proportion of total individual income that is attributable to essential (e.g., food or utilities) or committed (e.g., regular loan repayments) goods. According to this definition, *high* financial security is reflected by a larger proportion of residual income after essential and committed expenses, whereas *low* financial security is experienced by those with a low percentage of residual income following these expenses. Although this is not explicitly a fuel poverty indicator, individual-level financial security could be used to complement fuel poverty

statistics, given that *high* expenditure on necessities, a key component of which is energy, is one of the EPOV's (2020) primary indicators of fuel poverty.

Potential fuel stress

The definition of *fuel stress* is more nebulous. In some cases, the term has been used to describe the condition of spending more than 10% of income on energy (i.e., 10% fuel poverty) (Resolution Foundation, 2024), while it has also been used in journalistic spheres to describe energy affordability issues more generally (for example, see The Guardian (2022)). The term's usage in academic work, however, is limited. In the context of the current work, the term *potential fuel stress* describes the financial stresses that may be induced by area-level variation in energy costs. The potential fuel stress indicator is calculated by dividing the median inferred energy costs per unit of area (in this case, postal district) by essential expenditure. In other words, potential fuel stress is a broad estimate of the proportion of essential expenditure that is likely spent on energy, which can be used to provide rough insights into area-level energy expenditure trends as well as heat-or-eat trade-offs: if a high proportion of essential expenditure is spent on energy, then the concomitant consequence of this is low absolute expenditure on food.

Individual-level fuel poverty ratio

The calculation of an individual-level fuel poverty ratio is equivalent to dividing median postal district-level energy costs by total individual income; hence, this is an *individual-level* indicator of the fuel poverty ratio, as opposed to the Boardman (1991) household-level version. Although the individual-level fuel poverty ratio is not likely to be particularly accurate in isolation, given that household characteristics (e.g., household income, composition and the division of utility bills among occupants) cannot be accounted for, this approach can still provide *relative* insights into the fuel poverty ratio across Nottingham postal districts. In fact, all three of the proposed indicators are likely to have most utility as relative metrics of financial security and energy affordability at the area- or demographic-level, as discussed throughout the remainder of this chapter.

6.2. Data and methods

The data used in this chapter were individual-level financial records accessed via a collaboration with *Smart Data Foundry* (SDF), which is a data innovation organisation based at the University of Edinburgh. Specifically, this analysis utilises SDF's *Income Volatility Dataset* (n=~74.25 million weekly financial records, corresponding to ~1.11 million distinct customer records for the

financial year ending 2023) and is available upon request from SDF (see Smart Data Foundry (n.d.)). Given the highly sensitive nature of financial records, the code and data used in this analysis are omitted from this thesis's supplementary GitHub repository to comply with SDF's data protection policies[21]. The financial data include a range of variables, such as *income* (categorised as salary, expenditure, benefits, pension or other), *expenditure* (committed, essential, quality of life or other) and some sociodemographic characteristics (e.g., age band, gender and postal district). The individual-level granularity of financial data is beneficial for individual-level estimates of financial security or poverty; however, the estimation of fuel poverty is inherently linked to household characteristics and associated energy costs, which potentially limit the utility of financial data for fuel poverty quantifications. Despite this, the utility of the financial data for fuel poverty classifications (or estimating associated proxies) was explored via the three individual-level metrics of financial security and energy affordability, as defined in Section 6.1.

Financial data preprocessing: Generating annual financial records and a subset of Nottingham observations

The financial data required considerable preprocessing prior to the estimation of the fuel poverty indicators. The financial data, which originally referred to weekly financial records (n=~74.25 million), were aggregated to a yearly interval (n=~1.11 million financial records during the financial year ending (FYE) 2023, i.e., 3rd April 2022 to 2nd April 2023). Other relevant adjustments included the generation of a Nottingham (NG) postcodes subset[22], as the potential fuel stress and fuel poverty ratio indicators only applied to the City of Nottingham region, as discussed further in subsequent sections. The FYE 2023 Nottingham subset was initially composed of 11,041 observations. This is indicative of relatively high coverage across Nottingham's population, since 11,041 corresponds to around 3.35% of Nottingham's population—which is ~329,300 people (Nottingham City Council, 2023)—whereas the total dataset (1.11 million) accounts for around 1.63% of the UK population (~68 million). This may be because bank customers, or at least customers of certain banks, are more concentrated in urban areas; regardless, the Nottingham sample was deemed adequate for the estimation of applicable indicators: potential fuel stress and fuel poverty ratio.

[21] Note: the data are not available in this case as they are made available to specific users on a case-by-case basis. Further, the code is not available as the analysis was conducted in SDF's Trusted Research Environment; hence, only the final results were able to be exported.
[22] This included the following postal districts: NG1, NG2, NG3, NG4, NG5, NG6, NG7, NG8, NG9, NG11, NG12, NG13, NG80, NG90.

Methods: Financial security, potential fuel stress and the individual-level fuel poverty ratio

This section provides mathematical formulations for the financial security, potential fuel stress and individual-level fuel poverty ratio metrics, building on the theoretical descriptions presented previously. For financial security, the financial security score, FS, per individual, i, can be written as follows:

$$FS_i = \frac{TI_i - (EE_i + CE_i)}{TI_i} \tag{6.1}$$

Where TI_i is total income, EE_i is essential expenditure and CE_i is committed expenditure. The financial security indicator returns a continuous score, where a score of 0 means that the entirety of the individual's income is spent on essential (e.g., food and energy) or committed (e.g., housing costs) goods, whereas a score of 1 indicates very high financial security. The second indicator of interest, potential fuel stress, PFS, per individual, i, is written as follows:

$$PFS_i = \frac{EC_{pd}}{EE_i} \tag{6.2}$$

Where EE_i is essential expenditure and EC_{pd} is energy costs per postal district (i.e., median inferred energy costs for the postal district of individual, i). Median inferred energy costs per postal district were calculated using a combination of variables in the EPC database (DLUHC, 2024) and Ofgem (2025) unit price caps[23]. The results of this process are displayed in Table 6-1 alongside the number of homes (based on DLUHC (2024)) and the number of financial records (based on the SDF Nottingham subset), which can be used as an indicator of postal district-level sample coverage. Several postal districts, namely NG4, NG12 and NG13 (see highlighted rows in Table 6-1), have particularly poor coverage, as the number of homes, according to the EPC database, is lower than the number of individuals present in the financial data. As such, the median inferred costs in these areas may be less reliable. To combat this, the median inferred costs for the entire Nottingham sample (£2,185/year) were assumed for NG4, NG12 and NG13 customers.

[23] Note: see also **Chapter 7:** *Equations 7.6, 7.7* and *7.8* for a more detailed explanation of this calculation.

Table 6-1. Median inferred energy costs per Nottingham postal district, based on DLUHC (2024) and Ofgem (2025)

Postal district	Number of homes (EPC database)	Number of individuals (financial data)	Median inferred energy costs, EC_{pd} (£/year)
NG1	10057	151	1,390
NG2	12337	1078	1,965
NG3	15927	874	2,024
NG4	16	812	2,185
NG5	19605	1899	2,095
NG6	14482	750	2,152
NG7	24590	672	2,199
NG8	23698	1248	2,189
NG9	2224	1313	1,211
NG11	11047	610	2,201
NG12	16	934	2,185
NG13	80	700	2,185

Potential fuel stress quantifies the proportion of essential expenditure that is potentially attributable to energy, where a *high* PFS (approaching 1) indicates high expenditure on energy costs, and comparatively low expenditure on other necessities, especially food. This type of indicator may also be a useful proxy for area-level heat-or-eat trade-offs (see also Bhattacharya, et al. (2003)); for example, people living in a postal district with a relatively high PFS score may be expected to make heat-or-eat trade-offs more frequently, especially in the winter. Finally, the individual-level fuel poverty ratio, FPR, per individual, i, is written as follows:

$$FPR_i = \frac{EC_{pd}}{TI_i} \tag{6.3}$$

Where EC_{pd} (median inferred energy costs) and TI_i (total income) are both as previously defined. The individual-level fuel poverty ratio is similar to Boardman's (1991) approach; however, total income is measured at the individual level, and energy costs are inferred per postal district. This is arguably unsophisticated in relation to the original fuel poverty ratio; however, in this case, a high FPR score is still likely to be a valuable indicator of low income and potentially high energy costs, whereas an FPR score approaching 0 indicates high financial security and a reduced likelihood of fuel poverty. Moreover, given that individual-level FPR returns a continuous score (i.e., percentage of income spent on energy), there is scope to model the relationship between explanatory sociodemographic variables in the financial data (e.g., age, gender and benefits status) and the fuel poverty ratio score. This was achieved by estimating a linear regression model (Washington, et al., 2020) as follows:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_p X_{ip} + \varepsilon_i \tag{6.4}$$

Where the fuel poverty ratio score, Y, per individual, *i*, is a function of a constant term (i.e., the intercept), β_0, and a range of independent variables, X, plus a disturbance term, ε, which accounts for unexplained variance in the dependent variable, Y.

6.3. Results: The estimation of financial security and energy affordability indicators

This section presents the estimation results for the indicators of interest: financial security, potential fuel stress, and the individual-level fuel poverty ratio. As mentioned previously, a benefit of the financial data-based approach was that the data covered the entire UK; therefore, financial security estimates could be provided for the entire UK sample, while the accompanying selection of sociodemographic variables meant that the results of each indicator could be disaggregated according to these characteristics. The age and postal district variables were of particular interest, as the fuel poverty experiences of different age groups (Boardman, 2009) and geographies (Robinson, et al., 2018) tend to be disparate.

Results (I): Financial security in the UK

Individual-level financial security is the proportion of total income that is spent on committed and essential expenses per year (as per Equation 6.1). A high financial security score, approaching 1, signifies that essential and committed expenses are a relatively small financial burden. In contrast, a low score, approaching 0, indicates that these expenses are financially burdensome. In the context of fuel poverty, those with low financial security scores may be especially susceptible to volatile energy prices or economic decline more generally (e.g., inflation outgrowing income), a condition that is often described as energy precarity in the literature (Petrova, 2018). Table 6-2 provides summary statistics for financial security disaggregated by age group for the entire UK sample (n=1.11 million), while Table 6-3 displays the equivalent information for the Nottingham subset (n=11,041). Note that the mean and median financial security scores are presented, yet the values of both are closely aligned, indicating a normal distribution of scores per age group; hence, in this case, mean and median scores both provide valid impressions of financial security per group.

Table 6-2. Financial security per age group: Summary statistics for all observations (n=1,111,357)

Age group	Financial security: All observations		
	Mean	Median	Std. deviation
18–24 (n=71,896)	0.4086	0.4009	0.2149
25–34 (n=202,231)	0.3752	0.3657	0.2163
35–44 (n=197,817)	0.3799	0.3715	0.2185
45–54 (n=185,512)	0.3865	0.3779	0.2250

55–64 (n=182, 664)	0.3846	0.3810	0.2478
Over 65 (n=271,237)	0.3862	0.3943	0.2782

Table 6-3. Financial security per age group: Summary statistics for the Nottingham subset (n=11,041)

Age group	**Financial security: Nottingham**		
	Mean	**Median**	**Std. deviation**
18–24 (n=785)	0.4053	0.3946	0.2174
25–34 (n=2,181)	0.3841	0.3764	0.2187
35–44 (n=2,067)	0.3802	0.3687	0.2174
45–54 (n=1,893)	0.3831	0.3708	0.2270
55–64 (n=1,704)	0.3783	0.3767	0.2621
Over 65 (n=2,411)	0.4011	0.4067	0.2746

The financial security scores for the entire UK sample and Nottingham subset were remarkably similar, which is somewhat surprising, given that Nottingham is one of the most deprived local authorities in the UK (DLUHC, 2020; ONS, 2023a). A potential explanation for this degree of similarity is that the financial security indicator is proportional; hence, the financial security scores appear relatively consistent per age group in Nottingham and the rest of the UK, tending to range from 0.37–0.40 (i.e., 37–40% of income remaining, following essential and committed expenses). The lack of variation in the financial security scores is a considerable limitation, as discussed further in Section 6.4.

Although the level of variation in financial security scores across age groups was also modest, there are some potentially useful observations to be made. First, the 18–24 and over 65 age groups had higher financial security scores than other age groups, which potentially contravenes previous research, since energy precarity is generally more pronounced among young adults (ONS, 2023b; Petrova, 2018), as is energy insecurity (see **Chapter 4**: Table 4-4). The relationship between old age and financial security is less clear, given that over 65s have been shown to be at a relatively reduced risk of food and energy insecurity in some cases (ONS, 2023b), yet they are regularly cited as a demographic that is vulnerable to fuel poverty in others (Boardman, 2009). A likely explanation is that the financial security of over 65s is particularly variable, which is substantiated by the relatively high standard deviation in financial security scores for over 65s (SD = 0.2782). This might indicate that there are exogenous variables (e.g., household composition, employment status and disparities in pension income) that mediate financial security scores among this group. An approach that is able to account for unobserved heterogeneity within demographic groupings—such as the random parameters discrete outcome model used in **Chapter 4**—may be useful for disentangling the potential subgroupings of financial security among over 65s; however, this was out of scope in the current analysis.

Results (II): Potential fuel stress in Nottingham

The potential fuel stress indicator can be used to demonstrate cases where median household energy costs constitute a relatively *large* proportion of essential expenses, which might provide insights into the effects that high energy costs have on the ability to spend on other necessities (i.e., food). This is particularly relevant to the estimation of fuel poverty, and more specifically, the degree to which certain people are compelled to make spending trade-offs on food and energy. In this case, potential fuel stress was estimated (according to the process defined in Section 6.2: *Equation 6.2*) for the Nottingham subset[24], and was disaggregated by the age group (see Table 6-4) and postal district (see Table 6-5) variables. Similar to financial security, potential fuel stress is most useful as a relative indicator (i.e., the actual values are not particularly useful in isolation): *high* potential fuel stress (approaching 1) indicates that potential energy costs (i.e., the median per postal district) are likely to compose a large proportion of essential expenditure, meaning a comparatively small amount of essential expenditure can be dedicated to food. *Low* potential fuel stress (approaching 0) indicates the inverse relationship.

Table 6-4. Potential fuel stress per age group: Summary statistics for the Nottingham subset (n=11,041)

Age group	**Potential fuel stress: Nottingham**		
	Mean	**Median**	**Std. deviation**
18–24 (n=785)	0.1836	0.1229	0.1701
25–34 (n=2,181)	0.1364	0.0959	0.1376
35–44 (n=2,067)	0.1380	0.0917	0.1494
45–54 (n=1,893)	0.1385	0.0884	0.1538
55–64 (n=1,704)	0.1592	0.0990	0.1761
Over 65 (n=2,411)	0.1680	0.1181	0.1639

Table 6-5. Potential fuel stress per postal district: Summary statistics for the Nottingham subset (n=11,041)

Postal district	**Potential fuel stress: Nottingham**		
	Mean	**Median**	**Std. deviation**
NG1 (n=151)	0.1614	0.0972	0.1829
NG2 (n=1,078)	0.1376	0.0928	0.1457
NG3 (n=874)	0.1674	0.1172	0.1602
NG4 (n=812)	0.1936	0.1444	0.1643
NG5 (n=1,899)	0.1631	0.1145	0.1585
NG6 (n=750)	0.1855	0.1303	0.1777
NG7 (n=672)	0.2048	0.1408	0.1879
NG8 (n=1,248)	0.1754	0.1218	0.1693
NG9 (n=1,313)	0.1052	0.0657	0.1303
NG11 (n=610)	0.1618	0.1104	0.1587
NG12 (n=934)	0.0980	0.0622	0.1221
NG13 (n=700)	0.0898	0.0625	0.1082

[24] Note: All estimations including the median energy costs variable (EC_{PD}) were only conducted for the Nottingham subset. This is because estimating median energy costs for every UK postal district is a far more computationally intensive task; further, the coverage of the financial data is poorer in rural areas; hence, Nottingham was deemed a suitable case city for potential fuel stress and individual-level fuel poverty ratio estimates.

Unlike the financial security scores, there was considerable deviation between the *mean* and *median* potential fuel stress values. Relatedly, the standard deviation values were relatively pronounced, in many cases matching or exceeding mean values, which is indicative of a high level of in-group variation. As such, the median values of potential fuel stress were considered to be more robust than the mean, which is likely to have been affected by outliers; hence, all further discussion of the potential fuel stress results refers to the *median* values only.

Table 6-4 shows that potential fuel stress was highest among the 18–24 and over 65 age groups, while those aged 25–64 had largely similar scores. This trend appears counterintuitive initially, given the relatively high financial security of the 18–24 and over 65 groups (see Table 6-2); however, this relationship may be explained by the fact that these age groups are likely to have lower total income than other ages (i.e., 25–64, most of whom are likely in full-time employment) and, as a consequence, have lower absolute spends on essential goods. The result of this is that potential fuel stress scores (i.e., the ratio of energy costs to essential expenditure) may be unduly inflated in cases where essential expenditure is inherently low because of income-induced spending limitations. Although this may account for some of the differences in potential fuel stress scores across the age groups, it could also be the case that those aged 18–24 and over 65 do spend a disproportionate amount on energy and are more likely to be at risk of heat-or-eat trade-offs as a result.

Table 6-5 summarises potential fuel stress per Nottingham postal district. There is a more evident dichotomy in the (median) potential fuel stress scores of Nottingham postal districts: seven of the districts have *high* fuel stress scores exceeding 0.1 (NG3, NG4, NG5, NG6, NG7, NG8 and NG11) while the remaining five have relatively low scores below 0.1. As discussed throughout, the relativity of scores discussed in this chapter is of greatest importance and for an area-based indicator, such as the potential fuel stress scores presented here, a more effective interpretation of their meaning may be achieved via bivariate mapping (e.g., mapping potential fuel stress estimates alongside existing deprivation data—as previously demonstrated for LILEE fuel poverty and IMD in **Chapter 3**). In this case, however, mapping potential fuel stress was deemed unproductive, given that comparable datasets (e.g., IMD) are not available at postal district-level granularity. Regardless, postal district-level findings may hold more utility in terms of local governments' allocation of resources.

Results (III): The individual-level fuel poverty ratio in Nottingham

The final indicator of interest was the individual-level fuel poverty ratio, which was calculated by dividing the median inferred costs per postal district by total income (as per *Equation 6.3*). Similar to the original Boardman (1991) fuel poverty ratio, the individual-level fuel poverty ratio is a valuable indicator of high potential energy expenditure as a proportion of total income. There are, however, several notable limitations to the individual-level approach. Most notably, the assumption of consistent energy costs for individuals belonging to each postal district inevitably induces a degree of inaccuracy; however, like potential fuel stress, individual-level variation in the variables deduced from the financial data—total income, in this case—still provides some insights into the individual-level risk of fuel poverty. Table 6-6 displays the individual-level fuel poverty ratio per Nottingham postal district. Demographic crosstabulation (i.e., by age group) was not considered in this case, as the sociodemographic factors affecting the individual-level fuel poverty ratio were instead explored via the estimation of a linear regression model (see Table 6-8).

Table 6-6. Individual-level fuel poverty ratio per postal district: Summary statistics for the Nottingham subset (n=11,041)

Postal district	**Individual-level fuel poverty ratio**			
	Mean (%)	**Median (%)**	**Std. deviation (%)**	**Proportion above 10% (%)**
NG1 (n=151)	6.12	4.38	6.70	12.32
NG2 (n=1,078)	6.57	4.92	7.05	15.94
NG3 (n=874)	8.07	6.06	9.17	22.68
NG4 (n=812)	9.55	7.59	7.95	32.02
NG5 (n=1,899)	7.83	5.94	7.58	22.62
NG6 (n=750)	8.24	6.46	7.02	25.57
NG7 (n=672)	9.64	7.49	9.75	33.28
NG8 (n=1,248)	8.49	6.25	8.61	25.41
NG9 (n=1,313)	5.00	3.29	7.38	9.46
NG11 (n=610)	7.28	5.80	6.76	19.06
NG12 (n=934)	4.58	3.21	5.37	8.44
NG13 (n=700)	4.18	3.31	4.47	5.43

Table 6-6 demonstrates considerable variation in the typical individual-level fuel poverty ratio per Nottingham postal district. Similar to the interpretation of Table 6-5, the relatively high in-group variation (i.e., standard deviation statistics per postal district) indicates that the *median* column is likely to provide the most reliable insights into postal district-level statistics. Further, the *proportion above 10%* column describes the rate of 10% fuel poverty per postal district, but for individuals (i.e., these estimates are likely to be somewhat conservative).

Modelling the individual-level fuel poverty ratio

A basic linear regression model was estimated to explore the effect of sociodemographic variables on the individual-level fuel poverty ratio score (i.e., the dependent variable—a continuous outcome with minimum=0 and maximum=100), according to the process described in *Equation*

6.4. Table 6-7 displays descriptive statistics for independent variables that were deemed relevant. These included the available sociodemographic variables (age and gender), a *benefits* (i.e., state support) indicator variable, and two financial security-related variables that captured the proportion of total income dedicated to essential and committed expenditure. The sex, age and benefits variables are binary indicator variables and can be interpreted as such: a *mean* value of 52.38% for the 'sex (female)' variable indicates that 52.38% of the sample were female and 47.62% were male (see also **Chapter 4**: Table 4-3 for further notes on the interpretation of binary indicator variables). The proportional variables—'proportion of income designated to essential/committed expenditure'—are continuous variables, with possible values ranging from 0 to 100. The *mean* column value for the essential expenditure variable, for example, shows that the average proportion of total income spent on essential goods across the sample was 56.27%. The standard deviation is also presented for continuous independent variables to provide insight into the degree of variation in the associated mean statistic.

Table 6-7. Fuel poverty ratio model: Descriptive statistics for relevant independent variables (n=10,431)[25]

Variable description	**Min**	**Max**	**Mean**	**Std. deviation**
Sex (1 if female, 0 if male)	0	1	52.38%	–
Age (1 if aged 18–24, 0 otherwise)	0	1	7.10%	–
Age (1 if over 65, 0 otherwise)	0	1	21.91%	–
Benefits (1 if receiving state support, 0 otherwise)	0	1	14.17%	–
Proportion of income designated as *essential expenditure*	0	100	56.27%	22.31%
Proportion of income designated as *committed expenditure*	0	100	6.69%	9.52%

Table 6-8 presents the model estimation results, which can be interpreted as follows: the *t-stat* column indicates the level of statistical significance associated with each independent variable (where a t-stat>1.96 corresponds to p-value<0.05 and >95% level of confidence (l.o.c.)), in line with standard practice (Fountas, et al., 2021; Washington, et al., 2020). The *coefficient* column can be interpreted as follows: for the 'age (18–24)' variable, a positive coefficient of 2.49 indicates that individuals meeting this description (those aged 18–24) were predicted to have a fuel poverty ratio that was 2.49 percentage points higher than the reference group (those aged over 25), while controlling for other included variables (sex, benefits, and proportional expenditure indicators).

[25] Note: The Nottingham sample size reduced to 10,431 following the omission of 610 individuals who had incomplete or invalid information (i.e., missing age information or unrealistic expenditure values—less than 0 or more than 100); in other words, only fully complete and valid observations were included in the model. Further, the independent variables shown in Table 6-7 all met the variable inclusion criteria: variables with pairwise correlation coefficients of less than –0.3 or more than 0.3 were omitted to control for multicollinearity.

Table 6-8. Linear regression model results: Factors influencing the individual-level fuel poverty ratio (n=10,431)

Variable description	**Linear regression model: Fuel poverty ratio**	
	Coefficient	**t-stat**
Intercept	5.33	22.76
Sex (1 if female, 0 if male)	0.09	0.66
Age (1 if aged 18–24, 0 otherwise)	2.49	8.95
Age (1 if over 65, 0 otherwise)	1.11	6.40
Benefits (1 if receiving state support, 0 otherwise)	1.84	9.10
Proportion of income designated as *essential expenditure*	0.02	6.72
Proportion of income designated as *committed expenditure*	-0.03	-3.97
Observations	10431	
Log likelihood (constant only)	–36816.05	
Log likelihood (at convergence)	–36640.09	
R^2	0.03	

The model results show that those who were aged 18-24, aged over 65, in receipt of benefits or spending a relatively high proportion of their income on essential goods were all significantly more likely than their respective control groups (see *variable description* columns) to have a relatively high fuel poverty ratio score. It is also worth noting the seemingly low model fit indicated by an R^2 value of 0.03. Although this means that the model only explains ~3% of the variance in the dependent variable, explanatory power was not the primary aim of this exercise. Further, the low level of explanatory power is to be expected given that numerous relevant variables (e.g., household composition, *actual* energy costs, behavioural variation in energy consumption, *et cetera*) were not available. In this case, the directional effects of available independent variables were of most interest.

6.4. Discussion of results

This section presents a structured discussion of each indicator's relative utility versus traditional approaches, while also considering ways that each indicator might be enhanced with more detailed input data.

Financial security

The financial security estimates presented in this chapter provided insights into the *proportion* of total income spent on essential and committed goods. These findings show that this metric is potentially useful for demonstrating group-level differences in financial security; however, it is also inherently limited by its proportional nature, which was evidenced by the very modest level of variation between age groups (see Table 6-2). Further, the trend in financial security was somewhat counterintuitive, given that young (18–24) and older (over 65) adults had the highest financial security scores, despite often being classed as precarious or vulnerable age groups (ONS, 2023b; Petrova, 2018). This trend may also be a result of the proportional, as opposed to absolute,

estimation process. For example, if individual X1 has high income (e.g., £100,000/year) and high expenditure on essential and committed good (e.g., £70,000/year, collectively), the absolute residual income of X1 (£30,000/year) would still be higher than individual X2 (e.g., total income = £20,000; committed and essential expenditure = £10,000, financial security = 0.5), despite a lower financial security score (0.3) for individual X1.

This highlights a fundamental shortcoming of the proposed financial security metric: people generally tend to live within their means; hence, the proportional version of financial security is likely not a particularly useful metric for poverty (or fuel poverty) research, as it does not capture how residual income changes over time (in absolute terms), which is an important dimension of income volatility and precarity in the literature (Gallo, et al., 2014; Standing, 2011; Villegas, 2014). As such, further work may build on the metric proposed here by providing temporal estimations of financial security in absolute and proportional terms; this, however, was deemed out of scope in the current analysis, given that the primary aim was to analyse fuel poverty proxies, which tend to be measured at yearly intervals.

Potential fuel stress

The potential fuel stress metric provided broad estimates of energy unaffordability at the postal district- and group-level. As discussed in the results, the assumption of median energy costs per postal district is a considerable limitation of the fuel stress indicator, yet this was deemed unavoidable, given the postal district-level granularity of the financial data. Potential fuel stress was found to be highest among young (18–24) and old (over 65) adults, while those aged 25–64 had comparatively low scores. High potential fuel stress may indicate a correspondingly high risk of heat-or-eat trade-offs, given that the indicator is essentially the ratio of median energy costs to essential expenditure. *If* this is the case, then the aforementioned age groups (18–24 and over 65) may also be said to be more likely to have made heat-or-eat trade-offs in the study period (FYE 2023). It must be noted, however, that since potential fuel stress is a proportional indicator, it may suffer from similar deficiencies as the financial security metric; therefore, this feature of the potential fuel stress indicator—as a proxy for heat-or-eat trade-offs—requires further investigation.

Another limitation of the potential fuel stress approach is that there are no comparable metrics in the literature, to the best of the author's knowledge. This means that the values of potential fuel stress presented in this analysis are inevitably abstract, as what constitutes a *high* or *low* fuel stress is largely unknown. Nevertheless, the identification of relatively high potential fuel stress

among those aged 18–24 generally concurs with the literature, given that young adults are disproportionately affected by energy precarity (Petrova, 2018) and energy insecurity (see **Chapter 4:** Table 4-4). The increased fuel stress of those aged over 65 is less straightforward to interpret, however, as older adults have been identified as vulnerable in some contexts (Boardman, 2009), but relatively secure in others (ONS, 2023b).

In summary, the potential fuel stress indicator developed in this chapter may be useful for measuring specific dimensions of fuel poverty, most notably, the spending trade-offs on necessities that some people are constrained to make, especially in the winter. Despite this potentially valuable quality, the metric in its current form (i.e., based on median energy costs as opposed to individual- or household-specific costs) relies on assumptions that are overly simplistic. If the expenditure data (i.e., the financial data) were to be accurately integrated with more detailed energy costs data at the same granularity (e.g., individual- or household-level), the fuel stress indicator could provide more robust insights into the areas or groups that are at increased risk of heat-or-eat trade-offs.

Individual-level fuel poverty ratio

The final indicator considered in the financial data analysis was an individual-level version of the fuel poverty ratio. The limitations discussed above concerning the overly reductive inference of area-level median energy costs also apply to the individual-level fuel poverty ratio; however, these are not discussed further to avoid repetition. Moreover, the numerical values of the fuel poverty ratio per postal district (see Table 6-6) were not particularly insightful, mostly because postal districts are not a unit of area that are regularly used for comparable statistics; for example, LILEE and IMD statistics are summarised at LSOA-level granularity.

Despite the slightly counterintuitive nature of the individual-level fuel poverty ratio, group-level disparities can still provide valuable information regarding the relative proportion of income that is likely spent on energy. The estimation of a linear regression model provided insights into relative disparities in the individual-level fuel poverty ratio using a small set of explanatory variables: age, gender, benefits status and two expenditure-based variables (see Table 6-8). Both age-related (18–24 and over 65) variables significantly increased the likelihood of a *high* fuel poverty ratio, compared to their respective control groups, whereas the ‘sex’ variable had statistically insignificant effects. As expected, those who were in receipt of benefits had a significantly higher fuel poverty ratio (up 1.84 percentage points) than the control group (those who did not receive any state support). Relatedly, those with a relatively high proportion of

income dedicated to essential goods (an unknown portion of which was energy bills) were significantly more likely to have a high fuel poverty ratio; conversely, those with a relatively high proportion of income dedicated to committed expenses were less likely to have a high fuel poverty ratio (i.e., this variable was associated with lower fuel poverty ratios). A possible reason for the conflicting effects of the expenditure variables is that relatively high committed expenditure may in fact indicate higher financial security in some cases, given that committed expenses refer to fixed payments (e.g., loans, subscriptions, *et cetera*), and people with higher committed expenses may have greater spending power. Given that the essential and committed expenses variables cannot be disaggregated into individual items, this interpretation is made cautiously and should be investigated further.

Despite the limitations of the individual-level fuel poverty ratio, as well as the low explanatory power achieved by the linear regression model, it may still be a useful proxy for the original household-level fuel poverty ratio and, consequently, the affordability of energy. A particularly useful extension to this indicator would be to consider temporal fluctuations in the affordability of energy; however, to do so would require the availability of actual energy expenditure (i.e., a disaggregation of the *essential expenditure* variable to food, energy and any other goods). The availability of this data, which is available in certain circumstances (see Mould & Baker (2017), for example), would enhance the accuracy of the fuel stress and individual-level fuel poverty ratio indicators markedly.

6.5. Conclusions, limitations and further work

Three individual-level fuel poverty- or financial security-related metrics were estimated in this chapter via the analysis of a large financial dataset. In general, the analysis showed that financial data may have utility in terms of providing more immediate insights into fuel poverty and related conditions, assuming that financial data can be made available and be analysed more promptly than the data that contribute to official DESNZ statistics. However, until there is greater availability of *household-level* financial data, the metrics developed in this chapter have relatively little applicability as a primary means of quantifying fuel poverty. This is because the financial data explored in this instance refer to individual-level income and expenditure records, which means household composition and dynamics cannot be accounted for. Specifically, the analysis of individual-level essential expenditure variables is potentially an unproductive way of viewing fuel poverty, as in many cases, essential expenses are likely divided to an unknown extent among the household's occupants. In summary, the financial data explored in this chapter could theoretically be used to provide more instantaneous insights into fuel poverty, as well as more detailed

temporal variations (i.e., the analysis of weekly or monthly trends); however, the utility of financial data as a means to accurately quantify fuel poverty is inevitably limited by the fact that fuel poverty is a household condition and therefore is best measured by household-level variables. To remedy this crucial shortcoming of the financial data, data that are compatible with traditional household-level fuel poverty definitions must be explored. The following chapter (**Chapter 7**) achieves this via the simulation of synthetic households with corresponding household-level income and energy expenditure variables.

Aside from the general limitations of the financial data, several further indicator-specific limitations of the analysis presented in this chapter should be noted. First, the proportional nature of the financial security and potential fuel stress indicators may not be able to accurately account for people "living within their means". This is because a relatively low financial security score does not necessarily indicate low absolute residual income, as demonstrated previously. Similarly, a relatively high potential fuel stress score may simply indicate that absolute expenditure on necessities is low, but not necessarily in a way that affects a person's standard of living. A further analysis may consider absolute (i.e., based on the actual amount of residual income) versions of the financial security and potential fuel stress metrics. Second, the assumption of median household energy costs per postal district is bound to have had detrimental impacts on the robustness of the potential fuel stress and fuel poverty ratio indicators. This assumption effectively neglects the effects of household-level variation in energy efficiency and running costs on fuel poverty. Though this is plainly an oversimplified way of quantifying energy costs, the inference of median costs per postal district was the only available option in the current analysis. Further work may consider a more sophisticated analysis of the potential fuel stress and individual-level fuel poverty ratio indicators via the development of household archetypes using the financial data (e.g., inferring likely combinations of composition, efficiency and costs); however, this is a significant analytical task that was deemed out of scope in this case. Finally, the geographic granularity of the financial data (measured at the postal district level) limits the usefulness of all of the metrics; for example, most comparable datasets are measured per LSOA or MSOA, therefore, LSOA or MSOA-level maps could not be produced in this analysis to assess the closeness of the metrics to existing data (e.g., LILEE or IMD).

Despite the considerable limitations affecting the analysis of the financial data in this chapter, this type of dataset may have some utility for the quantification of fuel poverty in the future. The utility of the financial data in this context, however, is largely dependent on its constituent variables being more detailed (e.g., the itemisation of essential expenditure variables) and the production of household-level datasets, which are ultimately required to gauge fuel poverty, given that the

condition of being fuel poor depends on a range of household-level variables (income, energy efficiency and energy costs). If actual energy costs were able to be provided in this type of financial dataset, the utility of these data for fuel poverty classifications would increase markedly; however, as things stand, the financial data were considered too limited to conduct any of the fuel poverty measurement experiments proposed in **Chapter 5**.

Chapter 7: Developing and Validating Fuel Poverty Measurement Approaches using Synthetic Data

All models are wrong, but some are useful.

George E. P. Box

The aphorism, *all modes are wrong, but some are useful*, coined by George Box is a befitting reminder of the limitations of research. In many cases, data limitations predetermine the nature of research questions that are proposed. In the context of the current research, this is particularly true: granular household-level data for income, energy costs and composition, which are typically required for fuel poverty classifications, are not readily available. Further, the availability of real-world income data (as presented in **Chapter 6**) does not necessarily mean they possess utility in the context of poverty research; for example, the measurement experiments proposed in **Chapter 5** were not answerable using the financial data.

To combat the limitations of the **Chapter 6** analysis, this chapter presents an alternative synthetic data generation-based approach. Specifically, LSOA-level household income distributions are generated across the city of Nottingham, based on existing aggregate income estimates (i.e., the ONS's LSOA-level income point estimates) and other unit-level (i.e., per individual or household) data, namely, the *Understanding Society* longitudinal survey. The synthetic data output (unit-level household income paired with EPC records) facilitates the fuel poverty measurement experiments, allowing competing fuel poverty definitions to be compared in a meaningful way. Although the synthetic data are likely to be *wrong*, in the sense that they do not represent actual households, the analysis presented in this chapter shows they can still be highly useful for poverty-focused research.

Studying geographical distributions of household income data is extremely valuable when researching poverty and its associated harms. However, as discussed previously, such distributions are rarely available to researchers due to access and privacy challenges. The generation of synthetic income data is a promising approach that can overcome issues associated with the collection of real-world income data. In this chapter, a direct sampling approach is

developed to generate LSOA-level synthetic household income distributions in the city of Nottingham, UK. The resulting LSOA-level household income distributions (referred to throughout as Synthetic Nottingham Homes) can be used for various poverty-focused studies. The potential cross-disciplinary appeal of the Synthetic Nottingham Homes data resource, as well as the synthetic data generation approach, which could be extended to any other UK region, is discussed at greater length in the conclusions section of this chapter.

Chapter 7[26] contains three core parts as follows: i) the rationale underlying the synthetic data generation method; ii) the generation and pseudo-validation of LSOA-level synthetic income data (Synthetic Nottingham Homes); and iii) the completion of the **Chapter 5** fuel poverty measurement experiments using the synthetic output. Crucially, the fuel poverty experiments presented in this chapter demonstrate overlaps and disparities in the profile of fuel poor homes identified by various existing fuel poverty definitions, including 10%, five-fold 10%, LIHC, LILEE and MIS-based fuel poverty. The results of the experiments empirically substantiate many of the perceived pros and cons of existing definitions (as previously listed in Table 5-1), leading to the proposal of an amended Two-Step Fuel Poverty Measurement Framework. Further, the synthetic data generation approach is discussed in terms of its potential as a tool for answering poverty-related research questions at a granular level, i.e., household- or LSOA-level. In terms of this thesis's stated research questions, this chapter provides evidence for *Research Question D*:

> *How effective are competing definitions of fuel poverty (existing and novel) in terms of identifying homes that are unable to afford sufficient energy?*

Following the measurement experiments, a sensitivity analysis is conducted to show how the impending acceleration of energy transitions (e.g., if all homes were to achieve their potential energy efficiency) might affect fuel poverty and how the chosen definition in England might contribute to further obfuscation. This is reducible to the simple fact that the justness of the energy transition is not evaluable without fair and accurate measures of fuel poverty.

7.1. Background: A direct sampling approach to synthetic data generation

Synthetic data generation is a nascent approach that is used to combat data accessibility, privacy and sparsity issues. To date, synthetic data approaches appear most frequently in the medical literature (Giuffrè & Shung, 2023; Rajotte, et al., 2022) and they are used to address patient

[26] The findings of **Chapter 7** contributed to the following article: Generating Experimental Area-Level Synthetic Income Datasets for use in Poverty Research. *European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases*.

confidentiality issues and the inherent sparsity of many health-related datasets. In the context of poverty research, data accessibility, privacy and sparsity issues are also applicable to income, such that a meaningful sample of unit-level income data is often challenging or impossible to obtain. Birkin & Clarke (1989) previously adopted *synthesis*, i.e., a form of synthetic data generation before the term was coined, adopting iterative proportional fitting (IPF) and microsimulation to estimate small-area income distributions in Leeds based on the *1981 Census* and the *New Earnings Survey*. Though this study bears some resemblance to the current data generation task, the primary aim was to address missing observations in census data, whereas this analysis aims to generate a city-scale set of synthetic homes. Nonetheless, the approach used by Birkin & Clarke (1989) is comparable to the current exercise, in which aggregate data are used to infer microdata (i.e., unit-level, household characteristics) for the population of Nottingham. Further studies have explored similar methods to infer microdata; for example, Sakshaug & Raghunathan (2014) used large-scale *National Health Interview Survey* data to infer synthetic responses for small unsampled areas. The synthetic data were validated by comparing aggregate small-area statistics to larger surveyed areas. A similar validation approach is adopted in this chapter, as the LSOA-level synthetic data are compared to MSOA-level ONS data.

Another necessary consideration is the specific method chosen for the synthetic data generation. Generative AI techniques are becoming increasingly popular in the contemporary literature, particularly the use of large language models (LLMs), generative adversarial networks (GANs) and variational autoencoders (VAEs) (Goyal & Mahmoud, 2024); these methods, however, are computationally intensive and tend to rely on the presence of existing unit-level data. As a result, these approaches were considered unfeasible in the current study, and a *direct sampling* approach, which generates synthetic data based on target probability distributions, was adopted instead. The fundamental principle underlying all of the aforementioned methods is the generation of synthetic data that mimics the statistical properties of real-world data. In this case, a direct sampling method is applied to publicly available income and household-level data to extrapolate unit-level income distributions. Direct sampling is a relatively straightforward method, such that it is achieved by specifying a target probability distribution and applying constraints, in a similar vein to the IPF approach of Birkin & Clarke (1989), which constitutes a type of direct sampling.

Copula-based methods were also considered, given their previous deployment for the generation of unit-level synthetic data from aggregate sources (Kao, et al., 2012; Li, et al., 2020) and their ability to retain underlying variable dependencies, e.g., the relationship between household income and composition. Accounting for the marginal income distributions of different household

types would likely enhance the accuracy of the synthetic data, given the well-established relationship between household economic insecurity and certain household compositions, e.g., dual-income homes tend to have higher economic security (ONS, 2024a). However, in this case, LSOA-level household composition data were not readily available, while the Gross Disposable Household Income (GDHI) point estimates used to inform the synthetic data were equivalised; hence, it would be spurious to integrate further household composition information. As a result, the copula-based method was discarded on the basis that there are no underlying variable dependencies to account for, meaning that the direct sampling and copula-based methods would yield nearly equivalent outputs.

7.2. Data

The value of synthetically generated data is dependent on their representation of reality. To increase the likelihood of the synthetic data adhering to realistic conditions, a range of publicly available datasets were integrated to inform the generation of synthetic income distributions for Nottingham's LSOAs. Relevant datasets included GDHI estimates for small areas in England (ONS, 2024b); the *Understanding Society* longitudinal, UK household survey (University of Essex, Institute for Social and Economic Research, 2022); and general household information per LSOA (e.g., number of homes) (ONS, 2022e) (see Table 7-1 for an exhaustive list of relevant data). These datasets were integrated according to LSOA codes; however, an unavoidable limitation of this process was induced by recent changes to LSOA geographies. The LSOA boundaries used in previous chapters refer to those active from 2011. In 2021, LSOA geographies were updated by splitting or merging existing areas, a process undertaken every decade or so to ensure that LSOA populations remain approximately consistent (ONS, 2021b). Although this change came into force in 2021, lags affecting other datasets mean that 2011 LSOA geographies are still used in many cases; for example, GDHI estimates (released 2024) were calculated based on income data for 2002 to 2021 and use 2011 LSOAs. Similarly, IMD (released 2019) is recalculated every 5–10 years; therefore, current IMD scores are compatible with 2011 LSOAs. Incompatibility between 2011 and 2021 LSOA-coded data can be partially mitigated through the ONS's "best fit lookup" (ONS, 2024c)[27], although the release of this tool in 2024 is illustrative of the lag affecting the geographical coding of associated datasets. Given the issues discussed above, and for consistency with previous chapters, the 2011 LSOA boundaries were used throughout this chapter.

Data fusion: Integrating relevant datasets to inform synthetic data parameters

[27] Comparisons of 2011 and 2021 LSOAs in Nottingham show that the number of LSOAs reduced from 182 in 2011 to 177 in 2021. Further, in 170 cases, 2011 LSOAs remained the same in the 2021 release; hence, the majority of LSOAs were unchanged.

The ultimate aim of the synthetic data generation was to produce broadly representative household income distributions per Nottingham LSOA. This was achieved by determining likely income distribution parameters per LSOA, namely: sample size (number of households per LSOA), lower and upper bounds, the mean, the standard deviation and the likely shape (e.g., normal or log-normal) of the distribution. All of these parameters are known or can be inferred using publicly available data. Table 7-1 contains an exhaustive list of the data used to inform the synthetic data parameters. Given the incompatibility of 2011 and 2021 LSOA geographies affecting some data (namely, the number of households and EPC), a small number of values were imputed, as per the *missing data* column; the *parameter* column matches each dataset to the data generation parameters that they were used to inform (e.g., shape, lower/upper bounds, mean and standard deviation).

Table 7-1. Publicly available data fused to inform synthetic income data parameters

Dataset	**LSOA (2011 or 2021)**	**Missing data**	**Parameter**
Number of households (ONS, 2022e)	2021	Missing data (n) = 12 LSOAs Replaced with mean number of households (670)	Approximate number of households per LSOA, i.e., the quantity of synthetic data to be generated per LSOA
Gross Disposable Household Income (GDHI) estimates for small areas (ONS, 2024b)	2011	Missing data (n) = 0	Mean (equivalised) GDHI per LSOA
Understanding Society (University of Essex, Institute for Social and Economic Research, 2022)	2011	Missing data (n) = 0	Typical shape and standard deviation of income distributions among a real sample of English households
Index of Multiple Deprivation (IMD) (DLUHC, 2020)	2011	Missing data (n) = 0	Income standard deviation consistency across IMD ranks
EPC database (SAP – mean and SD) (DLUHC, 2024)	2021	Missing data (n) = 12 LSOAs Mean and SD SAP (i.e., scale for derivation of EPC) imputed using k-nearest neighbours (KNN) algorithm	LSOA-level energy efficiency, used to infer typical energy costs. Note: these data are not strictly related to the synthetic income data, but are used in the fuel poverty measurement experiments

An overview of ONS income types

Prior to the generation of the synthetic income data, further consideration had to be given to the specific definition of *income*; for example, *income* could refer to gross, disposable or net income, can be measured at individual- or household-level and, if measured at household-level, is often

equivalised to account for household composition (i.e., adjusted based on the combination of earning and dependant occupants). Figure 7-1 provides a simplified visualisation of the ONS's income categories (ONS, 2024d), which is used throughout this chapter to rationalise certain income adjustments. Green and red panels in Figure 7-1 represent income enhancements and deductions, respectively, whereas grey panels are the ONS's main income categories; for example, *original income* refers to total earnings (including private pensions), while *gross income* is *original income* including *state support* enhancements.

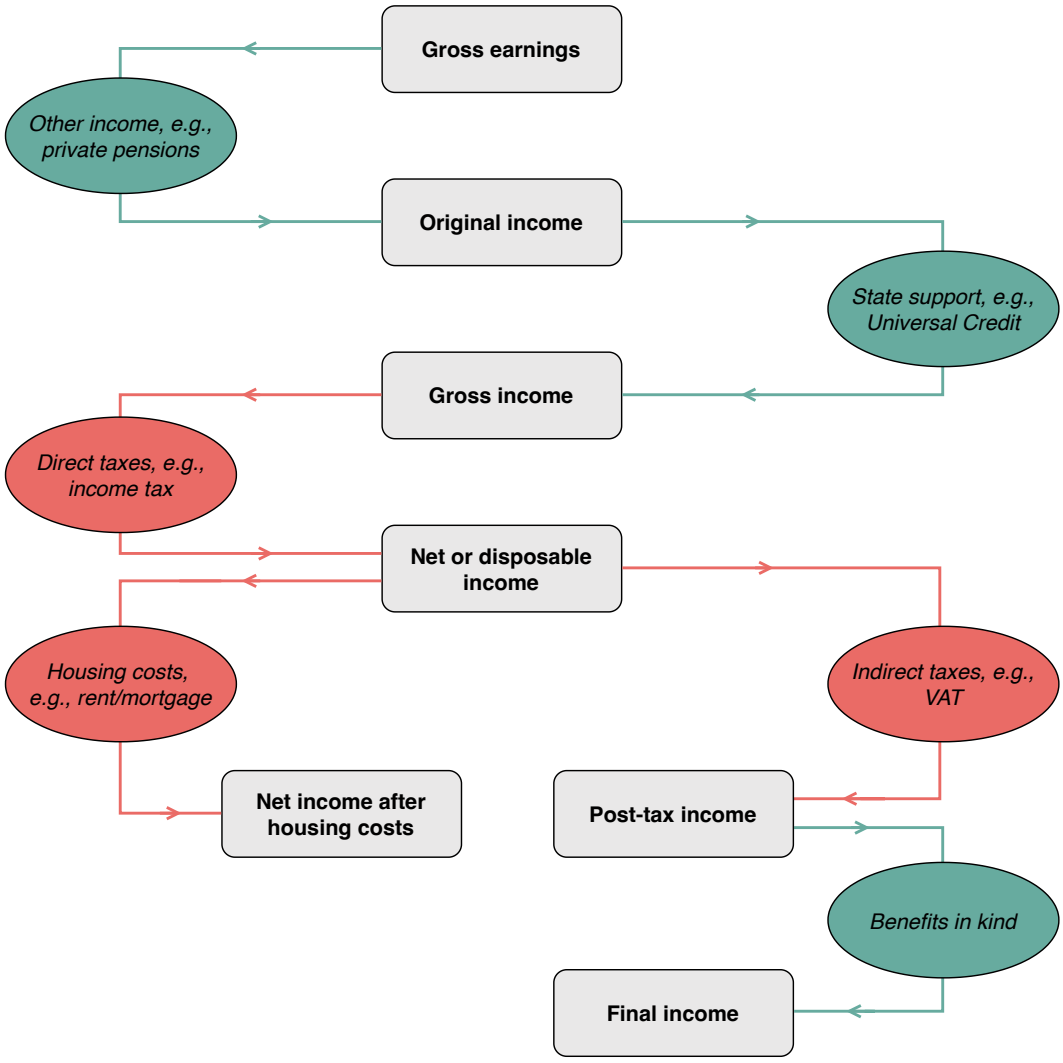


Figure 7-1. Simplified categorisation of ONS (2024d) income types[28]

The ONS's (2024b) income estimates for small areas refer to gross disposable household income (GDHI), while the *Understanding Society* income variable initially refers to unequivalised net household income. As shown in Figure 7-1, net income is equivalent to gross income minus direct

[28] Figure interpretation: green fill = enhancements/additions and red fill = deductions between income categories; for example, *net or disposable income* = *gross income* following the deduction of *direct taxes*.

taxes (e.g., income tax). Conversely, GDHI is not included in the ONS (2024d) income categorisation but is defined in separate documentation (ONS, 2024b) as: "*the amount of money left over for spending or saving after taxes, social contributions, and other income distribution measures have been taken into account".* GDHI is equivalised; therefore, the net disposable income data (retrieved from *Understanding Society*) should also be equivalised, as discussed further in the following sections. Equivalisation is typically performed at the *net or disposable income* stage, after direct tax deductions. For the purposes of this research, the ONS's *gross disposable household income* was considered to be effectively equivalent to *net household income* (NHI), as there is often no difference between both categories[29]; further, both GDHI and NHI can be equivalised, given that they are post-direct tax forms of income and are calculable before housing costs (BHC) or after (AHC).

7.3. Methods

This section elaborates on the methodological process underlying the generation of synthetic income distributions for Nottingham and the subsequent phases of analysis, including the validation of the synthetic data and the performance of fuel poverty measurement experiments. All code pertaining to the synthetic data generation process is provided in supplementary files (https://github.com/torransemple/thesis_supplementary_material/tree/main/Chapter_7/I)[30].
A high-level methodological overview of the synthetic data generation (*Steps 1–3*), the validation of the synthetic data output (*Step 4*) and the fuel poverty measurement experiments (*Step 5*) is displayed in Table 7-2.

Table 7-2. High-level methodological steps for the generation of synthetic data, validation and measurement experiments

Step	Data	Explanatory notes
1 – Data fusion	GDHI small area estimates Number of households EPC database LSOA 2011/2021 lookup	These data were fused to create a summary data frame: GDHI, number of households and average energy efficiency per LSOA in Nottingham
2 – Infer synthetic data generation input parameters	*Understanding Society* longitudinal survey	The *Understanding Society* data were used to infer other parameters required for the synthetic data generation, including income variability (i.e., standard deviation) and suitable lower and upper income limits
3 – Synthetic data generation	Combined data frame with a complete set of relevant parameters per LSOA: number	Synthetic data were generated for each of Nottingham's LSOAs using a direct sampling approach

[29] The most notable difference is that GDHI takes into account "other income distribution measures", which include social contributions or benefits in kind; in other words, other cash benefits provided by a person's employer (ONS, 2024e). In any case, NHI and GDHI are the most compatible income categories, given that they both refer to the income a household has left to spend after direct taxes (e.g., income tax) and state support (e.g., universal credit).
[30] Note: R code to reproduce the synthetic data generation is in 'CH7_I_synthetic_data_generation.Rmd'.

	of homes, mean income, income variability, lower & upper limits	
4 – Pseudo-validation	Synthetic data outputs: direct sampling Validation data: MSOA-level income estimates	This step validates the synthetic data in terms of their proximity to further ONS MSOA-level income estimates
5 – Fuel poverty measurement experiments	Synthetic income distributions per LSOA EPC database	Using the synthetic data output and the EPC database, this step conducts a selection of the fuel poverty measurement experiments that were proposed in **Chapter 5**.

Steps 1 (*data fusion*) and 2 (*infer synthetic data generation input parameters*) were outlined in the previous section; therefore, they do not merit further discussion here. Step 3 (*synthetic data generation*) requires further explanation. A direct sampling method was chosen for its relative simplicity and explainability, while methodological contributions were also considered tangential to the main purpose of this chapter, which is ultimately to conduct fuel poverty measurement experiments on a synthetic set of homes. The direct sampling approach can be described in mathematical notation as follows. All with respect to a given LSOA, j. Let Y_i represent the synthetic income for a given household, i; where μ_j represents mean income (i.e., the GDHI point estimates); σ_j represents inferred income standard deviation; U_j represents the upper bound for income; and N_j represents the number of households (i.e., the number of income data to be generated per LSOA). Then, for each LSOA, N_j independent and identically distributed random values, Z_i, are generated from a standard normal distribution, with mean=0 and standard deviation=1:

$$Z_i \sim N(0,1)\ for\ i = 1, \dots, N_j \tag{7.1}$$

Z_i is transformed to a log-normally distributed variable, Y_i, given that household income often follows a log-normal distribution (Kloek & van Dijk, 1978), as substantiated in Section 7.4:

$$Y_i = exp\ (\mu'_j + \sigma'_j Z_i) \tag{7.2}$$

Where μ'_j and σ'_j are expressed as:

$$\mu'_j = log\left(\frac{\mu_j^2}{\sqrt{(\sigma_j^2+\mu_j^2)}}\right) \tag{7.3}$$

$$\sigma'_j = \sqrt{\left(log\left(1 + \frac{\sigma_j^2}{\mu_j^2}\right)\right)} \tag{7.4}$$

The application of the upper bound (i.e., the estimated upper income limit) for the household-level values, i, per LSOA, j, ensures that the generated values remain within a realistic range, and is written as follows:

$$Y_i = min\left(Y_i, U_j\right) for\ i = 1, \dots, N_j \tag{7.5}$$

Following the synthetic data generation, Step 4 of the methodological process was to validate the output via comparisons with MSOA-level summary statistics retrieved from ONS (2024e). In this case, the mean average error, i.e., the mean difference between the synthetic and ONS's MSOA point estimates, and median absolute error, i.e., the equivalent calculation based on median differences, were used as evaluation metrics. This step is referred to as *pseudo-validation*, given the lack of unit-level ground truth data. Finally, Step 5 involved the estimation of fuel poverty according to various competing fuel poverty definitions (i.e., the fuel poverty measurement experiments proposed in **Chapter 5**). While these experiments mirror the recommendations of Section 5.4, those presented here are a more specific set of measurement experiments that can be conducted on English household data to better understand the modern appropriateness of competing fuel poverty definitions. Following the measurement experiments, a sensitivity analysis is conducted to show how the impending acceleration of energy transitions (e.g., if all homes were to achieve their potential energy efficiency) might affect fuel poverty and how the chosen definition in England might contribute to further obfuscation. This is reducible to the simple fact that the justness of the energy transition is not evaluable without fair and accurate measures of fuel poverty.

Among the original list of measurement experiments (see **Chapter 5**), the following were deemed possible:

> ***Experiment A:*** *Estimate the current rate of fuel poverty according to the 10%, LIHC and LILEE definitions, and determine the degree of overlap between all approaches*
>
> ***Experiment C:*** *Apply a five-level (or more), temporal version of the 10% definition to simultaneously measure the depth and entrenchment of fuel poverty*
>
> ***Experiment D:*** *Estimate the current level of MIS-based fuel poverty, i.e., apply the Scottish methodology (or similar) to English households*

Experiment F: *Apply various combinations of existing definitions: a) MIS-based + five-fold 10%; MIS-based + LIHC; MIS-based + LILEE. Each scenario can be used to show the degree of overlap between MIS-based fuel poverty and other approaches, or, inversely, to show the number of homes with inadequate living standards that are omitted by existing definitions*

Experiment A is relatively straightforward, as the estimation of 10%, LIHC and LILEE fuel poverty follows the processes previously described in **Chapter 2**; however, household-level energy costs must also be known for the estimation of 10%, LIHC and LILEE fuel poverty. To achieve this, the synthetic income data were assigned to actual EPC ratings, from which energy costs were subsequently inferred. The assignment of synthetic homes to existing EPC records was based on total floor area, such that the household with the highest synthetic income estimate for a given LSOA was assigned to the household with the highest total floor area, based on the assumption that higher household income is likely associated with higher household floor area and, consequently, higher energy consumption (Gao, et al., 2024). This generalisation likely led to inaccurate pairings of synthetic income and EPC ratings in some cases, as there was no easy way to validate the assignment process.

The EPC database includes modelled energy costs for heating, lighting and hot water. The sum of these variables represents a household's total modelled energy costs, referred to as *EPC-modelled energy costs* from hereon. Simple exploration of EPC-modelled costs shows that they are not particularly representative of real-world conditions. The median home in Nottingham has EPC-modelled costs of £726 per year; however, typical energy costs were £2,252 per year according to the most recent government estimates (DESNZ, 2024b). It seems likely that EPC-modelled costs are based on outdated energy prices and do not account for the significant rises in gas and electricity unit prices during the early 2020s; although, it is not entirely clear what unit prices were used for the DLUHC (2024) modelled costs. Regardless, the EPC-modelled costs were deemed irrelevant due to their likely underestimation of current typical energy costs.

To combat this inaccuracy, an alternative method was used to infer energy costs using updated energy unit prices (*inferred energy costs*). The inferred costs were derived from energy consumption variables in the EPC database, as well as Ofgem (2025) unit price caps and daily standing charges for gas and electricity. Inferred energy costs are represented by the following equation:

$$Inferred\ energy\ costs\ \left(\frac{£}{yr}\right) = Gas\ costs + Electricity\ costs \tag{7.6}$$

Where household gas costs are based on the annual modelled consumption of gas multiplied by the unit price cap for gas, plus the annual standing charge (daily charge multiplied by 365)[31]:

$$Gas\ costs = (Gas\ consumption * Gas\ price\ cap) + (standing\ charge * 365) \quad (7.7)$$

The equivalent calculation was performed to derive electricity costs. It should be noted that the EPC database only provides an overall estimation of energy consumption, rather than a breakdown per energy type. As such, it was assumed that all homes in Nottingham consume gas and electricity; further, it was assumed that the typical home consumes ~4.26 kWh of gas for every kWh of electricity. This ratio of energy consumption was based on typical consumption estimates per energy type, retrieved from Ofgem (2022), and was calculated as follows:

$$Typical\ energy\ split = \frac{Gas\ consumption\ (kWh)}{Electricity\ consumption\ (kWh)} = \frac{11{,}500}{2{,}700} = 4.26 \quad (7.8)$$

In other words, gas and electricity consumption account for approximately 80.99% and 19.01% of overall consumption, respectively. This assumption allowed the calculation of gas and electricity consumption estimates per home, as required for *Equation 7.7.* Using the above method, the median *inferred energy costs* for Nottingham was estimated as ~£2,185 per year. This value is close to DESNZ (2024b) estimates of typical household energy costs (~£2,250 per year), and, crucially, appears to be considerably more accurate than the outmoded *EPC-modelled costs*.

7.4. Synthetic data generation

This section provides the rationale underlying the selection of realistic income parameters for the synthetic microdata (i.e., household-level income data for the whole of Nottingham). As discussed in the methods, a range of parameters were required, namely, the distribution, the mean, the standard deviation and lower and upper limits. The rationale underlying the selection of each of these parameters is presented below.

The mean: GDHI point estimates for small areas in Nottingham

In this instance, the mean simply corresponds to GDHI point estimates for Nottingham (ONS, 2024b). Since the ONS's GDHI data are point estimates (i.e., mean GDHI per LSOA), it is not possible to manipulate or adjust GDHI further. Via reference to the ONS's income categories (see Figure 7-1), GDHI is essentially equivalent to net equivalised household income after direct taxes.

[31] 2025 unit price caps: 6.34 pence per kWh and 24.86 pence per kWh for gas and electricity, respectively. 2025 standing charges: gas = 31.65 pence per day; electricity = 60.97 pence per day (Ofgem, 2025).

For this reason, other categories of income data used in this chapter (notably, those retrieved from the *Understanding Society* data) were adjusted to represent GDHI or NHI.

Distribution, standard deviation and limits: Using *Understanding Society* data to inform realistic synthetic income parameters

The *Understanding Society* longitudinal household survey (University of Essex, Institute for Social and Economic Research, 2022) offered the necessary information to infer the remaining synthetic income parameters. In this instance, the 2022 release (based on 2021 data) was used as it was most harmonious with the GDHI point estimates, which were also based on 2021 data. Figure 7-2 displays the distribution of NHI per annum for all observations in the *Understanding Society* cohort (n=13,010), following the omission of extreme outliers[32] and missing data. According to the *Understanding Society* data, NHI among the sample was heavily right-skewed and followed a log-normal distribution (i.e., a standard type of non-normal distribution), with median and mean values of £35,192/annum and £40,522/annum, respectively. The Q-Q plot (see also Figure 7-2) also evidenced the assumption of non-normality, as considerable deviation from the diagonal reference line is indicative of non-normality. Further, an Anderson-Darling normality test was performed to add statistical weight to the assumption of non-normality. The test produced a statistically significant result (p-value=$<2.2\times10^{-16}$; less than critical value=0.05); therefore, the null hypothesis, that NHI is normally distributed, could be rejected. In other words, this initial analysis of NHI supported the generation of synthetic income data that follow a log-normal distribution, as opposed to a standard normal distribution.

[32] *Extreme outliers* are those exceeding the NHI 99.9th percentile, i.e., households earning more than £240,000 (NHI) per year.

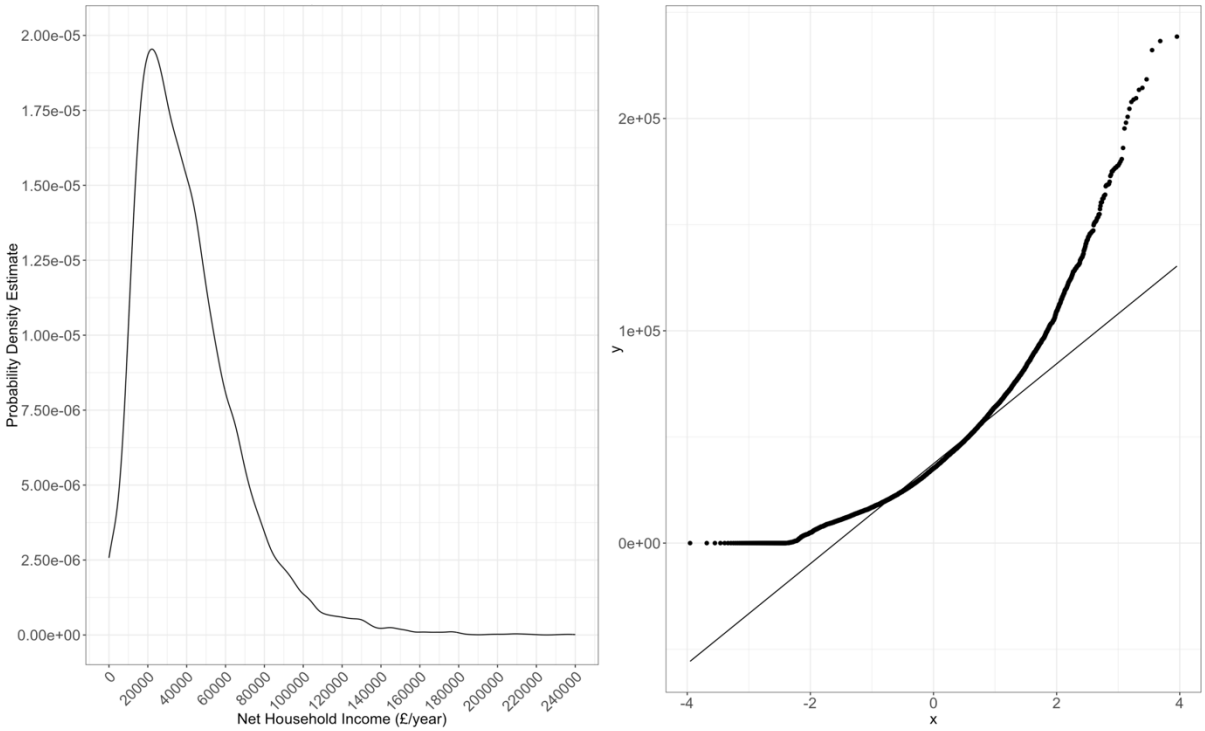


Figure 7-2. Understanding Society data. Left: net household income distribution (n=13,010), right: Q-Q plot showing non-normality of observations (University of Essex, Institute for Social and Economic Research, 2022)

It is possible that the distribution of NHI in Figure 7-2 might alter significantly following adjustments for different household compositions (i.e., equivalisation). To test this, Figure 7-3 displays unequivalised and equivalised NHI. In this case, NHI was equivalised according to the Organisation for Economic Co-operation and Development's (OECD, 2012) scale. Expectedly, the median equivalised NHI (£21,948) was significantly lower than its unequivalised counterpart (£35,192); moreover, the standard deviation of equivalised NHI (£13,618) was considerably less than for unequivalised NHI (£26,506). In spite of this, equivalised NHI still follows a log-normal distribution and is slightly more right-skewed than unequivalised NHI; hence, the assumption of a log-normal distribution was retained.

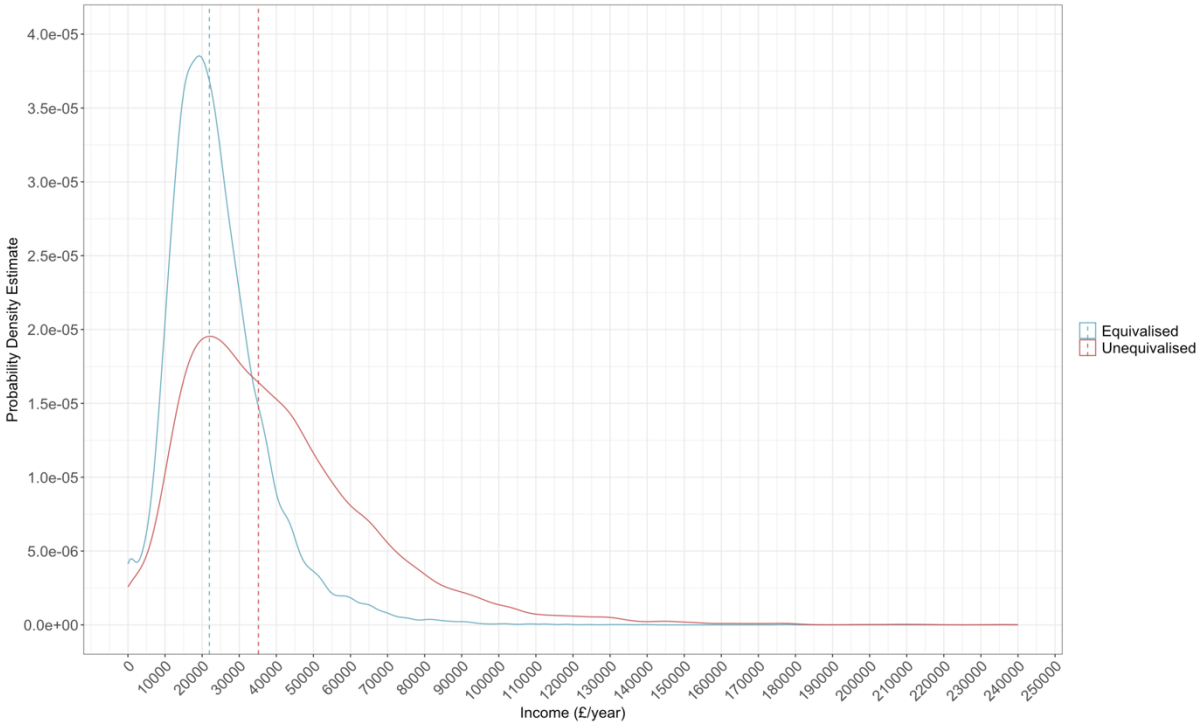


Figure 7-3. Understanding Society data. Equivalisation of net household income (n=13,010) (University of Essex, Institute for Social and Economic Research, 2022)

It is possible that income variability may be dependent on the relative deprivation of an area. The IMD quintile (1=most deprived to 5=most affluent) of *Understanding Society* participants' home (LSOA) areas was also known; therefore, NHI (which always refers to *equivalised* NHI from hereon) could be plotted per IMD quintile, as shown in Figure 7-4. NHI appears to increase in line with the participants' IMD quintile, which is expected, given that income is a core component of IMD calculations. Perhaps less expected is the seemingly small level of variation in NHI across the IMD quintiles. The disaggregation of NHI to IMD quintiles at this point was retained to enhance the accuracy of the synthetic data, as typical NHI data per IMD quintile can be used to infer suitable parameters, particularly standard deviation, for corresponding IMD quintiles in Nottingham's LSOAs.

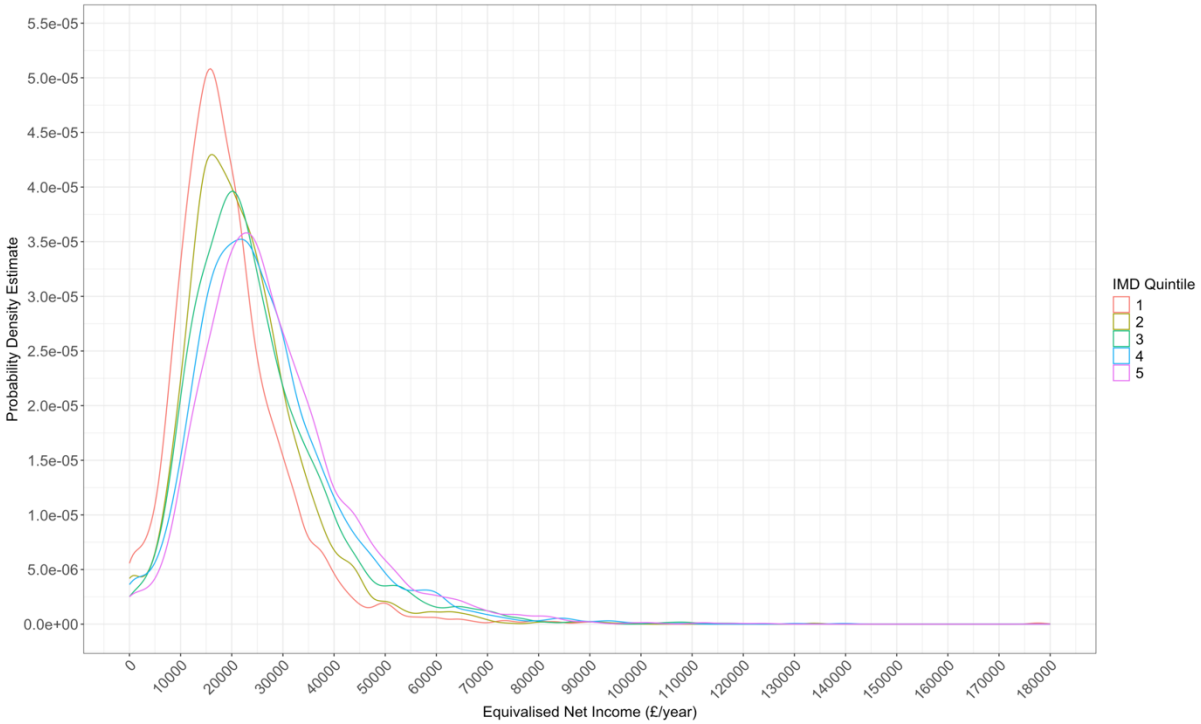


Figure 7-4. Understanding Society data. Equivalised net household income per IMD quintile (n=13,010) (University of Essex, Institute for Social and Economic Research, 2022)

Table 7-3 provides a summary of the mean, standard deviation and coefficient of variation, which is a measure of dispersion or relative standard deviation[33], per IMD quintile. Although the most affluent areas had a higher mean NHI, the coefficient of variation was highest for observations in the most deprived quintile and lowest in the most affluent. As discussed above, disaggregating the *Understanding Society* data by IMD quintile enhanced the specificity of standard deviation parameters for the synthetic data. This was achieved by rearranging the coefficient of variation formula to calculate standard deviation per Nottingham LSOA[34].

Table 7-3. Net household income: Mean, standard deviation and coefficient of variation per IMD quintile (University of Essex, Institute for Social and Economic Research, 2022)

IMD quintile	Mean NHI (£/year)	NHI standard deviation (£)	Coefficient of variation (SD/mean*100)
1 (n=2366)	19456.06	11341.06	58.29%
2 (n=2607)	22384.72	11868.94	53.02%
3 (n=2629)	24761.39	13754.25	55.55%
4 (n=2711)	26352.58	14371.88	54.54%
5 (n=2697)	27909.98	14568.40	52.20%

The rationale underpinning the lower and upper limit parameters is straightforward. £0 was selected as the lower limit, despite the possibility of negative NHIs in reality; in this case, however,

[33] Calculated as: $Coef.of\ variation = ({}^{NHI\ standard\ deviation}/_{Mean\ NHI}) \times 100$

[34] Calculated as: $Standard\ deviation\ per\ LSOA = Coef.of\ variation\ per\ IMD\ quintile \times Mean\ GDHI\ estimate\ per\ LSOA$

NHI was always considered to be equal to or greater than zero. Conversely, the selection of suitable upper limits was based on an established convention, such that the upper limit per LSOA was equal to mean income plus the standard deviation multiplied by 1.96 (i.e., the z-score equivalent to the 97.5th percentile). Using the previously defined notation (see Section 7.3), the calculation of LSOA-specific upper limits is as follows:

$$U_j = \mu_j + 1.96\sigma_j \tag{7.9}$$

It should be noted that this is not strictly an upper limit in a literal sense, but ensures that 95% of the synthetic data remain within this interval. Table 7-4 displays summary parameters (mean GDHI, number of households, standard deviation and upper limit) for 10 randomly selected Nottingham LSOAs. These LSOA-specific characteristics constitute the full set of parameters required to generate synthetic income distributions for Nottingham's LSOAs using the direct sampling approach described in the methods.

Table 7-4. Synthetic data parameters for randomly selected example LSOAs

LSOA 2011	Mean GDHI	Households	IMD quintile	Coefficient of variation	Standard deviation	97.5% upper limit
E01013979	43.71	606	5	52.20%	22.82	88.43
E01013983	24.39	606	2	53.02%	12.93	49.74
E01013931	40.03	740	3	55.55%	22.24	83.62
E01013965	26.89	611	1	58.29%	15.67	57.61
E01013977	50.87	747	4	54.54%	27.74	105.24
E01013893	25.54	619	1	58.29%	14.89	54.72
E01013856	29.55	623	1	58.29%	17.22	63.30
E01013934	28.51	626	2	53.02%	15.12	58.15
E01013984	39.46	626	5	52.20%	20.60	79.84
E01033398	23.05	626	2	53.02%	12.22	46.99

A direct sampling approach to synthetic data generation in Nottingham

The direct sampling approach was used to generate distinct synthetic income distributions per Nottingham LSOA. Figure 7-5 displays the synthetic income distributions aggregated to IMD quintiles (in an equivalent manner to the *Understanding Society* data in Figure 7-4), as it was deemed impractical to visualise the synthetic income distributions for all 182 of Nottingham's LSOAs. In other words, each quintile distribution below is the cumulative GDHI distribution for all Nottingham LSOAs within each IMD quintile (1=most deprived to 5=most affluent). As expected, median income per IMD quintile (denoted by dashed lines in Figure 7-5) increases as the LSOAs become more affluent and, in superficial terms, the distributions mimic the *Understanding Society* NHI data per IMD quintile. In Section 7.5, a more comprehensive evaluation of the synthetic data is performed to assess whether the LSOA distributions are representative of real-world conditions.

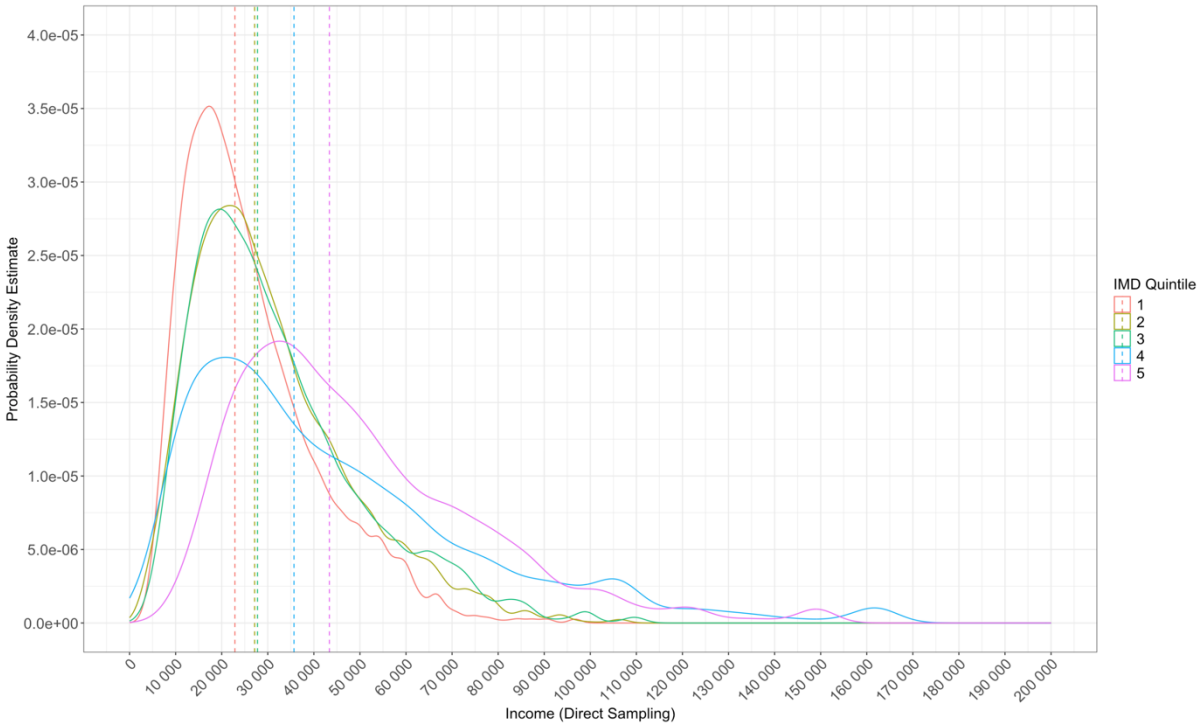


Figure 7-5. Synthetic household income distributions per IMD quintile in Nottingham (Direct Sampling) (n=125,297)

At this stage, the unit-level synthetic data were assigned to existing EPC records, according to the process discussed previously. Due to incompatibilities between the postcodes used in the EPC database (DLUHC, 2024) and the LSOA 2011 codes used for the GDHI estimates (ONS, 2024b), the assignment of the synthetic data to EPC records resulted in ~18% of observations being lost. As a result, the full sample of households (i.e., synthetic income paired with an existing EPC record) that were available for the subsequent fuel poverty measurement experiments was 105,570.

7.5. Results, Part I: Pseudo-validation of synthetically generated income data

Thus far, the methods underlying the generation of LSOA-specific synthetic income distributions in Nottingham have been expounded; however, the validity of the synthetic data has not yet been explored. To better understand the real-world representativeness of the synthetic data, this section presents a pseudo-validation. The process is referred to as a pseudo-validation, as the validation of the synthetic output is based on MSOA-level ONS ground truth data, given the unavailability of precise unit-level data. The pseudo-validation was conducted as follows: first, the synthetic income data were aggregated to MSOA-level distributions and average point estimates (i.e., mean income per MSOA), then the accuracy of the synthetic distributions (at MSOA-level granularity) was evaluated via comparison to the ONS's (2024e) MSOA estimates of NHI (before housing costs). An mean average error (MAE) of £5,787 and median average error (MedAE) of

£4,774 were achieved, suggesting relative alignment between the synthetic estimates and the ONS ground truth data (ONS, 2024e); however, the "acceptability" of the achieved MAE and MedAE in the current context is hard to evaluate in greater detail, given a lack of comparable studies. Further work may attempt a more comprehensive validation of the synthetic data process and output produced here; however, this necessarily requires access to larger samples of unit-level household income data.

7.6. Results, Part II: Fuel poverty measurement experiments

This section presents the results of the fuel poverty measurements that were conducted on the synthetic income data. As stated in the methods, Experiments A, C, D and F[35] were deemed possible given the synthetic data output (i.e., Synthetic Nottingham Homes), which at this point refers to the synthetic income data joined with existing EPC records in Nottingham. All code pertaining to the fuel poverty experiments on the synthetic Nottingham data is available in the supplementary files and the **Chapter 7** folder in this thesis's associated GitHub repository (see: https://github.com/torransemple/thesis_supplementary_material/tree/main/Chapter_7/II)[36].

Experiment A: Re-estimate 10%, LIHC and LILEE fuel poverty

Experiment A included the recalculation of fuel poverty according to all of the previously adopted English fuel poverty definitions, namely, 10%, LIHC and LILEE. The comparison of fuel poverty rates according to each definition allows the profile of fuel poor homes to be explored in greater detail; for example, insights can be provided into the rate of 10% fuel poverty in EPC A–C homes, which are omitted from LILEE statistics by default. The estimation of 10% fuel poverty is relatively straightforward and is equivalent to required energy costs divided by household income. As discussed in the methods, the energy costs variable was derived from the EPC database (DLUHC, 2024), while the synthetic income effectively refers to GDHI (i.e., equivalised gross household income before housing costs), given that GDHI was used to generate the synthetic data.

Table 7-5 displays the frequency and proportion of fuel poor homes among the synthetic Nottingham data according to the 10%, LIHC and LILEE definitions. The rate of 10% fuel poverty was 36.83%, corresponding to 38,833 homes. Further, the median fuel poverty ratio was 0.083 (i.e., the median Nottingham home in the synthetic sample, spends around 8.3% of income on energy), which is considerably higher than typical median value of 0.05 (or 5%) that originally

[35]Experiment F is not referenced explicitly in the following results; however, the experiment's purpose—to examine the overlap of competing fuel poverty definitions—is embedded within the discussion of Experiments A, C and D.
[36] Note: R code to reproduce the fuel poverty measurement experiments is in 'CH7_II_measurement_experiments.Rmd'.

informed the selection of the 10% threshold (see also **Chapter 2:** Table 2-1). This is further evidence that the 10% threshold is likely outmoded, as the typical fuel poverty ratio has shifted markedly since the invention of the 10% definition (see Boarman (1991)).

Table 7-5. Recalculating 10%, LIHC and LILEE fuel poverty among Synthetic Nottingham Homes (n=105,570)*

Definition	Number of fuel poor homes	Proportion of homes deemed fuel poor
10%	38,883	36.83%
LIHC	10,827	10.26%
LILEE*	19,318	18.30%

According to the LIHC definition, only 10.26% (n=10,827) of the synthetic homes were fuel poor. As stated previously, LIHC is the cooccurrence of higher-than-average (median) energy costs and a residual income below the official poverty line, after energy costs. For the LIHC classification thresholds, the 2021 poverty line, which is equivalent to 60% of median disposable household income, ~£18,840/year in monetary terms (ONS, 2022f), was used for the greatest compatibility with the GDHI estimates (ONS, 2024b) as these were also based on 2021 data[37]. The median energy costs threshold, however, refers to 2024, given the Ofgem (2025) unit prices and EPC database (DLUHC, 2024)[38] used previously. The median household energy bill was estimated to be £2,252/year in 2024 (DESNZ, 2024b). Figure 7-6 visualises the LIHC fuel poverty classification on a subset of synthetic homes (specifically, those originally displayed in Table 7-4). This reinforces the tendency of the LIHC definition to show a relatively modest rate of fuel poverty (Middlemiss, 2017), despite the relatively high energy costs among the Synthetic Nottingham Homes.

This oversight of the LIHC definition is further illustrated by the rate of 10% fuel poverty being around 3.6 times higher; in other words, many of the Synthetic Nottingham Homes were classed as *not fuel poor* by LIHC (Figure 7-6) but were *fuel poor* according to the 10% definition of fuel poverty. To visualise this, Figure 7-7 displays the initial LIHC fuel poverty classification disaggregated by 10% fuel poverty.

[37] Note: an obvious limitation concerns the uncertainty affecting the positioning of the poverty threshold, notably, the reference year chosen. If the 2023 poverty threshold was used instead—£20,700 (ONS, 2024f)—then the LIHC rate (based on the 2023 poverty line) would have been 12.47% and 21.59% for LILEE. Regardless, these estimates are still less than that of 10% fuel poverty.

[38] This leads to slight inharmony between the x- and y-axes in Figure 7-6, Figure 7-7 and Figure 7-8, in the sense that the x-axis refers to 2021 income norms, while the y-axis refers to 2024 energy costs/efficiency; this incompatibility was unavoidable, as it was not possible to obtain versions of GDHI and EPC data that referred to the same period.

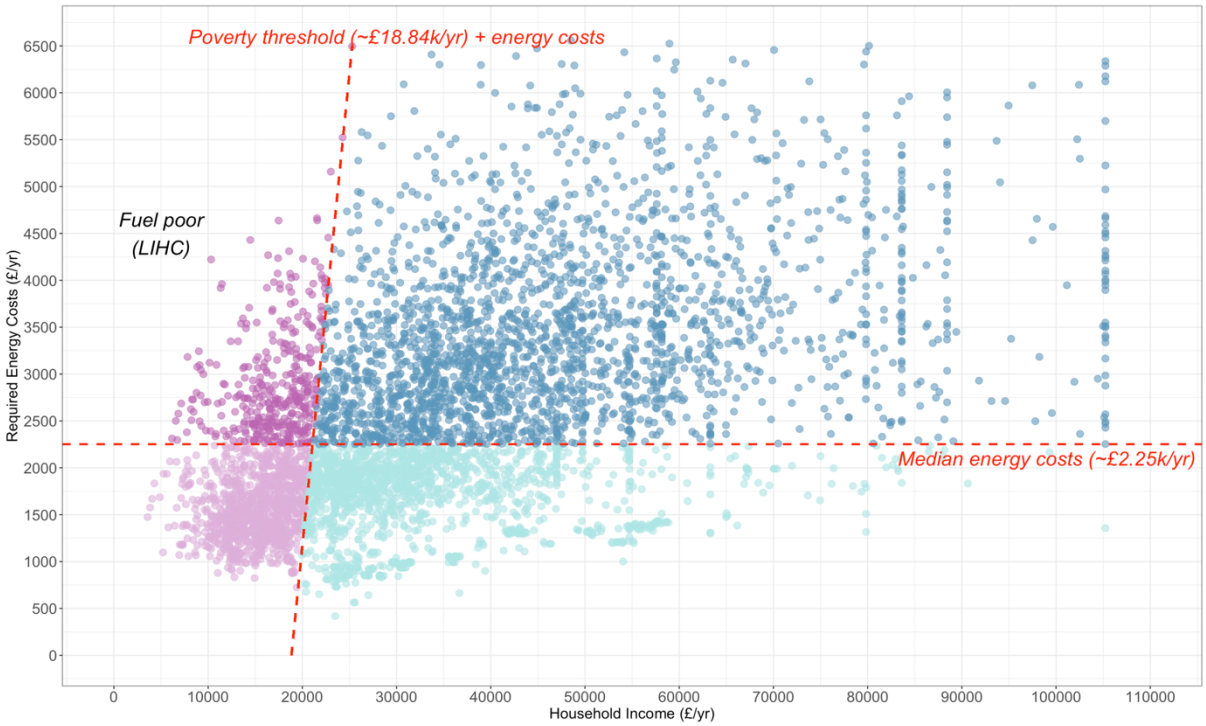


Figure 7-6. LIHC fuel poverty classification on Synthetic Nottingham Homes: LSOA subset (n=5,313)



Figure 7-7. LIHC fuel poverty classification disaggregated by 10% fuel poverty: LSOA subset (n=5,313)

18.30% of the synthetic homes were fuel poor according to the LILEE definition. It should be noted that the LILEE definition is referred to as *LILEE**, as the FPEER clause was replaced with a

simplified SAP-based criterion due to data limitations[39]. In any case, SAP and FPEER are essentially equivalent in most instances (DECC, 2014; BEIS, 2023). Figure 7-8 displays the equivalent fuel poverty classification scatter plot for the LILEE approach, where the approximate poverty threshold is the poverty line plus energy costs per household. The approximate nature of the poverty threshold in Figure 7-8 means that the LILEE category and counterparts (LIHEE, HILEE and HIHEE, as previously defined in Figure 2-5) are occasionally fuzzy. The dotted red lines running parallel to the poverty threshold capture fuzzy homes.

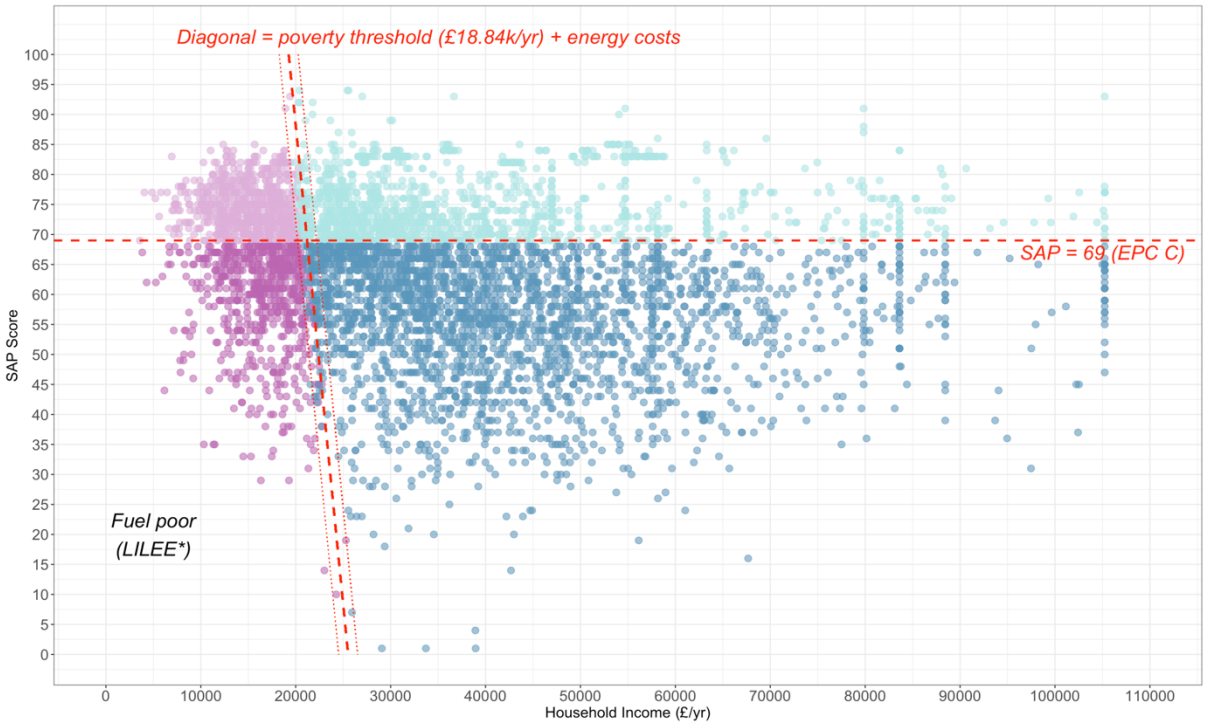


Figure 7-8. LILEE fuel poverty classification on Synthetic Nottingham Homes: LSOA subset (n=5,313)*

Figure 7-9 displays the overlap of 10% and LILEE fuel poverty. The distinction between *fuel poor* and *not fuel poor* according to 10% is less clear than in the equivalent LIHC plot (see Figure 7-7), which is mainly due to the absence of energy costs on the y-axis; hence, the precise 10% threshold cannot be marked on this plot. As discussed throughout previous chapters (see **Chapter 2:** Section 2.4 and **Chapter 4:** Section 4.6, specifically), a recurring concern with the LILEE methodology is that fuel poverty is likely to be overlooked in low-income high energy efficiency (LIHEE) homes, which are those in the top left quadrant of Figure 7-9. In this case, a considerable proportion of LIHEE homes were deemed fuel poor according to the 10% definition, while the same was also true for many high-income low energy efficiency (HILEE) homes (i.e., the bottom right quadrant). This reinforces previous findings that the LILEE definition does lead to an

[39] Specifically, FPEER is equivalent to a household's SAP score minus energy support payments (e.g., Warm Homes Discount). Information regarding energy rebates, which is required to accurately calculate FPEER, was not available.

underestimation of fuel poverty in low-income homes and also suggests that low-to-middle income homes, e.g., those with household income in the region of £25,000 to £40,000, are also likely in many cases to be fuel poor according to the 10% definition.

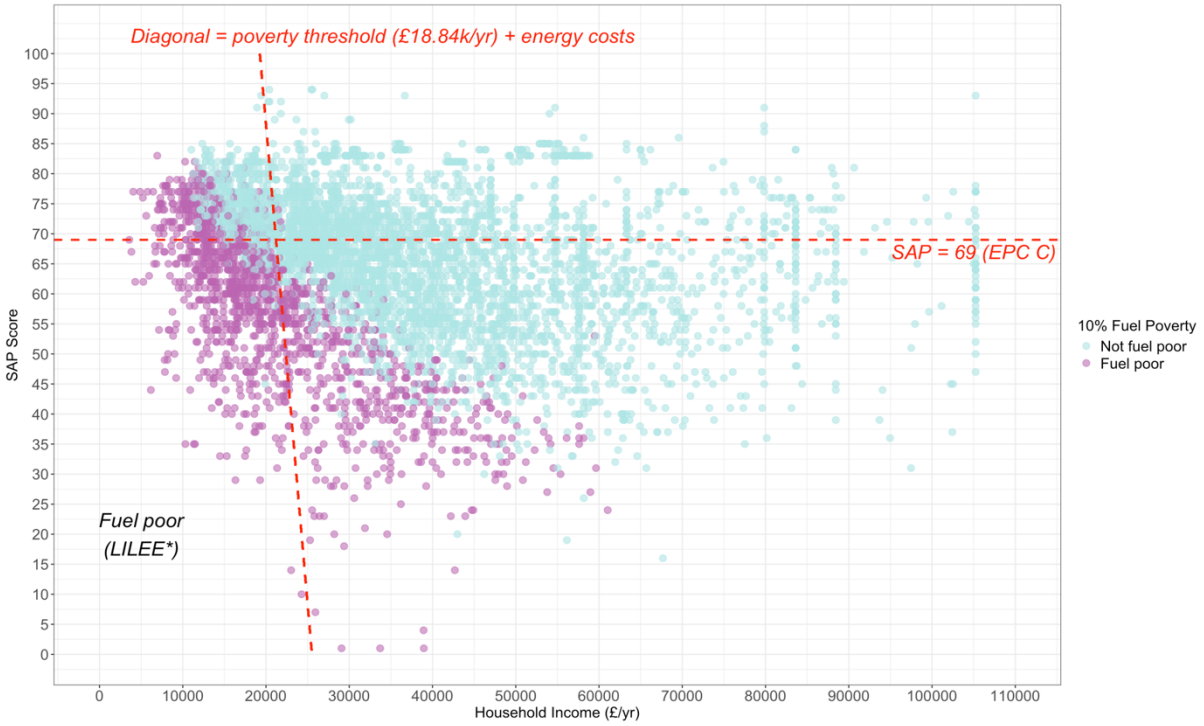


Figure 7-9. LILEE fuel poverty classification disaggregated by 10% fuel poverty: LSOA subset (n=5,313)*

The following crosstabulations display the rate of 10% fuel poverty per LILC, LIHC, HILC and HIHC (Table 7-6), and LILEE, LIHEE, HILEE and HIHEE categories (Table 7-7). The statistics in these tables consolidate the visual overlap of 10% fuel poverty with the LIHC and LILEE approaches. As expected, all LIHC fuel poor homes are also fuel poor according to 10%, while the vast majority of LILEE fuel poor homes (94.0%) are fuel poor according to 10%. The most obvious disparity is among lower-income homes with relatively low running costs (i.e., LILC homes according to the LIHC methodology or LIHEE homes according to LILEE). In these homes, the 10% definition captures the impact of high energy costs relative to household income (i.e., those spending more than 10% of income on energy), whereas the LIHC and LILEE poverty thresholds are inflexible in these cases, likely leading to an underestimation of fuel poverty. As discussed throughout previous chapters, this is a particularly pressing concern given modern energy price volatility and increases in the cost of living, which is felt most acutely by low-income households (Joseph Rowntree Foundation, 2023).

Table 7-6. Crosstabulation of LIHC and 10% fuel poverty among Synthetic Nottingham Homes (n=105,570)

Quadrant	10% fuel poverty (%)	
	Fuel poor	***Not fuel poor***
LIHC (n=10,827)	100.0%	0.0%
LILC (n=26,251)	63.4%	36.6%
HILC (n=29,372)	0.5%	99.5%
HIHC (n=39,120)	28.8%	71.2%

Table 7-7. Crosstabulation of LILEE and 10% fuel poverty among Synthetic Nottingham Homes (n=105,570)*

Quadrant	10% fuel poverty (%)	
	Fuel poor	***Not fuel poor***
LILEE (n=19,318)	94.0%	6.0%
LIHEE (n=17,760)	52.4%	47.6%
HIHEE (n=23,926)	0.6%	99.4%
HILEE (n=44,566)	25.3%	74.7%

The extent of 10% fuel poverty in higher-income homes with relatively high running costs (i.e., HIHC according to the LIHC methodology or HILEE according to LILEE) is also noteworthy. These homes are omitted from LIHC and LILEE fuel poverty statistics on account of having "high income"; however, around a quarter of these homes are still likely to be fuel poor according to 10%. It is also worth noting that the description of the HIHC and HIHEE quadrants as "high income" is evidently misleading, as many of these homes only marginally exceed the poverty threshold; hence, a significant portion of these homes are likely better described as *low-to-middle income*. In low-to-middle income homes with high energy costs, in particular, the LIHC and LILEE approaches are likely to considerably underestimate the rate of on-the-ground energy unaffordability and largely disregard the impact of increasing energy costs.

It is also informative to assess the level of 10% fuel poverty in homes with EPC ratings of A–C, which account for 39.5% (n=41,686) of the synthetic Nottingham data. For EPC A–C-rated homes, the rate of 10% fuel poverty across the entire sample was 22.7%. In stark contrast, the rate of LIHC fuel poverty among A–C-rated homes was 0.6%. Moreover, the rate of fuel poverty in these homes is 0% according to LILEE, due to the methodology's universal omission of what are deemed to be "efficient homes" (BEIS, 2021). As also evidenced via the subjective fuel poverty survey in **Chapter 4**, this tendency to overlook fuel poverty in more efficient homes is unjustified, as many occupants who live in EPC A–C-rated homes still struggle to afford basic levels of energy in the home.

Comparing LILEE* estimates to DESNZ subregional LILEE fuel poverty estimates

This section briefly evaluates the closeness of LILEE* estimates and the UK Government's subregional LILEE statistics (DESNZ, 2023b). This comparison was used to assess whether the LILEE fuel poverty methodology was replicated accurately, while it also provided tentative insights into the overall accuracy of the synthetic Nottingham data. To achieve this, LILEE fuel poverty statistics released in 2023 were used (BEIS, 2023), given that these were based on 2021 income and energy norms. Figure 7-10 displays the rate of DESNZ LILEE fuel poverty (x-axis) versus LILEE* (y-axis) per LSOA in Nottingham. Due to unavoidable incompatibilities between 2011 and 2021 LSOA codes, DESNZ LILEE and LILEE* fuel poverty rates could be compared for 152 eligible LSOAs (i.e., 30 LSOAs are omitted from Figure 7-10).

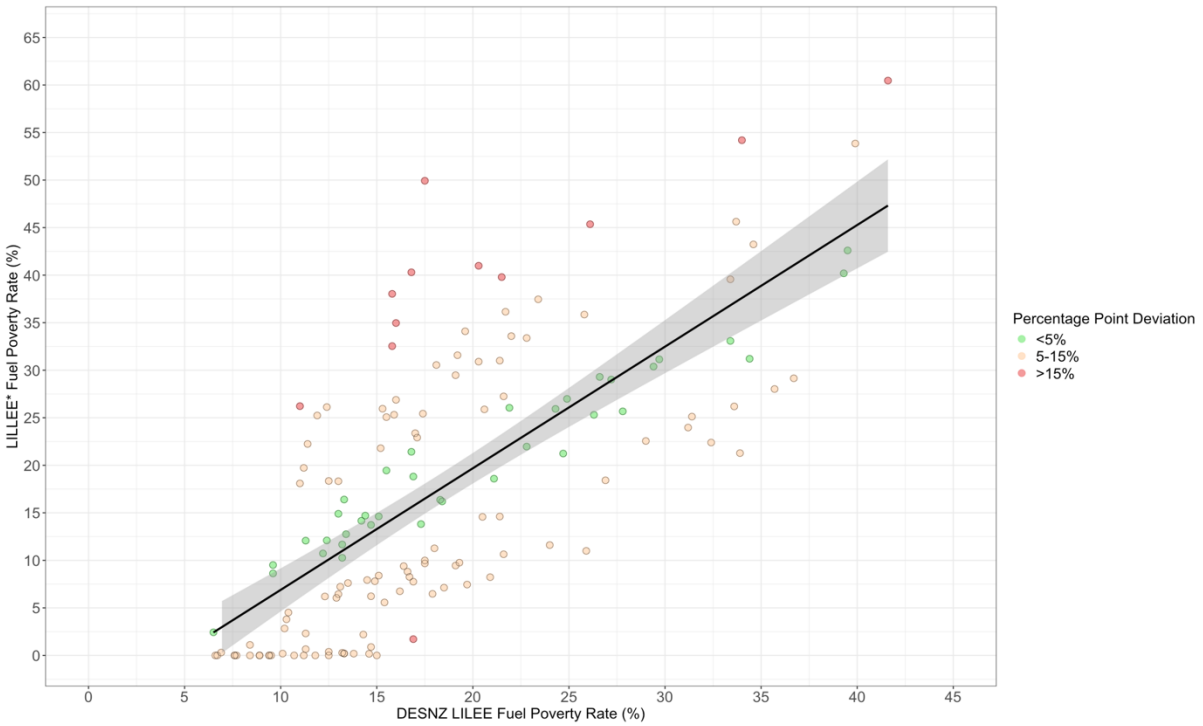


Figure 7-10. DESNZ LILEE versus LILEE fuel poverty per Nottingham LSOA (n=152)*

The pairwise correlation coefficient for DESNZ and LILEE* fuel poverty was 0.73, indicating a moderate-to-strong positive relationship between both variables; this is also demonstrated by the fitted linear model in Figure 7-10. Each of the points (i.e. LSOAs) was coloured depending on the closeness of DESNZ LILEE and LILEE* rates, where green LSOAs are those where DESNZ LILEE and LILEE* rates were within five percentage points, yellow denotes percentage point differences of 5–15% and red those with differences greater than 15%. The majority of LSOAs (~67%) fell

into the *moderately close* (5–15%) category, while ~24% were *close* (<5%) and ~9% were *disparate* (>20%).

In summary, the LSOA estimates of LILEE* fuel poverty were close in many cases to DESNZ statistics. This is probably at least partly attributable to inherent differences between the LILEE* and LILEE estimation process, most notably, the replacement of FPEER with SAP score. The cluster of yellow LSOAs in Figure 7-10 with DESNZ LILEE fuel poverty rates below 15% and corresponding LILEE* rates of below 5% is a particular concern. In these cases, the LILEE* estimates appear to considerably underestimate LSOA-level fuel poverty. A possible explanation is that LILEE* underestimates fuel poverty among this cluster of LSOAs (n=32) as they are among the most affluent in Nottingham. As such, it is likely that the initial synthetic income generation has not accurately captured the full spectrum of income heterogeneity in more affluent LSOAs, which consequently leads to an underestimation of LILEE* fuel poverty in these cases.

Experiment C: Five-fold 10% fuel poverty and the fuel poverty gap

Experiment C involved the re-estimation of fuel poverty indicators that are able to account for the depth, and, ideally, temporal shifts in fuel poverty. In this case, however, temporal data were not available; therefore, cross-sectional indicators are considered exclusively, in the form of five-fold (or five-level) fuel poverty and the fuel poverty gap. Five-fold 10% is essentially an extension to the original Boardman (1991) 10% definition, whereas the fuel poverty gap is the depth of fuel poverty in monetary terms, as proposed by Hills (2012). As discussed in **Chapters 2** and **5**, these types of indicators give a detailed overview of not only those who are deemed *fuel poor* but also the most *extreme* cases, as well as those on the verge of being fuel poor, which can be used to inform highly targeted remedial policies.

Table 7-8 displays the distribution of five-fold 10% fuel poverty among the Synthetic Nottingham Homes (n=105,570), where those spending less than 8% of household income on energy were considered *not fuel poor*, 8–10% corresponds to *marginal fuel poverty*, 10–13% is *fuel poverty*, 13–17% is *severe fuel poverty* and more than 20% is *extreme fuel poverty*. The five-fold version of the 10% definition is evidently more informative than the binary version presented in Experiment A. Pre-emptively identifying and addressing fuel poverty in areas with high rates of *marginal fuel poverty*, for example, could lead to reduced public spending on remedial measures in the long term. Moreover, the disaggregation of 10% fuel poverty to five levels potentially incorporates themes of energy precarity within fuel poverty measurement criteria, since a growing rate of marginal fuel poverty among certain demographics would be indicative of increased energy

precarity (Petrova, 2018). This information would not otherwise be captured by the binary version of the 10% definition.

Table 7-8. Estimation of five-fold 10% fuel poverty among Synthetic Nottingham Homes (n=105,570)

Five-fold 10% fuel poverty				
Not fuel poor (<8%)	***Marginal fuel poverty (8–10%)***	***Fuel poverty (10–13%)***	***Severe fuel poverty (13–17%)***	***Extreme fuel poverty (>20%)***
48,360 (45.81%)	18,327 (17.36%)	17,347 (16.43%)	15,479 (14.66%)	6,057 (5.74%)

Figure 7-11 shows the distribution of five-fold 10% fuel poverty among the previously utilised subset of Synthetic Nottingham Homes. Each of the oblique dashed lines defines the five levels of fuel poverty according to an intuitive colour gradient: *not fuel poor* (green) to *extreme fuel poverty* (red). As discussed above, the value of the five-fold formulation is in its ability to determine a specific household's proximity to bordering categories, which, towards the lower end of the income and energy costs axes, become more sensitive to external changes, such as volatile energy prices. Perhaps most notably, some homes with below median energy costs (~£2.25k/year) were still categorised as experiencing *severe* or *extreme* fuel poverty. This is noteworthy, as homes meeting this description would not be considered fuel poor according to the LIHC definition—and likely also LILEE—despite spending more than 13% of household income on energy. In a similar vein to Table 7-6 and Table 7-7, this is indicative of LIHC and LILEE's tendency to undercount fuel poverty in low- or low-to-middle income homes with relatively low energy costs (i.e., LILC or LIHEE homes in LIHC and LILEE terminology, respectively).

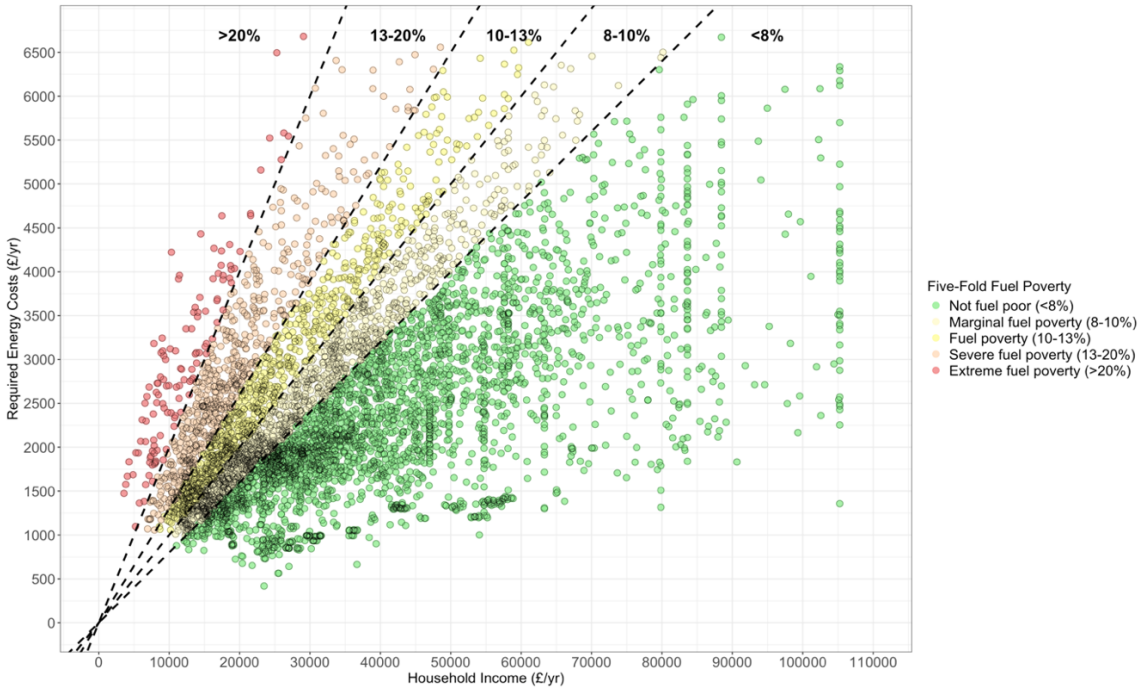


Figure 7-11. Five-fold 10% fuel poverty classification: LSOA subset (n=5,313)

Table 7-9 shows how the distribution of five-fold 10% fuel poverty varied by IMD quintile. The first IMD quintile corresponds to homes located in the most deprived 20% of LSOAs, while the fifth quintile describes the opposite end of the IMD scale (i.e., those located in the most affluent 20% of LSOAs). As expected, the rates of fuel poverty (10–13%), severe fuel poverty (13–20%) and extreme fuel poverty (>20%) were higher in relatively deprived (i.e., the 1st and 2nd IMD quintiles) and middling LSOAs (i.e., quintile 3). Similarly, the rate of marginal fuel poverty, which can be viewed as a proxy for energy precarity (i.e., those on the verge of being deemed fuel poor according to the 10% definition), was highest in the most deprived quintile, decreasing linearly to the lowest rate in the fifth quintile.

Table 7-9. Five-fold 10% fuel poverty per IMD quintile (n=105,570)

IMD quintile	**Five-fold 10% fuel poverty**				
	Not fuel poor (<8%)	***Marginal fuel poverty (8–10%)***	***Fuel poverty (10–13%)***	***Severe fuel poverty (13–17%)***	***Extreme fuel poverty (>20%)***
1 (n=61,789)	39.01%	18.09%	18.72%	17.85%	6.32%
2 (n=24,427)	50.55%	17.82%	15.19%	11.47%	4.97%
3 (n=12,615)	56.16%	17.34%	12.77%	9.24%	4.50%
4 (n=3,212)	54.27%	9.62%	10.24%	14.32%	11.55%
5 (n=3,527)	87.35%	8.45%	3.60%	0.60%	0.00%

The distribution of five-fold 10% fuel poverty in the 4th IMD quintile (i.e., middling to affluent LSOAs), however, is anomalous, as the rates of severe and extreme fuel poverty are unexpectedly high. It should be noted that a minority of Nottingham homes are located in affluent LSOAs (i.e., there are only 6,739 homes in the 4th and 5th IMD quintiles, collectively), given that IMD is based on UK averages and Nottingham is a relatively deprived region. This means that the distribution of five-fold 10% fuel poverty in the 4th and 5th IMD quintiles may be less reliable and particularly sensitive to outliers, given the relatively small number of Nottingham homes meeting this description. A likely explanation for the seemingly incongruous distribution of five-fold fuel poverty in the 4th IMD quintile concerns the demographic composition of these LSOAs. For example, two of the 4th IMD quintile LSOAs (LSOA codes: *E01013953* and *E01033410*) were previously identified as "outlying LSOAs" in **Chapter 3** (see Table 3-2), given the *high* level of LILEE fuel poverty despite a *low* (i.e., less deprived) IMD rank. The explanation that was previously provided for this was that both of these LSOAs belong to council wards with a pronounced student population: LSOA *E01013953* is in the council ward of Radford, and *E01033410* is in Lenton and Wollaton East. In both of these wards, students account for more than 60% of residents (see also Table 3-3) (ONS, 2022c). Following the logic that was also provided in **Chapter 3**, it is possible that high student populations can lead to contradictory income and IMD statistics for certain LSOAs.

Although the five-fold version of the 10% definition is more granular and informative than its binary counterpart, the fuel poverty gap adds a further layer of detail concerning the depth of fuel poverty in monetary terms. Specifically, the fuel poverty gap is defined by Hills (2012, p.9) as "*the amounts by which the assessed energy needs of fuel poor households exceed the threshold for reasonable [energy] costs"*. Specifically, the fuel poverty gap is calculated as the y-axis (energy costs) distance between a given fuel poor home (according to LIHC) and the median energy costs threshold (as previously visualised in Figure 7-6). Among the Synthetic Nottingham Homes that were earlier deemed to be fuel poor according to LIHC (n=10,827), the mean fuel poverty gap was £753, and the median was £521. It should be noted that the distribution of fuel poverty is heavily right-skewed; therefore, the median is likely the more informative statistic in this case. Table 7-10 expresses the mean and median fuel poverty gap per IMD quintile[40]. Interestingly, the fuel poverty gap tends to be higher in more affluent LSOAs. It is possible that homes in more affluent LSOAs tend to be bigger, in terms of total floor area and number of habitable rooms (DLUHC, 2024), while occupants are also more likely to be financially secure; hence, greater energy consumption and, consequently, higher required energy costs, may be the cause of deeper fuel poverty in these cases (Gao, et al., 2024).

Table 7-10. Mean and median fuel poverty gap per IMD quintile: LIHC fuel poor subset (n=10,827)

IMD quintile	Mean fuel poverty gap (£)	Median fuel poverty gap (£)
1 (n=7,463)	670.44	468.00
2 (n=2,137)	931.56	655.49
3 (n=782)	868.31	653.89
4 (n=443)	1071.09	850.08
5 (n=2)	NA	NA

Though the fuel poverty gap is a practical indicator of the depth of fuel poverty, it is based on the superseded LIHC definition, which, as shown previously, likely underestimates the true rate of fuel poverty. To resolve this, a competing fuel poverty gap metric was developed based on the five-fold 10% definition. Figure 7-12 shows an example of the *10% fuel poverty gap* in practice, where the starting coordinates of the green arrows A1, A2 and A3 each describe hypothetical homes in the *fuel poverty*, *severe fuel poverty* and *extreme fuel poverty* categories, all with assumed household energy costs of £3,000/year, as indicated by the blue line in Figure 7-12. The length of each arrow corresponds to the depth of fuel poverty in monetary terms; in other words, the amount by which household energy costs exceed the 10% fuel poverty threshold, indicated by the dashed line. A further addition to the Hills (2012) fuel poverty gap is the *fuel poverty buffer*, which is indicated in Figure 7-12 by arrows A4 and A5. These arrows describe the inverse of the 10%

[40] Note: homes belonging to the 5th IMD quintile had too few observations (n=2) to be included in fuel poverty gap estimations.

fuel poverty gap; in other words, the fuel poverty buffer is simply the amount that energy costs must increase for a given house to fall below the 10% fuel poverty line; hence, this only applies to homes in the *marginal fuel poverty* or *not fuel poor* categories.

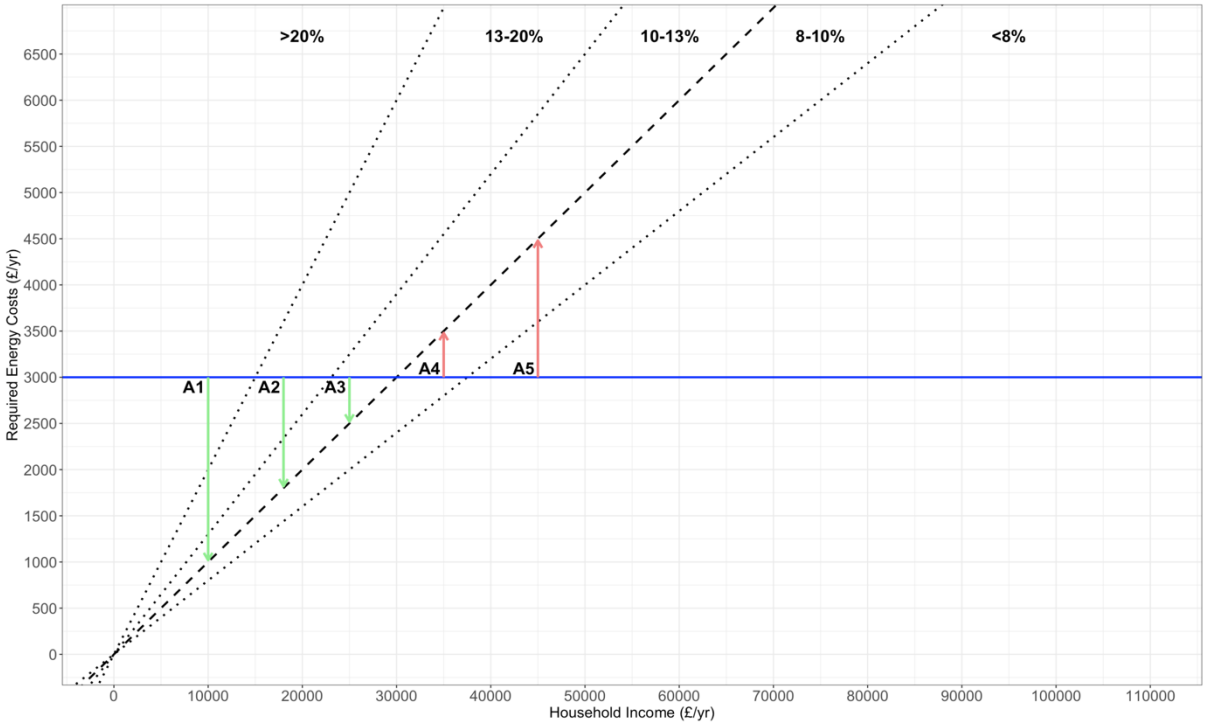


Figure 7-12. The 10% fuel poverty gap and buffer

A further extension to the fuel poverty gap and buffer is presented in Figure 7-13. In this case, the fuel poverty threshold has been altered to 8%, which can be thought of as a proxy for energy precarity. The approach is identical to that described previously; however, the focus on the 8% threshold may hold more utility in terms of the development of preventative, longer-term policies, as the dynamics of *not fuel poor* homes can be tracked with greater accuracy. For example, if energy costs outgrew household income, the proximity of homes to the 8% threshold in monetary terms (at individual or aggregate level) is likely a productive way of gauging energy precarity among homes that are typically overlooked in fuel poverty statistics. As shown in Table 7-10, the original Hills (2012) fuel poverty gap only focuses on the depth of fuel poverty in fuel poor homes (according to LIHC), meaning information regarding the monetary depth of fuel poverty is only known for around 10% of the Synthetic Nottingham Homes. In contrast, the proposed fuel poverty gap and buffer ensure that monetary statistics concerning closeness to a specified fuel poverty threshold (e.g., 8% or 10%) are calculable for all homes in the sample. In mathematical notation, the 10% fuel poverty gap (G_{10}) per home, i, can be represented as follows:

$$G_{10,i} = E_{c,i} - 0.10I_i \tag{7.10}$$

Where E_c is household energy costs, I is household income and the coefficient (0.10) represents the poverty threshold, which is 10% fuel poverty in this case. Adjusting the coefficient to 0.08 would represent the calculation of 8% fuel poverty (i.e., energy precarity). If *Equation 7.10* results in a positive value (i.e., $E_{c,i} - 0.10I_i > 0$) this indicates that a given home is fuel poor according to the 10% definition and G_{10} (the 10% gap) returns a positive monetary value (i.e., any of the green arrows in Figure 7-12). Relatedly, if *Equation 7.10* returns a negative or zero value (i.e., $E_{c,i} - 0.10I_i \leq 0$) the home is not fuel poor according to the 10% definition, and the 10% buffer (B_{10}) returns a negative monetary value (i.e., any of the red arrows in Figure 7-12).

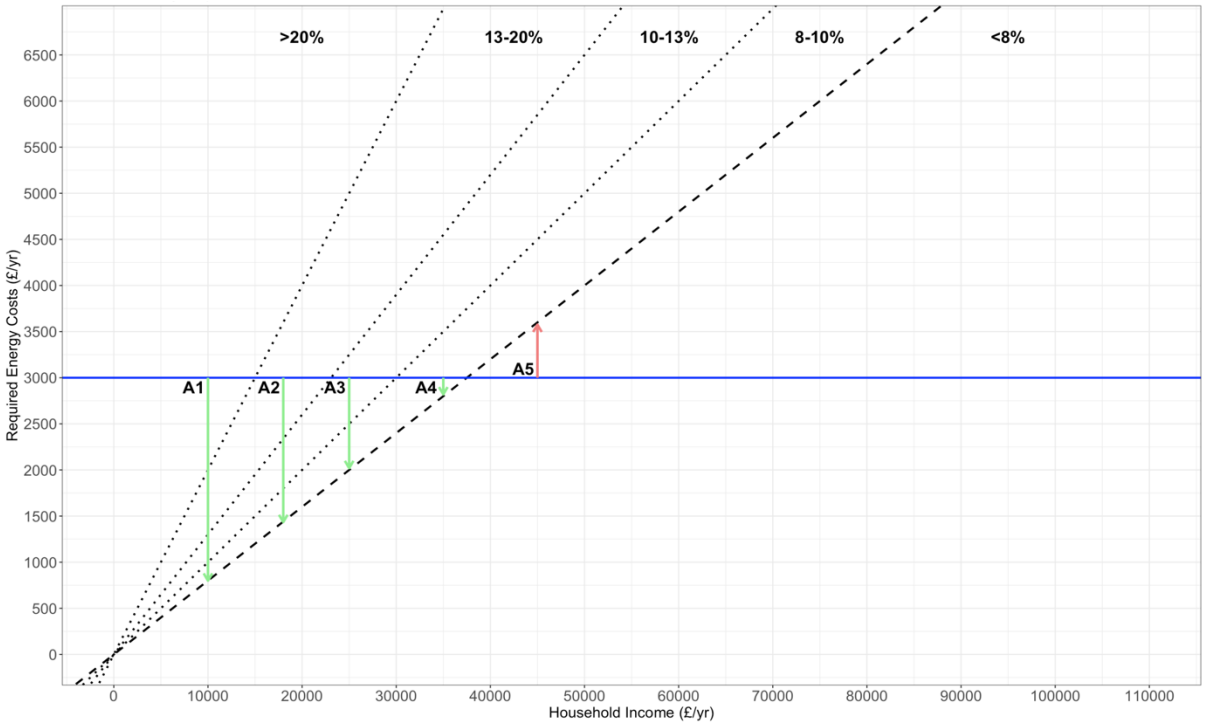


Figure 7-13. The 8% energy precarity gap and buffer

Based on the methods proposed above, Table 7-11 presents summary statistics for the 10% fuel poverty gap and buffer and the 8% energy precarity gap and buffer. The gap and buffer statistics are expressed in median and aggregate terms (i.e., summed across all homes). The gaps are considered to be positive values, since they estimate the amount of money required for a home to be lifted *above* the 8% or 10% threshold, while buffers are negative, as these refer to the increase in energy costs required for a home to fall *below* the stated threshold. As such, the interpretation of the gaps and buffers is as follows: a higher fuel poverty gap corresponds to more entrenched cases of fuel poverty; conversely, a low fuel poverty buffer indicates high energy precarity and a greater risk of falling below the given poverty threshold. In simple terms, the fuel poverty gap

should be minimised to lessen the depth of fuel poverty in already fuel poor homes, while the fuel poverty buffer should be maximised to prevent *not fuel poor* homes from becoming fuel poor or precarious.

Table 7-11. 10% fuel poverty and 8% energy precarity gaps and buffers: Synthetic Nottingham Homes (n=105,570)

Category	10% fuel poverty (£)		8% energy precarity (£)	
	10% gap (n=38,883)	10% buffer (n=66,687)	8% gap (n=57,210)	8% buffer (n=48,360)
Median household	596.83	−1080.80	682.73	−777.01
Aggregate	$3.05*10^7$	$-1.01*10^8$	$4.96*10^7$	$-5.52*10^7$

The median 10% fuel poverty gap was ~£573, which is slightly higher than the LIHC-derived median fuel poverty gap (~£521). As expected, the median 8% fuel poverty gap was higher (~£683), reflecting the additional distance between the 8% and 10% thresholds (see Figure 7-12 and Figure 7-13). The aggregate fuel poverty gaps were approximately £30.5 million and £49.6 million according to the 10% and 8% thresholds, respectively. The aggregate gaps are particularly useful in a policy context, as these are essentially an estimate of the total amount required in energy support payments (per year) to lift all homes above the 8% or 10% threshold. The median fuel poverty buffers were approximately –£1,081 and –£777 for the 10% (fuel poverty) and 8% (precarity) thresholds, respectively, exceeding the magnitude of the median fuel poverty gaps in both cases. This indicates that the median *not fuel poor* household is further from falling below the 8% or 10% poverty threshold than the median *fuel poor* household is from being lifted above the corresponding threshold. This is somewhat encouraging; however, more meaningful insights into the fuel poverty buffer, or the relationship between the gap and buffer, would likely be drawn from temporal data, as then the convergence or divergence of these statistics could be evaluated over time. Similarly, the aggregate fuel poverty and energy precarity buffers are not particularly meaningful in isolation, but changes in the aggregate buffers over time could provide insights into the dynamics of energy affordability in *not fuel poor* homes.

Experiment D: Estimate MIS-based fuel poverty

Experiment D involved the estimation of MIS-based fuel poverty among the Synthetic Nottingham Homes, as well as the estimation of 10% + MIS-based fuel poverty, which is the current definition of fuel poverty in Scotland (Scottish Parliament, 2019). As discussed in **Chapter 5**, the MIS-based fuel poverty definition gauges whether a home achieves a *socially acceptable standard of living,* after deducting required energy costs (Hirsch, et al., 2016; Scottish Parliament, 2019). The MIS budget income thresholds required to achieve a socially acceptable standard of living are adjusted for household composition to capture the varying financial needs of different household types (Loughborough University, Centre for Research in Social Policy, 2024), as displayed in Table 7-12.

The spending subcategories that constitute the *headline total* MIS budgets in Table 7-12[41] were as follows: *food*, *alcohol*, *clothing*, *water*, *council tax*, *household insurances*, *fuel*, *other housing costs*, *household goods*, *household services*, *childcare*, *personal goods and services*, *motoring, other travel costs*, *social and cultural participation* and *rent*. MIS budgets for 2021 were used here for consistency with the GDHI estimates, which were also based on 2021 data. It should be noted that the *headline total* MIS excludes rent and childcare costs; in other words, this is effectively MIS BHC, which was deemed to be compatible with the GDHI income variable (which is also BHC) in the synthetic Nottingham data. The *fuel* category was also omitted (i.e., deducted from the headline total MIS budget), given that energy costs are accounted for already in the Synthetic Nottingham Homes data.

Table 7-12. 2021 MIS budgets for different household compositions (Loughborough University, Centre for Research in Social Policy, 2024)

MIS household composition categories	2021 MIS budget (£/week)	2021 MIS budget (£/year)
Single	218	11,327
Couple	364	18,945
Single pensioner	199	10,331
Pensioner couple	308	16,006
Lone parent: 1 child	314	16,348
Lone parent: 2 children	393	20,420
Lone parent: 3 children	500	25,993
Couple: 1 child	415	21,594
Couple: 2 children	492	25,592
Couple: 3 children	623	32,420
Couple: 4 children	683	35,491

To utilise the breadth of composition-dependent MIS budgets, household composition had to be inferred for the Synthetic Nottingham Homes. To achieve this, typical household composition data for Nottingham were first explored (ONS, 2022g), a breakdown of which is displayed in Table 7-13 alongside corresponding MIS household composition categories and 2021 MIS budgets per composition. The household composition categories used by the ONS (2022g) and the MIS methodology (Loughborough University, Centre for Research in Social Policy, 2024) differ slightly; therefore, several of the ONS categories were aggregated to represent a single MIS category. For example, ~37.0% of Nottingham homes were assumed to be *single*-person homes, based on the aggregation of the ONS's '*one-person household'* categories[42], and so on for the other categories. It should also be noted that the specific number of children was not deducible based on the ONS categories (i.e., the only information provided is that of *dependant* or *non-dependant* children);

[41] Note: See Appendix: Chapter 7, Table 1 for an exhaustive list of the subcategories and corresponding expenditure value that contributed to the total MIS budget for 2021.
[42] Note: some ONS categories described as '*other household types*' were also assumed to be *single*. This is because there is no direct equivalent among the MIS composition categories; therefore, the assumption of *single* in these cases is a conservative generalisation of the MIS budget.

therefore, the minimum number of children (e.g., *couple: one child*, based on the MIS categories) was assumed in all cases.

Table 7-13. Typical household composition in Nottingham, corresponding MIS composition and assumed annual MIS budget

Household composition	Proportion of Nottingham homes (%)	Corresponding MIS household composition	Assumed MIS budget (£/year)
One-person household: Aged 66 years and over	10.83	*Single pensioner*	10,331
One-person household: Other	22.81	*Single*	11,327
Single-family household: Lone parent family, all children non-dependant	4.49	*Single*	11,327
Other household types: Other related household, other family composition	1.30	*Single*	11,327
Other household types: Other, including all full-time students and all aged 66 years and over	8.40	*Single*	11,327
Single-family household: Lone parent family with dependant children	9.18	*Lone parent:1 child*	16,348
Other household types: With dependant children	3.20	*Lone parent:1 child*	16,348
Single-family household: All aged 66 years and over	4.89	*Pensioner couple*	16,006
Single-family household: Married or civil partnership couple, no children	7.58	*Couple*	18,945
Single-family household: Married or civil partnership couple, all children non-dependant	3.89	*Couple*	18,945
Single-family household: Cohabiting couple family, no children	6.77	*Couple*	18,945
Single-family household: Cohabiting couple family, all children non-dependant	0.77	*Couple*	18,945
Single-family household: Married or civil partnership couple, dependant children	11.47	*Couple: 1 child*	21,594
Single-family household: Cohabiting couple family, with dependant children	4.41	*Couple: 1 child*	21,594

The estimated proportions of household composition types across Nottingham, according to the MIS labels, were as follows: *single* (37.0%), *lone parent: one child* (12.4%), *couple* (19.0%), *couple: one child* (15.9%), *single pensioner* (10.8%) and *pensioner couple* (4.9%). These composition categories were subsequently assigned to the Synthetic Nottingham Homes based on dwelling size. ONS (2022g) census data show that higher occupancy is generally associated with higher total floor areas, which is intuitive, given that there is a greater demand for habitable rooms as occupancy increases. Based on this generalisation, the household composition categories (and corresponding MIS budgets) were probabilistically assigned to the Synthetic Nottingham Homes depending on total floor area: an existing variable in the EPC data (DLUHC, 2024). In mathematical notation, the biased probability of the household composition variable, H, taking a value, t (i.e., one of the six predefined household composition categories), for each of the synthetic homes, i, was as follows:

$$P(H = t_i) = \frac{p_i(1+m\times A_{norm})}{\sum_j (p_i(1+m\times A_{norm}))} \quad (7.11)$$

Where p_i is a vector of probabilities (i.e., the proportion of each household composition category in Nottingham, according to ONS (2022g)), A_{norm} is the normalised total floor area (i.e., each home's total floor area divided by the maximum total floor area), with values between 0 (smallest total floor area) to 1 (largest total floor area) and m represents a 'multiplier' (with an assumed value of 2), which is used to subjectively weight the relationship between total floor area and household composition. The probabilistic assignment process generated a new variable—*inferred household composition*—where higher occupancy home types (e.g., *couple* or *couple: one child*) were more likely to be assigned to an existing synthetic home with a larger total floor area. This generalisation is an imperfect solution and induces another level of uncertainty in the resulting MIS-based fuel poverty estimates; however, this was deemed unavoidable in the current analysis, given that MIS budgets vary based on household composition.

Noting the assumptions and caveats discussed above, the estimated rate of MIS-based fuel poverty among the Synthetic Nottingham Homes was 19.90% (n=21,007); in other words, after deducting energy costs, these homes had a residual household income below 90% of the MIS budget for their respective household composition. As discussed for the previous definitions, housing costs are also typically deducted prior to fuel poverty classifications, and a similar consensus applies to the MIS-based method (Moore, 2012; Scottish Parliament, 2019); however, throughout this chapter the income variable (GDHI) was assumed to be before housing costs, as there was not a reliable way to infer housing costs without introducing further uncertainties into the analysis. As a result, all of the fuel poverty estimates discussed in this chapter are likely to be somewhat conservative. According to the two-clause 10% and MIS-based fuel poverty definition (which is also the Scottish Government definition), 40.41% (n=42,655) of homes were deemed fuel poor, suggesting that MIS-based fuel poverty (19.90%) and 10% fuel poverty (36.83%) likely overlap in many cases. In Scotland, the most recent statistics show a fuel poverty (MIS + 10%) rate of ~34% after housing costs (Scottish Government, 2025); thus, the equivalent prevalence among the synthetic homes, particularly when taking into account the relative deprivation of Nottingham (ONS, 2024e), is feasible.

Figure 7-14 shows the classification of MIS-based fuel poverty among single-parent households within the previously used LSOA subset. The five-level 10% thresholds were retained in this figure to show a unique advantage of the 10% + MIS formulation: homes at the lower end of the income spectrum that also lie in the <8% (not fuel poor) or 8–10% (precarity) categories of five-level 10%, can still be deemed fuel poor according to the MIS-based approach. As noted by the Scottish

Government (2017), this feature of the MIS-based approach acts as an additional safety net for those in low-income, energy-efficient homes, many of whom will struggle to afford sufficient energy. In the previously used terminology, this is equivalent to resolving the tendency of the LIHC and LILEE definitions to undercount LILC and LIHEE homes, respectively.



Figure 7-14. MIS-based fuel poverty among single-parent households: LSOA subset (n=660)

7.7. Discussion of results

In this chapter, synthetic income distributions were generated for Nottingham's LSOAs and assigned to existing EPC records. This facilitated the estimation of fuel poverty according to various competing approaches. The remainder of this chapter focuses on how the proposed fuel poverty depth indicators might be used in practice, while the narrative also refocuses on previous discussions of a fuel poverty definitions (or measurement framework) that satisfies modern needs (as recommended in **Chapter 5**).

Continuous, monetary indicators of fuel poverty

Continuous, monetary indicators of fuel poverty have the potential to solve many of the issues associated with traditional measurement approaches, which implicitly assume fuel poverty is most accurately measured in binary or categorical forms (e.g., *fuel poor* versus *not fuel poor*). The Hills (2012) fuel poverty gap was the first monetary indicator of the depth of fuel poverty,

although the indicator only applies to homes deemed fuel poor according to the now superseded LIHC definition. In this chapter, 8% and 10% versions of the fuel poverty gap were proposed to address the shortcomings of the LIHC-based fuel poverty gap. The 8% version is considered a proxy for energy precarity and reduces reliance on the potentially rigid and outmoded 10% threshold. Further, 8% and 10% fuel poverty buffers were proposed to gauge the amount by which energy costs would need to increase for a *not fuel poor* home to become precarious (8%) or fuel poor (10%). In theory, the simultaneous application of gaps and buffers can be used to assess the monetary closeness of *fuel poor* homes to the *not fuel poor* region (i.e., the fuel poverty gap) or of *not fuel poor* homes to becoming *fuel poor*. This approach encompasses the entire housing stock rather than only focusing on LIHC fuel poor homes, which is a significant limitation of the original Hills (2012) approach.

From a policy perspective, the function of the fuel poverty gap and buffer may differ; for example, the fuel poverty gap may be most useful for evaluating remedial works (i.e., minimising the aggregate fuel poverty gap) and also monitoring deep and entrenched cases. The fuel poverty buffer, however, likely has most use as a preventative indicator, in the sense that its primary function is to gauge the proximity of *not fuel poor* homes to the 10% fuel poverty or 8% energy precarity thresholds. Although both of these metrics focus on distinct thresholds, which is a characteristic of the 10% definition that has previously been criticised (Hills, 2012; Moore, 2012), there is at least reduced reliance on the 10% threshold, specifically. Moreover, the proposed gap and buffer metrics could theoretically be adapted to suit any threshold of the five-fold 10% scale or any other relevant threshold (e.g., median energy costs). The aggregate 8% and 10% gap and buffer may also have considerable appeal as a tool to measure the effectiveness of remedial fuel poverty strategies. The aggregate fuel poverty gap is inherently valuable as it effectively describes the amount required in energy support payments per year to lift all fuel poor or precarious homes above a particular threshold. The aggregate fuel poverty buffer is less intuitive, in the sense that the sum of household-level fuel poverty buffers does not have a direct interpretation; however, the ratio of the aggregate fuel poverty gap to the fuel poverty buffer is perhaps a more useful metric. For example, considering the aggregate 10% fuel poverty gap (~£31 million) and buffer (~£101 million) (see Table 7-11), which are both now assumed to be positive values, the *10% fuel poverty quotient*[43] can be written as follows:

$$10\%\ Fuel\ poverty\ quotient = {}^{Aggregate\ 10\%\ gap}/_{Aggregate\ 10\%\ buffer}$$

[43] Note: this value is referred to as the *fuel poverty quotient* to avoid confusion with the existing *fuel poverty ratio*, which is a term used to describe household energy costs divided by income (i.e., the calculation of fuel poverty according to the 10% definition).

$$=>\ 10\%\ fuel\ poverty\ quotient\ (synthethic\ homes) = \frac{31{,}0459{,}234}{101{,}014{,}853} = 0.30 \quad (7.12)$$

Based on this formulation, an increasing aggregate fuel poverty gap *or* decreasing aggregate fuel poverty buffer results in a higher fuel poverty quotient; in other words, the fuel poverty quotient can be used as a high-level tool to assess the depth of fuel poverty (i.e., the gap) relative to the closeness of *not fuel poor* homes to a given fuel poverty threshold (i.e., the buffer). Specifically, the fuel poverty quotient may be used as a temporal measure of energy costs inequality: an increasing quotient is indicative of increasing inequality and a decreasing quotient of reducing inequality. The quotient can also be written in terms of the 8% threshold (or any other threshold that facilitates the calculation of paired gap and buffer statistics), if the aim is to assess marginal or precarious cases of fuel poverty.

Proposing a modern-day fuel poverty measurement framework

This section discusses how the findings of the measurement experiments can be used to inform future fuel poverty measurement frameworks. First, and most evidently, fuel poverty should be measured according to multiple indicators, as also recommended by the most recent European Parliament (2023) guidance. Relying on any of the English definitions (i.e., 10%, LIHC and LILEE), alone, leads to varying forms of measurement bias (as also discussed at length in **Chapter 5**). The re-estimation of 10% fuel poverty among the Synthetic Nottingham Homes provided further evidence that the 10% threshold is not necessarily representative of modern income and energy norms. The median fuel poverty ratio was found to exceed 0.8 among the Synthetic Nottingham Homes, which is considerably higher than the approximate median ratio in the 1990s, 0.05—the figure that originally justified the 10% threshold (Boardman, 1991). The five-fold version of 10% fuel poverty partially solves concerns over the rigidity of the 10% threshold. Although the 10% threshold still describes *fuel poverty*, the range of fuel poverty categories (i.e., *not fuel poor (<8%)*, *marginal (8–10%)*, *fuel poor (10–13%)*, *severe (13–20%)* and *extreme (>20%)*) reduces reliance on the veracity of the 10% threshold. Graphical representations of the five-fold 10% approach showed that some low-income homes with relatively low running costs can still suffer severe or extreme fuel poverty; conversely, the LIHC and LILEE definitions tend to undercount fuel poverty in these cases.

Examining the overlap between different fuel poverty definitions, including 10% fuel poverty with LIHC and LILEE, also provided valuable insights into the measurement inaccuracies of relative fuel poverty definitions. Based on these overlapping profiles of fuel poverty (see Table 7-6 and Table 7-7), it was found that a majority of lower-income homes with relatively low energy costs

(i.e., LILC and LIHEE homes, according to LIHC and LILEE terminology) were still fuel poor according to the 10% definition. This provides further evidence that relative indicators of fuel poverty like LIHC and LILEE underplay the impact of volatile and rising energy costs in low-income homes, as also noted by Middlemiss (2017) and in this thesis (see **Chapter 4:** Section 4.6). A fuel poverty measurement framework that addresses the shortcomings of the previously described approaches should achieve the following:

i) Reduce reliance on the outmoded 10% threshold
ii) Include a safety net for low-income low costs homes
iii) Provide additional information on the depth of fuel poverty and energy precarity in fuel poor and *not fuel poor* homes in monetary terms
iv) Be compatible with the measurement of a just energy transition.

Based on these characteristics, and the results of the fuel poverty experiments, this thesis proposes the Two-Step Fuel Poverty Measurement Framework (see Figure 7-15) as a potential solution. According to the proposed framework, homes are classed as fuel poor according to the five-fold 10% + MIS-based fuel poverty definition (*Step 1*) and the depth of fuel poverty and the depth of fuel poverty is measured in continuous, monetary terms (*Step 2*), depending on the classification of a given home at the five-level 10% stage.

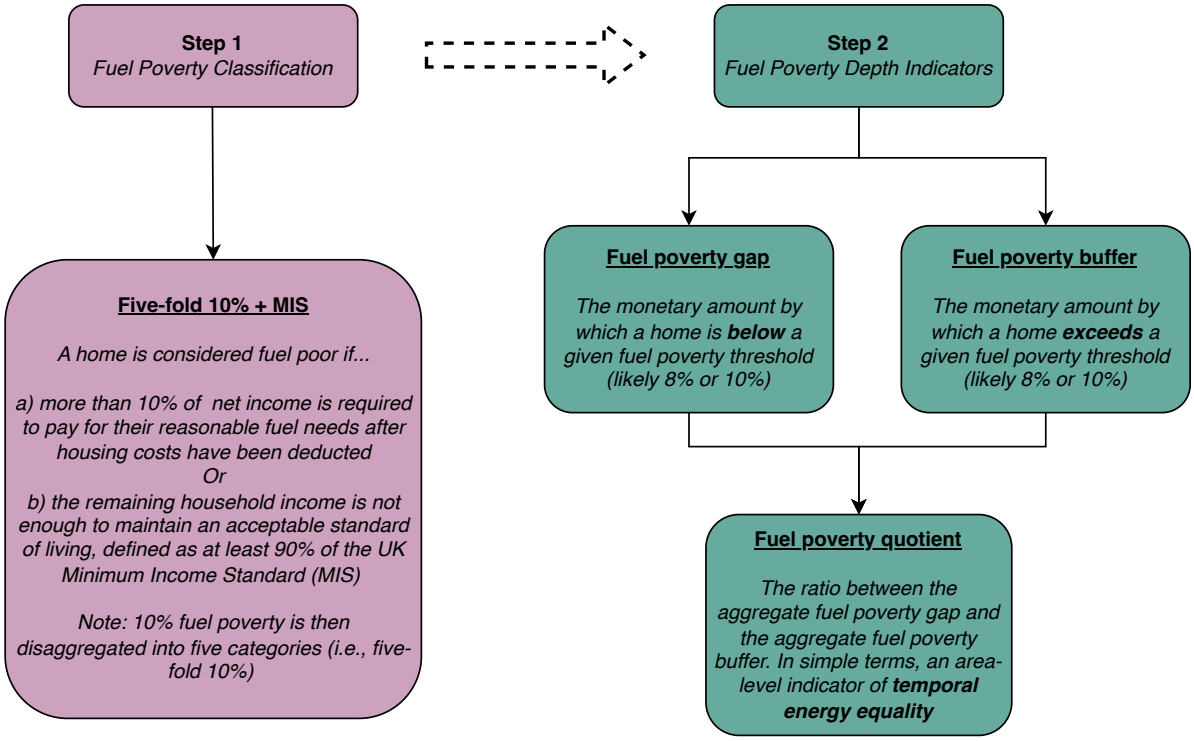


Figure 7-15. Proposal of a Two-Step Fuel Poverty Measurement Framework (TSMF)

Step 1 is almost equivalent to the 10% + MIS-based definition of fuel poverty used in Scotland (Scottish Parliament, 2019), excepting the post hoc disaggregation of the 10% clause to five levels (i.e., five-fold 10% fuel poverty). As discussed throughout, it is likely that the 10% + MIS-based approach is a more comprehensive approach to quantifying fuel poverty than the relative English definitions (LIHC and LILEE). Primarily, this is because of the dual clause (i.e., 10% + MIS), which ensures that some low-income homes with relatively low energy costs. that are in some cases deemed *not fuel poor* according to other definitions (in this case 10%), are not overlooked in fuel poverty statistics if a socially acceptable standard of living cannot be met following the deduction of energy costs. In practice, the incorporation of the MIS-based clause is an effective method for combatting the likely underestimation of fuel poverty in low-income homes with relatively low running costs. Although the 10% + MIS-based approach is effective in this regard, significant emphasis is still placed on the dated 10% fuel poverty threshold; therefore, fuel poverty is also reported per level of the five-fold 10% scale. Though this approach still contains potentially arbitrary, rigid thresholds (at 8%, 10%, 13% and 20%), the level of information provided in terms of the distinction between marginal cases (e.g., those in the 8–13% region) and extreme cases (>20%) is more useful than simple binary classifications. Further, accounting for spatiotemporal shifts between the five-fold 10% categories could provide valuable information regarding the depth and entrenchment of fuel poverty, as also suggested by Bridgen & Robinson (2023).

Step 2 refers to the continuous monetary indicators of energy precarity (8%) and fuel poverty (10%) in terms of depth (i.e., the energy precarity and fuel poverty gaps) and the proximity of *not fuel poor* or *non-precarious* homes to the 8% or 10% threshold (i.e., the energy precarity and fuel poverty buffers). The energy precarity and fuel poverty quotient (i.e., the ratio between the aggregate gap and aggregate buffer) can be used to provide further area-level insights into rising or decreasing energy costs inequality. Like the five-fold 10% definition, these monetary indicators are likely to have most utility as temporal gauges of shifting fuel poverty norms; for example, an increasing quotient is indicative of increasing inequality, while a decreasing quotient indicates the inverse. Another benefit of the proposed monetary indicators is that fuel poverty could theoretically be evaluated across the entire housing stock, as opposed to only focusing on cases where a home is already fuel poor. This may be particularly valuable for developing preventative fuel poverty policies, as the proximity of *not fuel poor* homes to a given fuel poverty threshold is likely to become increasingly important in the near future, if the full breadth of societal effects associated with energy transitions are to be accurately quantified. The consideration of changing conditions in *not fuel poor* homes is also an important aspect of measuring and countering energy

precarity (Petrova, 2018), the effects of which are obscured by the sole use of relative indicators like LIHC and LILEE.

7.8. Conclusions, limitations and further work

In summary, the fuel poverty measurement experiments provided valuable insights into the isolated performance of various existing definitions, including 10%, LIHC, LILEE, five-fold 10% and MIS-based fuel poverty, as well as the overlapping profile of fuel poor homes identified by each. Based on the various negative and positive characteristics of existing definitions, a Two-Step Fuel Poverty Measurement Framework was established. The framework, which includes the five-fold 10% + MIS formulation (Step 1) and continuous monetary indicators of fuel poverty (and energy precarity) gaps and buffers (Step 2), was proposed to address the previously identified deficiencies of existing fuel poverty definitions. Further analysis of the Two-Step framework is provided in **Chapter 8** to test the methodology's responsiveness to changing external circumstances; for example, changing income and energy norms and the decarbonisation (or increasing energy efficiency) of the housing stock.

Aside from the fuel poverty measurement experiments, the LSOA-level income generation approach developed in this chapter has considerable potential as a simulation tool for decision support. Specifically, the Synthetic Nottingham Homes resource can be used to test prospective policies on a sample that is broadly representative of the Nottingham population. In fact, the synthetic data are used for this purpose in **Chapter 8**, where the sensitivity of a range of fuel poverty definitions (including the Two-Step approach) to changing external conditions is analysed. Theoretically, the Synthetic Nottingham Homes dataset could be used for other related analyses, for example, studies of income poverty.

Several notable limitations related to the analyses in this chapter should be noted. First, the synthetic income distributions were based on the ONS's GDHI point estimates, which refer to an equivalised form of income taken before housing costs (BHC) and after direct taxes. This may have resulted in the fuel poverty estimates being overly conservative, given that official fuel poverty estimates tend to use after housing costs (AHC) income variables (DESNZ, 2024a). Further, energy costs variables are typically equivalised to reflect varying energy consumption requirements in different household types (DESNZ, 2024a); however, this was not possible in the current analysis since GDHI point estimates are already equivalised (i.e., the resulting synthetic data are already adjusted for composition in effect). Another limitation concerns incompatibilities between certain datasets utilised for the synthetic data generation and the measurement experiments; for

example, merging the LSOA-coded datasets (e.g., GDHI and EPCs) resulted in the loss of data due to incompatible 2011 and 2021 LSOA geographies. Despite these limitations, as well as the various assumptions and caveats discussed throughout, the fuel poverty measurement experiments are still relatively robust, particularly as the absolute accuracy of the underlying synthetic data does not invalidate the comparison of competing definitions and the profile of homes they deem fuel poor.

Further work may address these limitations by building on the LSOA-level synthetic income generation approach that was trialled in this chapter. More detailed source data, for example, such as GDHI estimates paired with typical household composition for small areas, could significantly enhance the accuracy of the synthetic output and facilitate the use of more advanced data generation techniques, which tend to rely on underlying relationships in the source data. Similarly, detailed ground truth data (e.g., a high-coverage sample of unit-level household income for a set of LSOAs) would allow a more robust validation of the resulting synthetic data, as the pseudo-validation in this case relied on comparisons with further area-level income estimates.

Chapter 8: Testing the Responsiveness of Fuel Poverty Definitions to Changing Economic Circumstances

> *Relative poverty fails to account for changes in wealth evenly distributed among the population, despite people becoming better or worse off.*
>
> Mellish (n.d.)

To this point, the LILEE definition has been comprehensively discredited, a range of existing fuel poverty definitions have been critically reviewed, and the Two-Step Fuel Poverty Measurement Framework has been proposed as a possible solution to the modern quantification of fuel poverty. The previous chapters extensively compared competing fuel poverty definitions via a range of qualitative and quantitative analytical techniques; however, less attention has been afforded to practical implementation. No consideration has been afforded to the sensitivity of competing fuel poverty definitions to changing external circumstances, for example. This is particularly important given that the findings of previous chapters suggested that existing definitions (especially LIHC and LILEE) do not respond proportionately to changes in the primary drivers of fuel poverty (i.e., energy prices, income and energy efficiency) over time. As such, this chapter aims to consolidate the proposed Two-Step approach via a sensitivity analysis, demonstrating varying levels of responsiveness to changing external circumstances among relevant definitions: 10%, LIHC, LILEE and the Two-Step approach. The specific external circumstances considered include energy efficiency upgrades to the housing stock, which are theoretically probable given housing decarbonisation targets, and fluctuations in the fuel poverty ratio (i.e., incommensurate growth in energy costs and income), which may also occur as a result of the UK's current overreliance on natural gas imports. For this reason, the sensitivity analysis focuses on two independent scenarios, as follows: i) increased household energy efficiency—specifically, all homes were assumed to meet their *potential energy efficiency*; and ii) an abrupt rise in the fuel poverty ratio—in other words, energy price inflation was assumed to outgrow income.

8.1. Background: Sensitivity analysis for policy evaluation

Sensitivity analysis is a method that involves the alteration of certain input parameters or assumptions to assess the effect on an output (Kunselman, 2023), and is especially common in the medical and epidemiological literature (de Souza, et al., 2016; Schneeweiss, 2006). Some studies have adopted similar approaches to analyse economic and social issues; for example, Marques Junior (2017) explored the effect of varying fiscal policy on macroeconomic outcomes, while Dudel (2017) considered the effect of varying equivalence scales on poverty estimates. Dudel's (2017) study is particularly close in nature to the sensitivity analysis presented in this chapter, in which the responsiveness of the Two-Step Measurement Framework to changing external conditions is explored. Specifically, the level of response is evaluated via comparisons to traditional fuel poverty definitions (10%, LIHC and LILEE). The ability of the Two-Step approach to respond to fluctuating energy prices and, more specifically, changing fuel poverty ratio norms is of particular interest, given that LIHC and LILEE have been shown to explicitly understate the effects of increasing energy expenditure on fuel poverty. The sensitivity analysis presented in this chapter considers two distinct scenarios, as follows:

1. *Assuming that all homes reach their "**potential energy efficiency**", and energy unit prices and household income remain fixed, how would the rate of fuel poverty change according to the 10%, LIHC, LILEE and Two-Step (five-fold 10% + MIS) approaches?*
2. *Assuming that the energy efficiency of the housing stock remains stable and **energy prices outgrow income**, how would the rate of fuel poverty change according to the 10%, LIHC, LILEE and Two-Step approaches?*

Although the exact conditions presented by both of these scenarios may not occur, or at least not in the immediate future, they are plausible, and the exploration of their effects on fuel poverty is a productive exercise for developing fuel poverty policies that are resilient to changing social and economic circumstances.

8.2. Data and Methods

The data used in this analysis were the Synthetic Nottingham Homes (i.e., paired synthetic income and EPC records for 105,570 Nottingham homes—see **Chapter 7:** Section 7.4 for further details on this dataset). Each synthetic home already has the following relevant information: *synthetic household income*, *inferred energy costs*, *current energy efficiency* (i.e., SAP score) and *potential energy efficiency* (i.e., potential SAP). All of these variables were previously defined in **Chapter 7** (see Sections 7.3 and 7.4) except for *potential energy* efficiency, which the DLUHC (2024) define

as the energy efficiency rating that a home may plausibly achieve if all household-specific energy-saving improvements (i.e., retrofits) were implemented. The Ofgem (2025) energy unit prices were also used to infer updated energy costs that reflected the conditions of scenario 1, where the energy efficiency of the housing stock increased, hence, energy costs decreased, and scenario 2, where energy prices outgrow income, hence, energy costs increased. R code to reproduce the analysis presented in this chapter is available in this thesis's associated repository (see: https://github.com/torransemple/thesis_supplementary_material/tree/main/Chapter_8)[44].

Scenario 1 of the sensitivity analysis required the re-estimation of household energy costs, assuming that all homes achieved their potential energy efficiency, while energy unit prices and household income were assumed to remain fixed. Improved household energy efficiency should theoretically lower domestic energy consumption and the amount consumers spend on energy. The calculation of potential energy costs followed an almost identical process to that described in **Chapter 7** (see *Equations 7.6*, *7.7* and *7.8*), utilising household-specific potential energy ratings from the EPC database (DLUHC, 2024) and Ofgem (2025) unit price caps and standing charges. In other words, *potential* energy costs were inferred by summing *potential* electricity and gas costs, as follows:

$$Potential\ energy\ costs\ \left(\frac{£}{yr}\right) = Potential\ gas\ costs + Potential\ electricity\ costs \tag{8.1}$$

As previously discussed in **Chapter 7**, the gas and electricity costs components were based on the unit price cap for gas and electricity, plus the annual standing charge (i.e., the daily charge multiplied by 365)—see also *Equation 7.7*). The same 'typical energy split' assumption (see *Equation 7.8*) was used to determine the ratio of gas to electricity consumption: ~4.26 kWh of gas for every kWh of electricity[45]. Applying this method to the EPC database's *potential* efficiency and consumption variables returned median *potential energy costs* of £1,330/year among the Synthetic Nottingham Homes, which is less than the median *current* inferred energy costs (£2,185 per year). This is to be expected, given that the median potential SAP used to calculate potential costs was considerably higher (88) than the current median SAP (66) (DLUHC, 2024). The remaining variable used in scenario 1 was household income, which was assumed to be fixed; therefore, no further adjustments were required in this case.

[44] Note: R code to reproduce the sensitivity analysis is in 'CH8_sensitivity_analysis.Rmd'.
[45] Note: in reality, it is highly likely that upgrading all homes to their potential energy efficiency rating would affect the ratio of gas to electricity consumption, but to an unknown degree. As such, it was deemed most consistent to use 4.26 as the gas-electricity split factor.

Scenario 2 explored the effects of an increasing fuel poverty ratio (i.e., energy prices outgrowing income inflation), which required several more assumptions to be made. The nature of these assumptions is slightly more complex than in scenario 1, as sophisticated forecasts of energy prices and income are hard to achieve, given the convoluted interdependency of domestic and international economics. Variance in the fuel poverty ratio, however, is arguably the most direct indicator of changing external circumstances, given that it is a direct quantification of energy expenditure as a proportion of income. As a result, scenario 2 was performed by considering a potential worst-case scenario, where typical household energy costs were assumed to rise at the rate recorded between 2020 and 2022, which was approximately 78.38% (typical costs rose from £1,286 to £2,294, as shown in Table 8-1). In contrast, household income growth was assumed to be low, mimicking the rate of income growth between 2020 and 2022 (up around 1.46%). It is worth noting that the rates of growth used to infer worst-case-scenario values are an overly reductive way of viewing changes in energy prices, given that these figures only refer to the median home and are therefore not necessarily applicable to all homes. Further, if energy prices were to rise by a further 78.38%, there would likely be a corresponding decrease in energy consumption; in other words, people would alter their behaviour to avoid incurring costs as high as those presented in this analysis. Nevertheless, the purpose of this exercise is simply to show how different fuel poverty definitions and measurement frameworks *would* respond, given a drastic change in external circumstances.

Table 8-1. Fuel poverty ratio (2020–2022) and the assumption of a worst-case scenario

Year	Typical household energy costs (£/year)	Median household income (£/year)	Fuel poverty ratio
2020	£1,286	£31,883	0.040
2021	£1,333	£32,529	0.041
2022	£2,294	£32,349	0.071
Worst-case scenario	**£4,092**	**£32,821**	**1.246**

The figures displayed in Table 8-1 refer to nationwide averages; hence, the worst-case-scenario rates of change (+78.38% for energy costs and +1.46% for income) were also applied to each of the Synthetic Nottingham Homes. Table 8-2 displays the results of this process: median energy costs were £3,898 in scenario 2, while median income was £26,800. Table 8-2 also summarises the variables used in both sensitivity analysis scenarios with respect to the original Synthetic Nottingham Homes data (see grey fill) used in the **Chapter 7** measurement experiments. The arrows, displayed in parentheses, show how the variables in scenarios 1 and 2 compared to the Synthetic Nottingham Homes baseline, where an upwards arrow indicates a higher median value than the baseline, a downwards arrow indicates the inverse, and a horizontal arrow denotes no change.

Table 8-2. Sensitivity analysis: Summary statistics for assumed variables (n=105,570)

Conditions	Median energy costs (£/year)	Median household income (£/year)	Median energy efficiency (SAP)	Fuel poverty ratio
Synthetic Nottingham Homes (baseline)	£2,185	£26,414	66	0.083
Scenario 1	£1,330 (↓)	£26,414 (→)	81 (↑)	0.050 (↓)
Scenario 2	£3,898 (↑)	£26,800 (↑)	66 (→)	0.145 (↑)

8.3. Results, Part I: Fuel poverty in scenarios 1 and 2

This section presents the results of the sensitivity analysis. Scenario 1, which assumed that all homes reached their potential energy efficiency, and energy unit prices and household income remained fixed, is considered first. The scenario 1 results are initially presented in Table 8-3 for the entire Synthetic Nottingham Homes sample (n=105,570), whereas subsequent visualisations refer to LSOA-level changes among a sample of 164 applicable LSOAs. The poverty thresholds used for the LIHC and LILEE estimations presented in this section remained the same as those employed in **Chapter 7**: the 2021 poverty line, ~£18,840/year (ONS, 2022f), and a median energy costs threshold of £2,252/year, which was the typical household energy bill in 2024 (DESNZ, 2024b). It is worth noting, however, that if a large number of homes were to reach their potential energy efficiency, as proposed in scenario 1, the median costs threshold used for LIHC estimations would likely be lower than the £2,252/year value assumed in this case.

Table 8-3 displays the scenario 1 results in the form of fuel poverty rates per definition for the baseline case, i.e., the values already presented in Table 7-5 (see **Chapter 7**: Section 7.6), and the scenario 1 conditions. Each column can be interpreted as follows: *proportion fuel poor: baseline* refers to the fuel poverty rates presented in **Chapter 7**; *proportion fuel poor: scenario 1* instead refers to the estimated fuel poverty rates, given the conditions of scenario 1 (i.e., all homes having achieved their potential energy efficiency, while energy unit prices and income were held constant); *absolute change versus baseline* is simply the percentage point difference between the *baseline* and *scenario 1* columns; and the *relative change versus baseline*[46] column shows the relative change in fuel poverty (per definition) between scenario 1 and the baseline.

[46] For example, in the case of 10%, the relative change versus baseline value was calculated as follows: relative change = $(^{36.83\ -\ 16.19}/_{36.83}) \times 100\ =\ 56.04\%\ reduction.$

Table 8-3. Scenario 1 results: Rate of 10% LIHC, LILEE and Two-Step fuel poverty versus baseline (n=105,570)[47]

Definition	Proportion fuel poor: Baseline	Proportion fuel poor: Scenario 1	Absolute change versus baseline	Relative change versus baseline
10%	36.83%	16.19%	–20.64%	–56.04%
LIHC	10.26%	2.51%	–7.75%	–75.54%
LILEE*	18.30%	3.74%	–14.56%	–79.56%
Two-Step (10% + MIS)	40.41%	24.26%	–16.15%	–39.41%

The scenario 1 results suggest that fuel poverty, according to all tested definitions, would decrease if there were significant improvements to the energy efficiency of the housing stock, while assuming that income and energy unit prices remain static. This is to be expected and is easily explained by well-established logic: improved household energy efficiency leads to lower consumer energy costs, which consequently leads to the alleviation of fuel poverty. Despite the criticisms of energy-efficiency-focused fuel poverty definitions that have been made repeatedly throughout this thesis, an extensive domestic energy efficiency programme is evidently a key component of the longer-term solution to fuel poverty. However, the 10% and Two-Step indicators show that 16.19% and 24.26% of the Synthetic Nottingham Homes remained fuel poor, despite the hypothetical, large-scale energy efficiency upgrades assumed in this analysis. This again reiterates a common theme that has been discussed in the findings of previous chapters: LIHC and LILEE focus on the measurement of energy-efficiency-induced fuel poverty, which inevitably omits many low-income homes, while the 10% and Two-Step approaches are able to capture both energy-costs-induced fuel poverty (and, implicitly, energy-efficiency-induced fuel poverty), yet they also capture income poverty, which is necessarily tethered to people's ability to afford adequate energy. This is also evidenced by the low rate of fuel poverty identified by LIHC (2.51%) and LILEE (3.74%), as well as the most substantial relative decrease in fuel poverty from the baseline to scenario 1 conditions. This demonstrates the ideological tendency of the LIHC and LILEE definitions, which posit that fuel poverty can be eradicated through energy efficiency upgrades alone. To reiterate the general narrative throughout previous chapters, fuel poverty persists in many low-income homes with relatively low running costs; hence, the low level of fuel poverty identified by LIHC and LILEE in scenario 1 is both spurious and concerning.

Scenario 2 assumed that the energy efficiency of the housing stock remained stable and energy prices outgrew income. Unlike scenario 1, which assumed a politically ambitious approach to energy efficiency upgrades across the housing stock, scenario 2 considers what might be perceived to be a worst-case scenario, where the energy efficiency of the housing stock remained as is and energy price growth surpassed income. Specifically, energy costs were assumed to have

[47] Additional notes on Table 8-3: LILLE fuel poverty is again referred to as LILEE*, given the lack of available FPEER ratings (as discussed in **Chapter 7**). Further, the *Two-Step approach* in this case, simply refers to 10% + MIS-based fuel poverty, as the five-fold version of 10% is not as easily summarised in this table format, while depth indicators are considered later in this chapter. These notes also apply to Table 8-4.

appreciated by 78.38%, while income was assumed to appreciate by a comparatively modest 1.46%. As noted previously, a limitation of the current analysis is that average growth rates were applied to the Synthetic Nottingham Homes universally, which is likely reductive. In reality, the effects of energy unit price appreciations[48] are unevenly distributed and vary depending on a range of factors (e.g., consumption habits and household energy efficiency).

Table 8-4. Scenario 2 results: Rate of 10% LIHC, LILEE and Two-Step fuel poverty versus baseline (n=105,570)

Definition	Proportion fuel poor: Baseline	Proportion fuel poor: Scenario 2	Absolute change versus baseline	Relative change versus baseline
10%	36.83%	78.51%	+41.68%	+113.17%
LIHC	10.26%	33.35%	+23.09%	+225.05%
LILEE*	18.30%	21.41%	+3.11%	+16.99%
Two-Step (10% + MIS)	40.41%	78.75%	+38.34%	+94.88%

The scenario 2 results show that energy prices outgrowing income results in an increased rate of fuel poverty according to all of the tested definitions; however, the absolute change in fuel poverty versus baseline conditions is radically different. The LILEE fuel poverty rate is least affected by the scenario 2 conditions, increasing by only 3.11% (in absolute terms). This demonstrates the LILEE definition's lack of response to rising consumer energy costs. As discussed throughout previous chapters, this characteristic of the LILEE approach means that the effects of increased energy costs on fuel poverty are largely disregarded. Moreover, the very modest increase in fuel poverty under the scenario 2 conditions, which might be thought of as a worst-case scenario, shows that the LILEE definition is predisposed to identifying a relatively low rate of fuel poverty. In other words, the rate of LILEE fuel poverty is only likely to decrease over time, assuming that the energy efficiency of the housing stock improves, yet cases of income- and energy-costs-induced fuel poverty will continue to be overlooked.

A similar interpretation applies to the LIHC estimates in scenario 2. Although the rate of LIHC fuel poverty increased three-fold (i.e., a relative change of over 200% versus the baseline rate), the absolute rate of fuel poverty (33.35%) is still likely to be an underestimate, given the dire scenario proposed in this analysis. It should also be noted that the relative change in the rate of LIHC fuel poverty in this analysis is likely inflated by the assumption that the median energy costs threshold for the UK (£2,252/year) would remain constant in such circumstances. This assumption was made because it was not feasible to make accurate UK-wide estimates of median energy costs based on the EPC database (DLUHC, 2024); hence, the default LIHC median costs threshold (i.e., the threshold employed in **Chapter 7**) was used. However, if LIHC were re-estimated using the

[48] Note: A more sophisticated approach based on unit price changes for gas and electricity was considered; however, this approach was deemed unfeasible due to a lack of information concerning the household factors that might alter a given home's susceptibility to energy price changes. As a result, the median rate of appreciation in consumer energy costs (78.38%) was assumed in all homes (see also Table 8-1).

broadly inferred *worst-case scenario* median energy costs (see Table 8-1) as the energy costs poverty threshold, the rate of LIHC fuel poverty in scenario 2 would only have been 12.08%, constituting a 1.82% absolute increase in fuel poverty. In other words, the rate of LIHC fuel poverty is highly dependent on the median energy costs threshold, which is equivalent to UK-wide median costs. Regardless, the scenario 2 rate of LIHC fuel poverty (33.35%) is relatively low as an absolute rate of fuel poverty, given the comparable rate of 10% fuel poverty (78.51%).

The 10% and Two-Step (10% + MIS) definitions produced a more pronounced response to the scenario 2 conditions, identifying ~79% of the sample as fuel poor. Although this may seem unrealistically high, the worst-case scenario conditions likely merit a commensurate response in fuel poverty rates. In fact, the relative rise in 10% fuel poverty in scenario 2 (+113.7%) versus the baseline is arguably conceivable, given that 10% fuel poverty rose from ~18% in 2020 to ~37% in 2023 (DESNZ, 2024a) (i.e., a relative increase of ~106%), following significant and largely unforeseen increases in energy prices (DESNZ, 2023a). A fuel poverty rate of ~79%, however, indicates that the vast majority of low- and middle-income homes would be, given these conditions, considered fuel poor. This is not necessarily a negative from a measurement perspective; however, the fact that the 10% and Two-Step methods *could* conceivably identify such a high rate of fuel poverty is likely to be unattractive from a political perspective. Relatedly, the tendency of the LIHC and LILEE definitions to remain relatively stable despite drastic economic change may be politically expedient.

8.4. Results, Part II: LSOA-level fuel poverty in scenarios 1 and 2

This section briefly considers the LSOA-level dynamics of fuel poverty (according to all tested definitions) in sensitivity analysis scenarios 1 and 2. This is a particularly useful exercise for visually demonstrating shifts in fuel poverty rates for each set of conditions versus the baseline. The LSOA-level results of the sensitivity analysis in scenarios 1 and 2 are displayed for the 10% (Figure 8-1), 10% + MIS (Figure 8-2), LIHC (Figure 8-3) and LILEE (Figure 8-4) definitions. In each of these figures, the dashed diagonal line represents the baseline rate of fuel poverty (i.e., if there was no change in fuel poverty, the points would intersect this line), and the positioning of the points (i.e., the LSOAs) in the top left section (increasing fuel poverty versus the baseline rate) or bottom right section (decreasing fuel poverty versus the baseline rate) shows how the scenario 1 and scenario 2 conditions affect LSOA-level fuel poverty. For example, Figure 8-1 displays 10% fuel poverty in scenario 1 (*left*) and scenario 2 (*right*) conditions, showing that fuel poverty reduced markedly in scenario 1 conditions (increased efficiency of the housing stock), while

scenario 2 conditions (energy prices outgrowing income) produced contrasting effects, and a pronounced rise in fuel poverty versus baseline conditions.

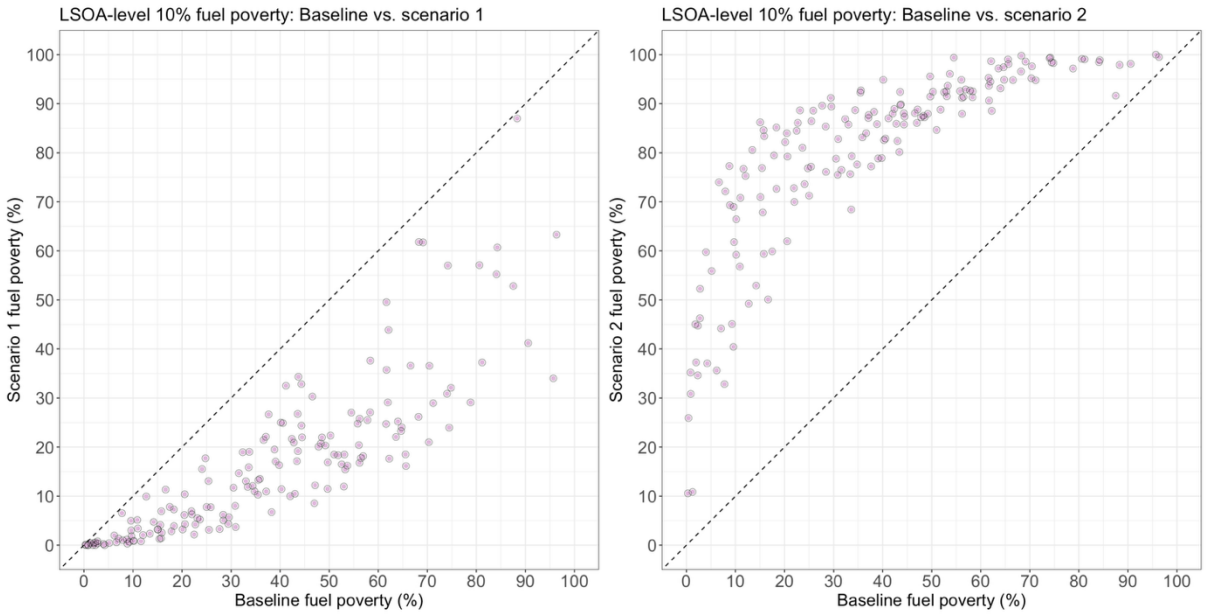


Figure 8-1. LSOA-level 10% fuel poverty: Baseline rate of 10% versus scenario 1 (left) and scenario 2 conditions (right)

The dynamics of 10% fuel poverty shown in Figure 8-1 are to be expected. As evidenced in previous research (Middlemiss, 2017; Moore, 2012), the 10% definition is more able to directly account for changes in the fuel poverty ratio; however, the Hills (2012) review argued that the 10% definition overstates the influence of energy costs. In this case, the fuel poverty ratio decreased in scenario 1 and increased in scenario 2, leading to the corresponding decline and rise in 10% fuel poverty in the left and right plots, respectively. This has several implications. First, scenario 1 shows that 10% fuel poverty can be remedied via significant energy efficiency upgrades, assuming that energy unit prices and income remain stable. However, very high rates of fuel poverty remain in some LSOAs, which is likely due to either income poverty or a combination of both income poverty and an inability to upgrade certain homes. Second, scenario 2 showed that if energy prices were to outgrow income at a rate similar to that observed between 2020 and 2023 (DESNZ, 2024b), fuel poverty would rise significantly across all Nottingham LSOAs. This highlights that a substantial increase in the fuel poverty ratio would negatively impact the vast majority of Nottingham homes, leading to a pronounced rise in LSOA-level 10% fuel poverty.

Figure 8-2 displays the equivalent results for the 10% + MIS definition (i.e., the Scottish Government definition), which is almost identical to the *classification* step of the Two-Step framework (see **Chapter 7:** Figure 7-15). The dynamics of 10% + MIS-based fuel poverty are

closely aligned with those of 10%, which is partly due to the fact that both utilise the 10% fuel poverty ratio threshold, but also because both of these approaches prioritise income- and energy-costs-induced fuel poverty. The main difference between the 10% and 10% + MIS approaches is evident in scenario 1 (see Figure 8-2: *left*). Although increased energy efficiency also produced a decline in 10% + MIS-based fuel poverty for almost all LSOAs, the decline in fuel poverty was not quite as pronounced as for the 10% definition alone, as also demonstrated by the lesser relative change in 10% + MIS (see Table 8-3). This is because the 10% + MIS-based formulation also accounts for living standards at current MIS budget rates (see Table 7-12); hence, an extra safety net is included for those who cannot afford a socially acceptable standard of living following energy costs.

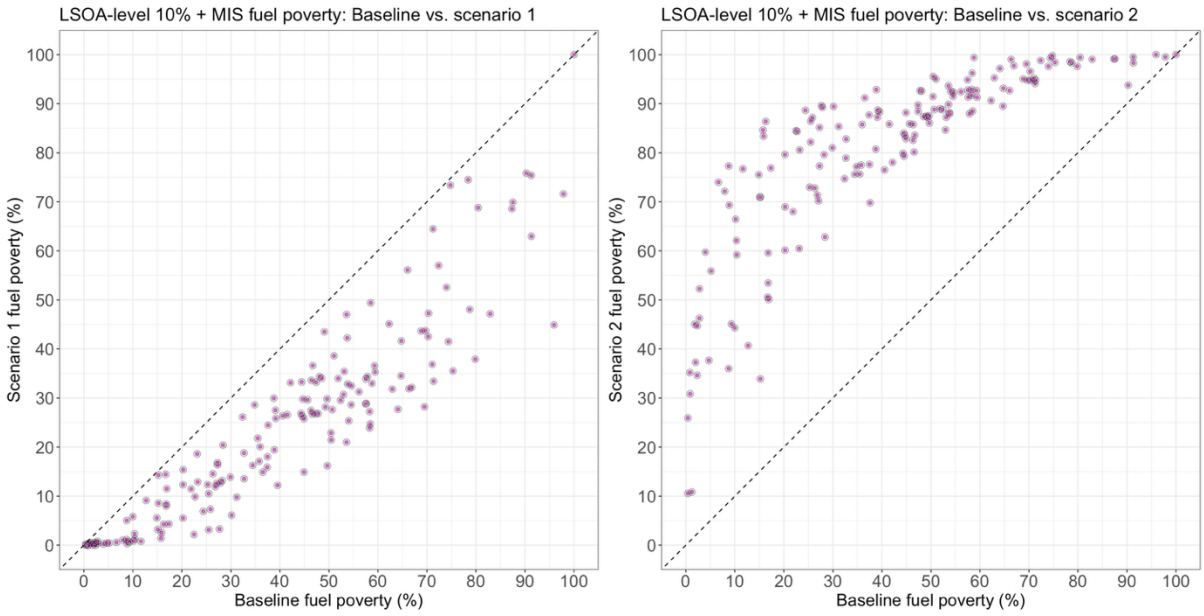


Figure 8-2. LSOA-level 10% + MIS-based fuel poverty: Baseline rate of 10% + MIS versus scenario 1 (left) and scenario 2 conditions (right)

Figure 8-3 (LIHC) and Figure 8-4 (LILEE) display the sensitivity analysis results in both scenarios according to the relative fuel poverty definitions (LIHC and LILEE)[49]. For the LIHC definition, scenario 1 conditions led to a significant reduction in LIHC fuel poverty, except in a handful of outlying cases. As argued throughout previous chapters, this is likely because the LIHC definition overstates the importance of energy-efficiency-induced fuel poverty, which is demonstrated by the fact that an overwhelming majority of LSOAs in scenario 1 had an LIHC rate of around or below 10%, but many of these LSOAs had much higher rates of 10% or 10% + MIS-based fuel poverty.

[49] Note: The axes limits in Figure 8-3 and Figure 8-4 are lower, as the maximum rate of LSOA-level fuel poverty does not exceed ~85% in the case of LIHC and ~70% in the case of LILEE; therefore, the 0–100 axes limits would have led to significant clustering and overlapping of points. As such, care should be taken when comparing the 10% and 10% + MIS plots with the LIHC and LILEE counterparts.

Perhaps surprisingly, LIHC did show more responsiveness to the scenario 2 conditions, as fuel poverty rose markedly in many LSOAs. However, the LIHC statistics presented in this sensitivity analysis are caveated by the assumption that median UK-wide energy costs would remain constant in each scenario, which is potentially unlikely, as the scenario 1 and 2 conditions would be unlikely to be Nottingham-specific were they to materialise. As already demonstrated, raising the LIHC median energy costs threshold to reflect the rise in energy costs among the Synthetic Nottingham Homes would result in much lower LSOA-level rates of LIHC fuel poverty in scenario 2.

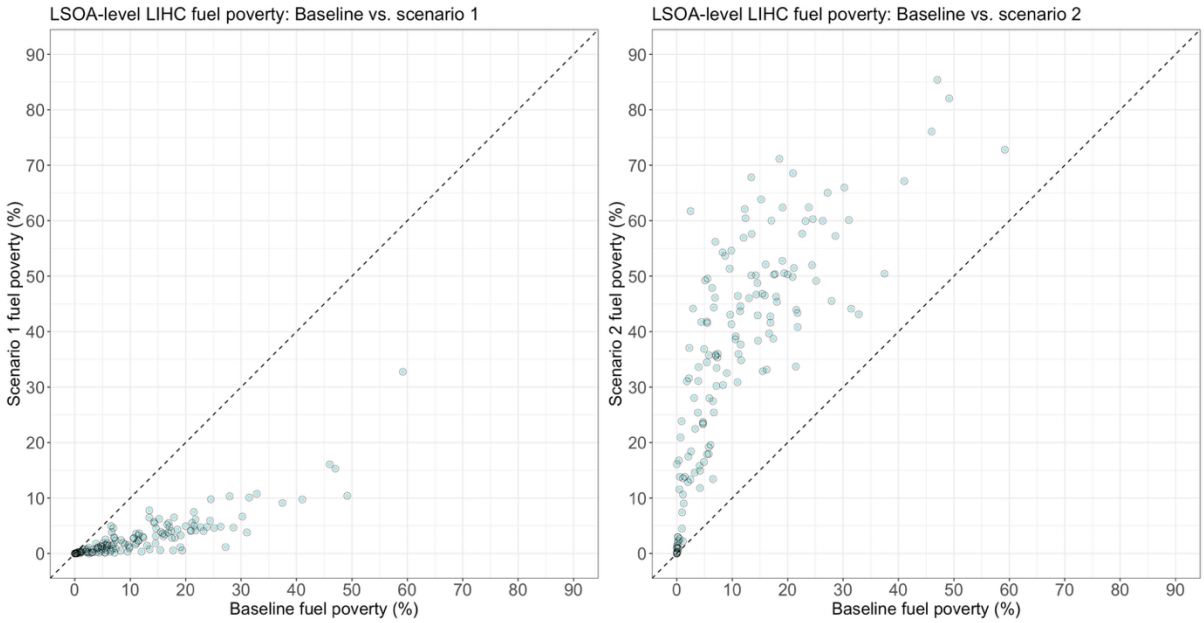


Figure 8-3. LSOA-level LIHC fuel poverty: Baseline rate of LIHC versus scenario 1 conditions (left) and scenario 2 conditions (right)

For the LILEE definition, the results of the sensitivity analysis are particularly informative and help to consolidate the findings of previous chapters. Scenario 1 conditions (see Figure 8-4: *left*) represent a similar trend to the equivalent LIHC plot: increased energy efficiency of the housing stock, while holding energy unit prices and income constant, leads to significantly reduced rates of LSOA-level LILEE fuel poverty. This concurs with previous arguments that the eradication of fuel poverty, according to the LILEE definition, could be achieved (although only nominally) by upgrading the energy efficiency of the housing stock and neglecting other root causes, namely income poverty and energy price volatility. This is patently fallacious, given that many LSOAs with *low* rates of LILEE fuel poverty, still suffer high rates of income poverty (see Figure 8-1: *left* and Figure 8-2: *left*); therefore, residents of these LSOAs still spend a disproportionate amount of their income on energy, despite widespread energy efficiency improvements. The scenario 2 rates of fuel poverty (see Figure 8-4: *right*) typify an even more concerning aspect of the LILEE

measurement approach. As expected, a significant rise in the fuel poverty ratio (i.e., energy prices rising steeply and income remaining approximately fixed) only generates a modest response in LILEE fuel poverty rates. This is especially concerning, given that the equivalent 10% and MIS + 10% analyses estimated that the majority of Nottingham LSOAs would have fuel poverty rates of more than 70% in such conditions. To reiterate: the LILEE definition is illogically focused on energy-efficiency-induced fuel poverty, to the extent that energy efficiency upgrades are the only way that fuel poverty can be eradicated and, even more crucially, radical increases in the fuel poverty ratio only result in modest increases in LILEE fuel poverty rates.

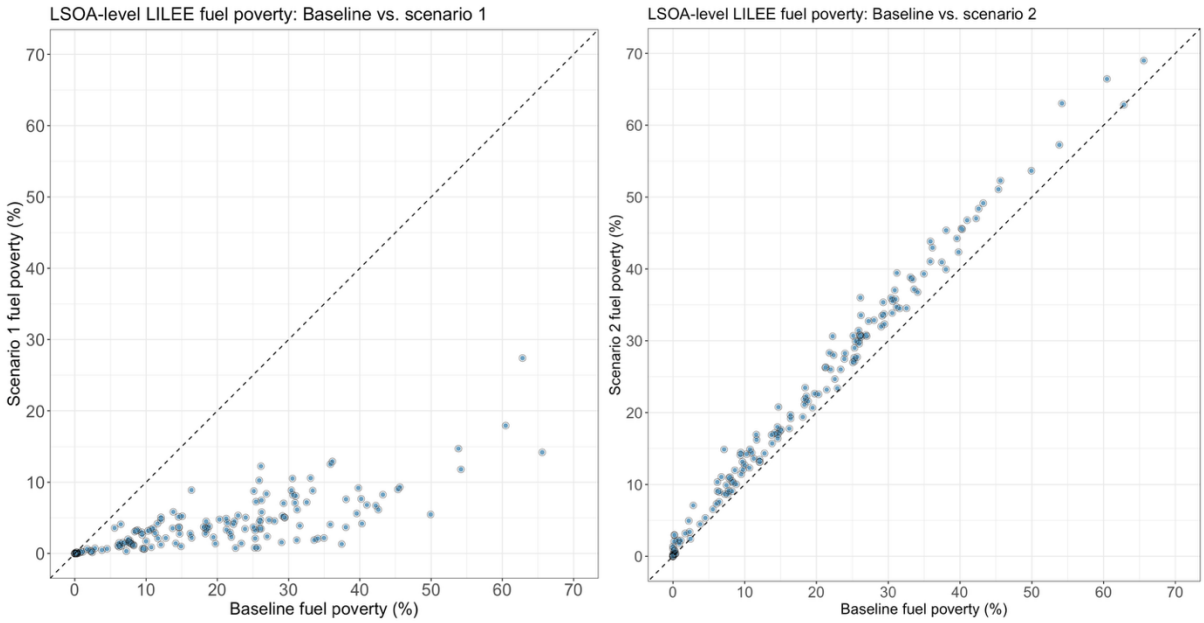


Figure 8-4. LSOA-level LILEE fuel poverty: Baseline rate of LILEE versus scenario 1 (left) and scenario 2 conditions (right)

The accuracy of the 10%, LIHC, LILEE, and 10% + MIS (Two-Step) approaches is inherently debatable. As previously discussed, the selection of the "best" or "fairest" measurement framework is subjective and depends on competing political ideologies (see also **Chapter 5:** Section 5.4). However, the most valuable finding of the sensitivity analysis does not concern the precision of the tested definitions. Instead, the most valuable information is provided by each definition's *response to changing external circumstances*. By definition, a poverty metric (or definition) must be able to quantify the extent to which the root causes of poverty overlap, fluctuate and respond to broader economic change. Bearing this in mind, the sensitivity analysis presented here provides the most absolute indication that the LILEE definition is not possibly fit for purpose, as it demonstrably neglects changes in the ratio of energy costs to income. Conversely, the 10% + MIS approach and, to a lesser extent, the 10% definition in isolation, directly account for living standards, changes in the fuel poverty ratio and, implicitly, changes in

the energy efficiency of the housing stock, as evidenced by the degree of response in poverty rates in scenarios 1 and 2.

LSOA-level fuel poverty depth indicators

Although the LSOA-level evaluation of fuel poverty rates provided insights into how changing external conditions might affect poverty rates, this analysis did not consider how these conditions might affect the depth of fuel poverty. To address this, this section examines how the Two-Step measurement approach's fuel poverty depth indicators would be affected by the scenario 1 and scenario 2 conditions. The aggregate fuel poverty gap (the cumulative monetary depth of fuel poverty per area) and buffer (the cumulative monetary distance between non-fuel-poor homes and a given poverty threshold) are particularly valuable for remedying existing cases of fuel poverty and preventing others from falling into it. Similarly, the fuel poverty quotient, which is the ratio between the aggregate gap and aggregate buffer per area, is a valuable measure of area-level energy inequality over time. As discussed in **Chapter 7**, an increasing quotient indicates increasing inequality, while a decreasing quotient indicates the opposite.

To demonstrate this aspect of the Two-Step approach, Table 8-5 displays the aggregate fuel poverty gap, buffer, and corresponding quotient for the baseline, scenario 1, and scenario 2 conditions. The results refer to the previously used LSOA subset of the Synthetic Nottingham Homes data (n=5,313), with average values for the entire Nottingham homes dataset (n=105,570) also included. As expected, the depth-based indicators show that scenario 1 conditions lead to reduced energy inequality, whereas scenario 2 conditions lead to a pronounced rise. Given that a comparison of all ten example LSOAs is not straightforward, the subsequent discussion focuses on two particularly interesting cases: E01013965 and E01013977 (highlighted in Table 8-5). The results for the entire Nottingham homes dataset (the "Nottingham" row) also provide valuable citywide insights. These two LSOAs were selected because they are at opposite ends of the socioeconomic spectrum. E01013965 is in the 1st IMD quintile, ranking among the most deprived 20% of English LSOAs, whereas E01013977 is in the 4th IMD quintile, making it one of the most affluent areas in the city (see **Chapter 7:** Table 7-4 for further context). From here on, these will be referred to as the *deprived* and *affluent* LSOA examples.

Table 8-5. Aggregate 10% fuel poverty gap, aggregate 10% buffer and 10% fuel poverty quotient for LSOA subset (n=5,313) in baseline, scenario 1 and scenario 2 conditions[50]

Area	Baseline			Sensitivity analysis 1			Sensitivity analysis 2		
	Agg. gap	Agg. buffer	10% Quot.	Agg. gap	Agg. buffer	10% Quot.	Agg. gap	Agg. buffer	10% Quot.
E01013979	$4.6*10^4$	$5.7*10^5$	0.08	$6.5*10^3$	$1.2*10^6$	0.01	$7.1*10^5$	$9.4*10^4$	7.54
E01013983	$1.8*10^5$	$2.7*10^5$	0.66	$7.2*10^4$	$5.7*10^5$	0.13	$9.2*10^5$	$2.2*10^4$	41.98
E01013931	$3.9*10^4$	$1.2*10^6$	0.03	$2.9*10^3$	$1.8*10^6$	<0.01	$5.1*10^5$	$5.3*10^5$	0.95
E01013965	$2.8*10^5$	$1.4*10^5$	1.98	$5.4*10^4$	$6.0*10^5$	0.09	$1.4*10^6$	$7.5*10^3$	183.80
E01013893	$1.8*10^5$	$4.7*10^5$	0.38	$8.4*10^4$	$7.5*10^5$	0.11	$7.5*10^5$	$1.2*10^5$	6.13
E01013977	$2.1*10^3$	$1.6*10^6$	<0.01	<0.01	$2.2*10^6$	<0.01	$2.2*10^5$	$6.6*10^5$	0.33
E01013856	$8.6*10^4$	$4.9*10^5$	0.17	$1.1*10^4$	$9.1*10^5$	0.01	$6.8*10^5$	$1.0*10^5$	6.56
E01013934	$9.5*10^4$	$3.3*10^5$	0.28	$1.8*10^4$	$8.2*10^5$	0.02	$9.0*10^5$	$2.7*10^4$	32.85
E01013984	$2.7*10^4$	$5.6*10^5$	0.05	$5.4*10^2$	$1.1*10^6$	<0.01	$5.2*10^5$	$1.1*10^5$	4.81
E01033398	$8.1*10^4$	$4.5*10^5$	0.18	$3.7*10^4$	$6.3*10^5$	0.06	$5.4*10^5$	$8.9*10^4$	6.07
Nottingham	$3.1*10^7$	$1.0*10^8$	0.30	$9.3*10^6$	$1.7*10^8$	0.05	$1.6*10^8$	$3.3*10^7$	4.72

The socioeconomic separation of these two areas unsurprisingly leads to contrasting fuel poverty depth indicators. As shown in Table 8-5, the baseline 10% fuel poverty quotient in the deprived example was 1.98. This means the aggregate monetary depth of fuel poverty was approximately £280,000, roughly two times the magnitude of the aggregate buffer in baseline conditions (~£140,000). The fuel poverty quotient then dropped to 0.09 in scenario 1, indicating that significant energy efficiency upgrades would considerably reduce the depth of fuel poverty and provide a larger buffer for *not fuel poor* homes. Conversely, the quotient in scenario 2 rose significantly, to the point where the aggregate fuel poverty gap was approximately 183.8 times the magnitude of the aggregate buffer. The scenario 2 results in particular demonstrate how a further major economic event—such as the unprecedented rise in energy costs between 2020 and 2023—might affect the depth of fuel poverty in areas with an already high prevalence of the condition. It is also worth noting that while the LILEE fuel poverty rate in this LSOA was only ~37% in scenario 2, the rate of 10% + MIS was ~98%. This difference emphasises the LILEE definition's lack of response to worsening conditions in homes that were already economically precarious in the baseline scenario.

The 10% fuel poverty quotient statistics for the affluent LSOA exhibit a similar trend: the quotient was originally very low (<0.1) in baseline conditions, given that the aggregate gap was also ~0,

[50] Table notes: 'Agg, gap' = 10% aggregate fuel poverty gap; 'Agg. buffer' = 10% aggregate fuel poverty buffer; '10% Quot.' = 10% fuel poverty quotient (ratio of gap to buffer per unit of area); all gap and buffer statistics are monetary values (i.e., GBP).

and remained low in scenario 1 (increased energy efficiency) as expected. The quotient rose to 0.33 in scenario 2, which means that the aggregate fuel poverty gap constituted around a third of the aggregate buffer. Although the dynamics of the quotient in this case mimic those of other LSOAs, particularly the relative rise in scenario 2 conditions, the LSOA still remained relatively secure. The main takeaway is this: already-deprived LSOAs are likely to be disproportionately affected by potential worst-case scenario conditions (i.e., scenario 2) because the existing depth of fuel poverty and the precarity of *not fuel poor* homes is more acute in these areas. Relatively affluent areas, conversely, have a very low (or zero) fuel poverty rate originally, and a large fuel poverty buffer; hence, potential worst-case scenario conditions do not result in significant energy inequality in these areas.

8.5. Discussion and Conclusions

The analyses in this section serve as a necessary demonstration of the proposed Two-Step Measurement Framework's viability as an alternative approach to measuring fuel poverty in England. Both scenarios confirmed the numerous measurement deficiencies of the existing LIHC and LILEE approaches. The LILEE definition, in particular, was again shown to neglect the influence of high absolute or proportional energy expenditure in many low- and middle-income homes under potential worst-case conditions (see scenario 2). Furthermore, both LIHC and LILEE likely overstate the role that energy efficiency upgrades alone would have in reducing fuel poverty (see scenario 1).

Conversely, the 10% and 10% + MIS-based approaches (i.e., part one of the Two-Step framework) responded to each set of conditions more logically, showing the potential but limited impact that energy efficiency upgrades might have. The 10% and 10% + MIS formulations also responded accordingly when energy prices outgrew income. Finally, the application of depth indicators (i.e., part two of the Two-Step approach) demonstrated the most novel and valuable aspect of the framework. The estimation of area (LSOA)-level gap, buffer, and quotient statistics provided insights into how each set of conditions affected the monetary depth of fuel poverty. The fuel poverty quotient is a particularly useful indicator of temporal energy (in)equality, as it can track the ratio of the aggregate fuel poverty gap to the aggregate buffer over time. Given the ongoing energy transition and housing decarbonisation agendas, a metric of this nature may be especially valuable for tracking the area-level dynamics of fuel poverty in a way that is not confined to the typical binary classifications (i.e., fuel poor or not fuel poor).

Chapter 9: Conclusions and Policy Recommendations

> *Poverty is not created by poor people. It has been created and sustained by the economic and social systems that we have designed for ourselves; the institutions and concepts that make up that system; the policies that we pursue.*
>
> Muhammad Yunus

Muhammad Yunus's words on the manufactured nature of poverty resonate with the core findings of this thesis. Governments design poverty definitions, which are then used to determine who is poor and, consequently, who is worthy of support. The level of fuel poverty currently experienced in England, and further afield, is a political choice. Relatedly, the way fuel poverty is conceptualised and measured is necessarily ideological. The LILEE definition's inclusion of the EPC (or FPEER) criterion, for example, is inherently tethered to parallel political agendas, including the incentivisation of energy efficiency upgrades and the minimisation of energy market volatility. Despite the seemingly inescapable politicisation of fuel poverty and its measurement, there are alternatives to the LILEE definition that more closely resemble the lived experiences of those suffering from its symptoms. The most logical starting point would be to adopt a fuel poverty definition that at least captures the social impact of energy price volatility, which the 10% definition previously achieved, but modern relative fuel poverty definitions (like LIHC and LILEE) fail to do.

This chapter recapitulates the thesis's main findings and central policy recommendation, which is to reconsider the official fuel poverty definition in England. Following this, the remainder of this chapter summarises chapter-by-chapter findings and associated policy recommendations, before the thesis's limitations and opportunities for further work are discussed.

9.1. Review of aims and research questions

This section relates the thesis's findings to the aims and research questions that were stated in the introductory chapter. The thesis's overarching was to quantify the extent to which modern definitions, especially LILEE, underestimate fuel poverty and, in response, propose a novel framework that provides a more robust and responsive assessment. This overarching aim was

achieved via the discreditation of the LILEE definition in **Chapters 3–4**, while the **Chapter 7** measurement experiments and the sensitivity analysis in **Chapter 8** provided sufficient evidence to suggest that the Two-Step measurement approach may be a valuable successor to LILEE. In terms of the thesis's original research questions (see Table 0-1) and associated research objectives, Table 9-1 shows how each were addressed by each of the thesis's core contribution chapters (3–8).

Table 9-1. Research questions, objectives and evidence

Research question	Research objective(s)	Evidence (inc. relevant chapter)
Research Question A: Given the LILEE definition's universal omission of energy-efficient households, is fuel poverty (i.e., the actual ability of occupant(s) to afford adequate energy) currently underestimated in England, and if so, to what extent?	**RO1:** Analyse the geography of LILEE fuel poverty and deprivation data	**Chapter 3:** The bivariate geographical analysis showed that LSOA-level LILEE fuel poverty and IMD data were surprisingly disparate.
	RO2: Estimate the number of vulnerable homes omitted from LILEE statistics	**Chapter 3:** The estimation of homes omitted by default from LILEE statistics (i.e., with EPC ratings of C or above) showed that a considerable proportion of these homes (6.5% in Nottingham and 4.4% in London) were also financially vulnerable and, as a consequence, likely unable to afford adequate energy.
Research Question B: What are the salient determinants of subjective fuel poverty during a cost-of-living crisis?	**RO3:** Measure and analyse subjective fuel poverty (household energy security) in London	**Chapter 4:** The rate of subjective fuel poverty was around 145% higher than the equivalent rate of LILEE fuel poverty; further, the rate of subjective fuel poverty in EPC A–C- and D–G-rated properties was essentially equivalent. **Chapter 4:** The RPOP model estimation results showed that being aged under 25 or over 65, having a prepayment meter or a health condition and low absolute income all significantly increased the likelihood of subjective fuel poverty (or household energy insecurity).
Research Question C: Are existing fuel poverty definitions compatible with parallel political agendas, including the decarbonisation of housing and a just energy transition?	**RO4:** Critically review existing fuel poverty definitions	**Chapter 5:** The development and application of the FPDEF approach showed that the English definitions (10%, LIHC and LILEE) have limited modern applicability. The Scottish Government approach (10% + MIS) was identified as the most effective existing definition.
Research Question D: How effective are competing definitions of fuel poverty (existing and novel) in terms of identifying homes that are unable to afford sufficient energy?	**RO5:** Estimate fuel poverty indicators using real-world data	**Chapter 6:** The financial data analysis found that individual-level indicators of financial security and fuel poverty have modest utility as an additional means of quantifying fuel poverty.
	RO6: Validate competing fuel poverty definitions on household-level data	**Chapter 7 & 8:** The measurement experiments evidenced overlapping and contradictory profiles of fuel poverty identified by competing definitions. The Two-Step Measurement Framework was proposed as the optimal solution to measuring fuel poverty in the modern context.

9.2. A recapitulation of the main findings and policy recommendations

The remainder of this chapter recapitulates the main findings of each core contribution chapter (i.e., **Chapters 3–8**). Figure 9-1 provides a chapter-specific summary of the thesis's main contributions to knowledge and corresponding policy recommendations.

The first core contribution of this thesis was an empirical critique of the LILEE definition. This was achieved via analyses of publicly available EPC and geographical data in **Chapter 3** and a household energy security (or subjective fuel poverty) survey in **Chapter 4**. The **Chapter 3** findings suggested that a sizeable proportion of financially vulnerable, EPC A–C-rated homes were wrongly omitted from fuel poverty statistics, while the geographical analysis also demonstrated surprisingly low rates of LILEE fuel poverty in relatively deprived areas. Though these findings were suggestive of measurement deficiencies in the LILEE approach, the most compelling evidence was captured by the household energy security survey. The **Chapter 4** findings consolidated theoretical concerns with the LILEE definition, showing that the rate of subjective fuel poverty was approximately 145% higher than the corresponding rate of LILEE fuel poverty. Statistical variance testing also demonstrated that subjective fuel poverty rates were not dissimilar in EPC A–C and D–G-rated homes, casting substantial doubt on the LILEE definition's SAP-based clause and its focus on energy efficiency-induced fuel poverty more generally. In summary, the collective findings of the empirical critique strongly evidenced the significant measurement deficiencies of the LILEE definition. As such, the findings of this thesis suggest that the LILEE definition should be succeeded by an alternative measurement approach that more accurately captures real-world experiences of fuel poverty.

Chapter 5 involved the development of a Fuel Poverty Definition Evaluation Framework (FPDEF) to compare a range of existing fuel poverty definitions. The FPDEF was used to evaluate existing fuel poverty definitions in terms of three primary dimensions: conceptualisation, methodological operationalisation and policy utility. More specifically, the application of the FPDEF facilitated a critical review of existing fuel poverty definitions, exploring a range of key issues including relative versus absolute quantification, compatibility with adjacent political agendas and susceptibility to politicisation. In short, the findings indicated that the traditional fuel poverty definitions have limited value in the current political and economic context. The 10% definition uses an outmoded and, consequently, arbitrary threshold, whereas the LIHC and LILEE definitions both understate the effects of changing energy price norms and are therefore unable to accurately respond to the potentially adverse impacts of energy transitions. In addition, the LIHC and LILEE definitions were suggested to be products of austerity-era politics, in which the responsibility for fuel poverty was redirected to the consumer, diminishing the government's need to intervene. To

summarise, the critical review presented in **Chapter 5** presented further evidence that existing definitions suffer from a range of measurement deficiencies, susceptibility to political bias and, in the case of the LIHC and LILEE approaches, incompatibilities with other climate change-related policies (i.e., the measurement of a just energy transition). The Scottish Government's 10% + MIS-based definition was found to have the most modern relevance as an alternative, existing means of quantifying fuel poverty.

Chapter 6 explored the utility of a large financial dataset for fuel poverty classifications. Given that the financial data referred to individual-level records, financial security, potential fuel stress and fuel poverty ratio indicators were estimated at the individual level. This presented a considerable issue, given that critical household-level information was unknown, which is especially limiting when estimating a household condition like fuel poverty. Despite considerable data limitations, the individual-level metrics of fuel poverty and financial security provided some valuable insights into group- and area-level variation in energy affordability; however, no notable policy recommendations resulted from **Chapter 6**.

Chapter 7 explored successors to the LILEE definition via the analysis of household-level data. To achieve this, the Synthetic Nottingham Homes resource was generated, allowing for a series of fuel poverty measurement experiments. The measurement experiments led to several key outcomes:

- The profile of fuel poor homes identified by the 10%, LIHC, LILEE, and 10% + MIS definitions.
- Novel fuel poverty depth indicators—the 8% or 10% gap, buffer, and quotient—were developed.
- The five-fold version of the 10% definition was identified as an approach that reduces reliance on the validity of the outmoded 10% poverty threshold while providing more information on severely affected and financially precarious homes.

These findings culminated in the proposal of the Two-Step Measurement Framework, which combines the five-fold 10% definition with an MIS-based clause (Part I) and the new depth indicators (Part II). The sensitivity analysis in **Chapter 8** demonstrated that this framework has a significantly improved ability to respond to energy price volatility over time, especially when compared to the LIHC and LILEE definitions. Furthermore, the fuel poverty quotient was shown to be an effective measure of temporal energy inequality in possible future scenarios.

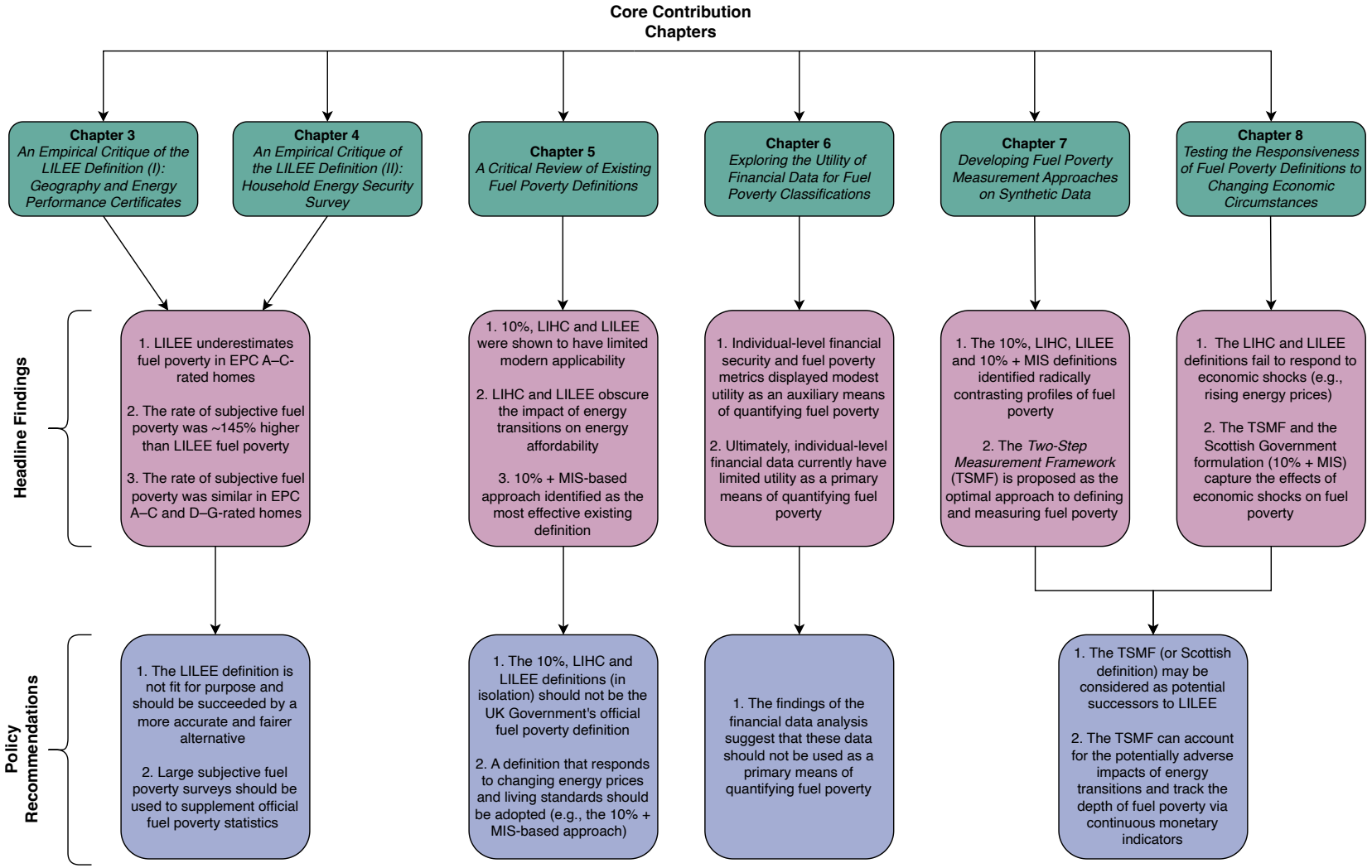


Figure 9-1. A summary of headline findings and associated policy recommendations per core contribution chapter

In conclusion, this thesis has demonstrated that the LILEE fuel poverty definition considerably underestimates the number of fuel poor households in England. This research supports the theoretical argument that relative measures can fail to capture the full scope of poverty, particularly when compared to fairer, more absolute approaches like the Scottish 10% + MIS-based definition and the Two-Step framework proposed here. Furthermore, this thesis has shown that continuous fuel poverty depth indicators could be a crucial tool for tracking the impact of remedial strategies and energy equality over time. For these reasons, the principal recommendation of this thesis is that the Two-Step Measurement Framework may be a viable successor to the LILEE definition. This thesis primarily focuses on the conceptual and statistical rationale for an amended fuel poverty measurement framework; accordingly, further investigation into the associated data infrastructure and computational processes is required to more robustly assess the political feasibility of the TSMF.

9.3. Limitations and opportunities for further work

The findings of this thesis are subject to a range of limitations, many of which are inherent to the utilisation of disparate secondary datasets. A particularly notable constraint was the lack of household-level financial information in the **Chapter 6** analysis, which inevitably affected the utility of the resulting financial security and fuel poverty metrics. The critical review of existing fuel poverty definitions in **Chapter 5**, while rigorous, involved a degree of subjective assessment that was mitigated by the use of the FPDEF. The synthetic data generation in **Chapter 7** could also be improved with more robust income distribution input parameters, while the validation of the synthetic data would benefit from the availability of unit-level ground truth data. A further general limitation is the lack of attention afforded to the operational utility of fuel poverty definitions as policy support mechanisms (e.g., the specific targeting of financial support or housing upgrades). This thesis treats fuel poverty definitions primarily as diagnostic tools to identify fuel poor populations, rather than a means of resource allocation. Addressing the latter was considered out of scope, as the translation of fuel poverty statistics into remedial action is ultimately the discretionary purview of local and national government.

Further work may address many of these limitations. The development of household archetypes using existing financial records, for example, would facilitate a more granular analysis of financial security and fuel poverty across a large and potentially highly valuable dataset. Similarly, the availability of more detailed expenditure variables in financial datasets would radically improve the reliability of fuel poverty-related analyses. Furthermore, the synthetic data resource created in this thesis provides a valuable baseline to which more sophisticated approaches can be

compared. It would be beneficial for future work to reproduce the measurement experiments in **Chapter 7** using real-world data to ensure the assumptions underlying the synthetic income distributions in Nottingham did not affect the findings.

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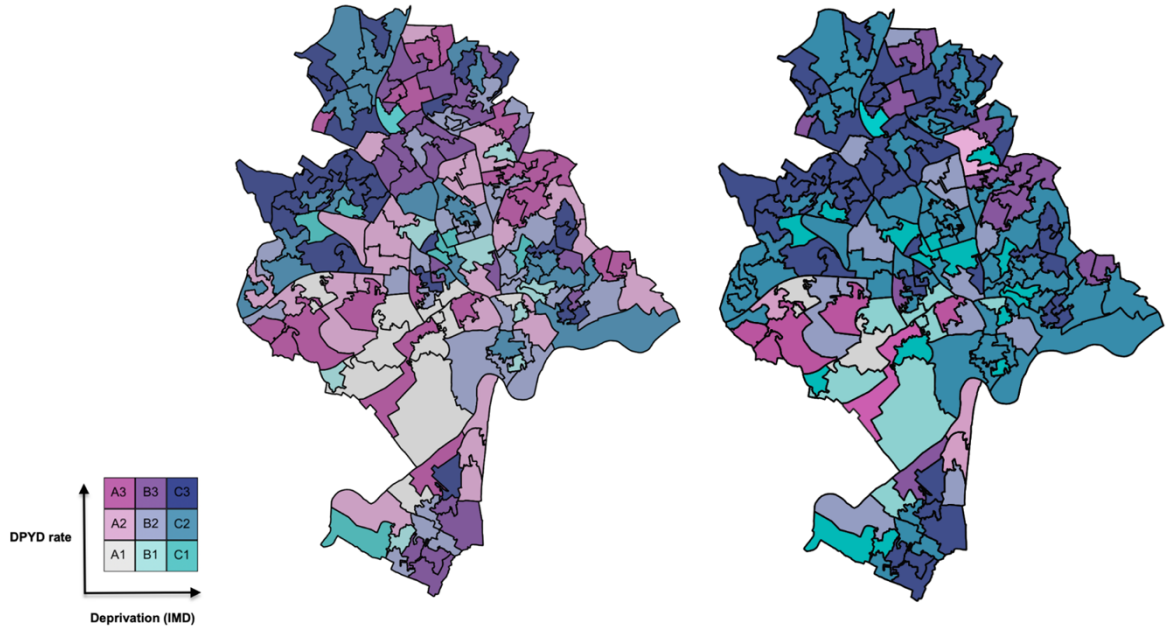
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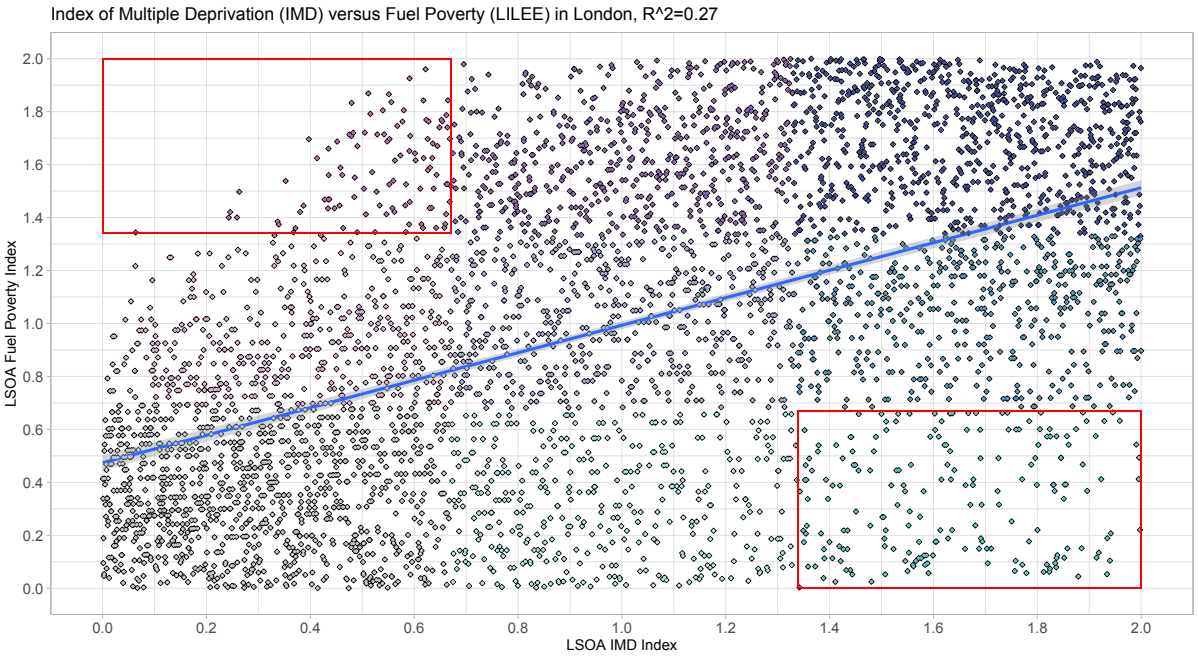
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Appendices

Appendix: Chapter 3



*Chapter 3, Figure 1. Left: Deprivation (**Nottingham baseline**) versus dihydropyrimidine dehydrogenase (DPYD) test rate in Nottingham; Right: Deprivation (**England baseline**) versus DPYD test rate in Nottingham*



Chapter 3, Figure 2. IMD plotted against fuel poverty (LILEE) per LSOA in Greater London (n=4,659 LSOAs)

Appendix: Chapter 7

Chapter 7, Table 1. Pseudo-validation: MSOA point estimates for competing approaches

MSOA code	Approach (£/annum)		
	Direct Sampling	ONS GDHI	ONS NHI
E02002868	29609	30691	27500
E02002869	23581	23983	22500
E02002871	29454	30552	25000
E02002872	23949	24822	23800
E02002873	26856	27392	23400
E02002874	30733	31513	27200
E02002875	30230	30216	23500
E02002876	29083	29667	25800
E02002877	36045	36751	33000
E02002878	25926	26198	18800
E02002879	36282	36632	26200
E02002880	26687	27297	22200
E02002881	29573	28933	23300
E02002882	42497	43972	37500
E02002883	35573	35096	26100
E02002884	26555	26510	23800
E02002885	24378	24779	19200
E02002886	33038	32951	24700
E02002887	25414	25649	22700
E02002888	28480	29126	22100
E02002889	20331	20258	29500
E02002890	18867	18265	25900
E02002891	28751	29092	24200
E02002892	25616	26439	23800
E02002893	18683	18994	20900
E02002894	44666	44924	31100
E02002895	63246	60585	46100
E02002896	33864	33506	23100
E02002897	39854	40843	31600
E02002898	19738	19883	28200
E02002899	23873	24502	23400
E02002901	38868	38089	29700
E02002902	25050	25313	25000
E02002903	28627	29359	25500
E02002904	28054	28813	24000
E02006834	24219	24688	26500
E02006904	27871	27622	43600
E02006905	32294	32657	25900

Chapter 7, Table 2. MIS budget components (£/week) per household composition (Loughborough University, Centre for Research in Social Policy, 2024)

2021 MIS budget component categories	*Single*	*Couple*	*Single pensioner*	*Pensioner couple*	*Lone parent: 1 child*	*Couple: 1 child*
Food	50.99	83.13	47.10	75.25	57.91	89.90
Alcohol	6.10	12.20	8.05	12.37	5.40	10.47
Tobacco	0.00	0.00	0.00	0.00	0.00	0.00
Clothing	9.46	18.93	7.91	15.82	23.43	33.64
Water rates	6.09	6.09	6.09	7.18	10.37	10.37
Council tax	18.68	24.93	18.68	24.93	21.82	29.08
Household insurances	1.57	1.76	1.48	1.55	1.27	1.32
Fuel (*omitted)	13.50	16.73	11.01	15.07	15.93	17.27
Other housing costs	1.48	1.48	2.99	2.99	1.94	1.94
Household goods	10.05	12.22	15.39	17.55	24.78	25.67
Household services	7.66	10.41	8.84	10.77	13.64	10.84
Childcare (*omitted)	0.00	0.00	0.00	0.00	262.08	262.08
Personal goods and services	17.62	31.38	18.52	38.67	30.93	40.88
Motoring	0.00	0.00	0.00	0.00	64.33	64.86
Other travel costs	43.30	86.65	15.42	19.16	6.30	32.49
Social and cultural participation	44.82	75.16	48.20	81.56	52.25	63.81
Rent (*omitted)	95.45	106.67	78.99	86.81	86.81	86.81
Headline total	231.32	381.06	209.68	322.87	330.31	432.55