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Beyond headcount statistics: Exploring the utility of energy poverty gap indices in policy design

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ABSTRACT

Recent energy price spikes have led to increased energy poverty among low-income households living in inefficient homes. Accurate statistics on energy poverty help inform resource allocation and better target relief schemes and retrofit funds. Existing indicators are predominantly defined in terms of a headcount ratio – the share of population living below a certain threshold or poverty line. In this paper we draw from the literature on income poverty evaluation to argue that the use of more elaborate energy poverty gap indices can substantiate the design and monitoring of energy poverty policies, by not only considering incidence but also intensity and inequality of energy poverty across households. We demonstrate that the choice for a particular energy poverty (gap) indicator makes the implicit welfare choices of energy poverty policies explicit. We illustrate our arguments for the case of the Netherlands, using recently developed microdata statistics on energy poverty, and an imposed energy price shock. We show that spatial targeting of relief funds based on incidence would neglect the full depth of energy poverty deprivation. Finally, we argue that visualisation techniques from the income poverty literature help to comprehend different poverty orderings and draw comparisons between time periods, regions, and subgroups.

1. Introduction

In 2021 and 2022, energy prices rose sharply in Europe. Because of geopolitical uncertainty and the transition towards a low-carbon energy system, high energy prices as well as strong energy price fluctuations are likely to persist for some time (Mišík, 2022; Pahle et al., 2022). This puts pressure on household expenses and leads to more energy poverty, particularly among low-income households living in energy inefficient homes. Energy poverty – the inability to secure sufficient domestic energy services that allow for participation in society – can have deteriorating effects on livelihoods (Bouzarovski and Petrova, 2015). Previous studies have demonstrated its negative impact on physical health (Liddell and Morris, 2010), mental health (Liddell and Guiney, 2015), stress (Longhurst and Hargreaves, 2019), social isolation (Harrington et al., 2005) and absenteeism (Howden-Chapman et al., 2007).

In most European countries, policymakers have responded to the energy price surge by creating energy cost relief schemes that support households in paying their energy bills. Accurate statistics on energy poverty can help inform policymakers to design effective support measures that target households most in need of support. In this paper we draw from the literature on income poverty evaluation (Foster and Shorrocks, 1988a, 1988b, 1988c; Sen, 1976) to argue that the use of carefully designed energy poverty gap indices can substantiate the design and monitoring of energy poverty policies. We also show that the choice for a particular energy poverty (gap) indicator makes the implicit welfare choices of energy poverty policies explicit.

The wish to alleviate energy poverty in high-income countries is not new. Over the past decade, the alleviation of energy poverty has become an important policy and research area in most high-income countries, more or less following the UK where the issue had already been debated since the 1990s (Bouzarovski et al., 2021; Primc et al., 2021). Governments and other relevant stakeholders are increasingly committing themselves to the universal 'right to energy' and take measures accordingly (Hesselman et al., 2021). The European Commission, for instance, has made tackling energy poverty a key pillar of its 'Renovation Wave' strategy (2020) and Social Climate Fund proposal (2021). Moreover, EU law obliges member states to monitor domestic energy poverty (European Union, 2019). National governments in the US (Bednar and Reames, 2020), the UK (Department of Business Energy and Industrial Strategy [BEIS], 2021b) and the Netherlands (Ministerie van

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Binnenlandse Zaken en Koninkrijksrelaties [BZK], 2021) have even started to use energy poverty indicators to allocate resources for energy poverty alleviation to subnational authorities, which underlines the importance of reliable statistics.

Data and definitions of energy poverty used by policymakers differ across countries and over time, following longstanding debates on indicators in the academic literature (Romero et al., 2018; Siksnelyte-Butkiene et al., 2021; Thomson et al., 2017). This led to many proposals to quantify the multidimensional nature of energy poverty (see for an overview Hills, 2012; Pelz et al., 2018; Tirado Herrero, 2017). Remarkably, however, despite this variation of energy poverty metrics, in most countries (with the UK being an important exception) energy poverty indicators are predominantly defined in terms of a headcount ratio – the share of population living below a certain threshold or poverty line. However, in a seminal article on the theory of poverty evaluation, Amartya Sen (1976) already argued that a poverty indicator should not only be sensitive to the number of people below the poverty line ('incidence'), but also to the extent of the shortfall of the income of the poor from the poverty line ('intensity') and to the distribution pattern of the incomes among the poor ('inequality'). After all, for the design of effective poverty policies it is important to know if increasing poverty is due to more people becoming poor (the headcount ratio), to increasing deprivation of the poor (poverty gaps, i.e. shortfalls below the poverty line) or because of a more unequal distribution of the poverty gaps. In the literature on poverty evaluation this led to the development of a class of poverty indicators that allow for decomposing aggregate poverty changes into these contributing factors (Aristondo et al., 2010; Clark et al., 1981; Foster and Shorrocks, 1988a, 1988b, 1988c; Jenkins and Lambert, 1997, 1998a, 1998b; Kakwani, 1999).

These poverty indicators, that have become known as the so-called class of Foster, Greer and Thorbecke indicators (Foster et al., 1984), relate directly to welfare considerations because of their inherent poverty orderings – not all poor are considered to be equally poor (Foster and Shorrocks, 1988c). This contrasts the headcount ratio that does not consider welfare effects of (changes in) poverty inequality: since it only counts whether or not households are poor it can only measure changes in welfare effects around the poverty line, while poverty changes among households that remain (far) below the poverty line remain unnoticed. In other words, the headcount ratio is unequipped to measure the extent to which policies provide more support to households in greater need (Simshauser, 2021). Evidently, this is an important limitation for developing and evaluating energy poverty policies that aim to alleviate the negative welfare effects of rising energy prices among low-income households (Sefton, 2002). The matter at hand is exemplified by a recent assessment of the Spanish social tariff conducted by Bagnoli and Bertoméu-Sánchez (2022). The authors concluded that the policy had hardly been successful in its aim to alleviate households from energy poverty. However, this inference was solely based on the 'headcount'. Thus, positive welfare effects for households that remained energy poor were by definition neglected.

Besides improving the accuracy of energy poverty monitoring, the use of poverty gaps in official statistics can also stimulate political accountability and commitment. An exclusive focus on the headcount ratio might even tempt policymakers to direct energy poverty alleviation measures disproportionally to households close to the poverty thresholds because this may yield the largest reduction in number of poor people against the lowest cost of alleviation. The use of a more elaborate poverty gap indicator would make such a welfare policy choice explicit and enables to show the welfare trade-off between such a policy choice and an alternative focus on primarily supporting the most deprived households (Heindl, 2015). Moreover, defining and calculating (changes in) an aggregated energy poverty gap can indeed help to project the 'cumulated social costs' (Imbert et al., 2016) or social welfare effects of energy poverty, while a microlevel analysis of energy poverty gaps would allow for a better understanding of welfare differences between households and thus raise awareness of specific vulnerabilities (Tirado Herrero, 2017).

The UK government and several scholars (Faiella and Lavecchia, 2021; Foster et al., 2000; Heindl, 2015; Meyer et al., 2018) have used poverty gap indices to improve energy poverty measurements. However, to the best of our knowledge, the energy poverty literature, remarkably enough, lacks an in-depth study of how to use decomposable poverty indices to evaluate the welfare trade-offs inherent to energy poverty reduction policies that aim to reduce energy poverty incidence, intensity or inequality, or some combination of these goals.

The aim of this paper is therefore to provide an elaborate discussion on the practical implications of using the Foster-Greer-Thorbecke indices in the field of energy poverty. In doing so, we focus on the use of energy poverty gap indices and show how they can be used to examine the intensity and inequality of energy poverty while allowing for decomposition and comparison. Following Sen (1976) and Ravallion (2016), we argue that headcount poverty measurements do not meet the monotonicity axiom (when poor households become poorer, figures must rise) and the transfer axiom (after regressive transfers from poor to richer households, figures must rise), whereas the Foster-Greer-Thorbecke indices meet both axioms. Furthermore, we introduce the so-called TIP curves from Jenkins and Lambert (1997) to the energy poverty literature, in line with the notion to decompose aggregate poverty trends into changes of, respectively, the incidence, the intensity and the inequality of the poverty – the three Is of poverty according to Jenkins and Lambert (1997, 1998a, 1998b). We argue that this is a potentially useful approach to grasp poverty distributions and draw robust comparisons between regions, time periods, and subgroups. We illustrate our arguments with a microdata assessment of energy poverty patterns in the Netherlands, and show that while incidence was relatively low, part of Dutch households dealt with rather intense energy poverty. This implies that targeting of resources to alleviate energy poverty based on incidence only would neglect the full depth of their deprivation.

The organisation of the paper is as follows. In Section 2 we describe how the poverty orderings from development economics could enrich insights from institutionalised energy poverty indicators. In section 3 we introduce the dataset and explain the conducted transformations. In section 4 we illustrate the use of poverty gap indices by performing an analysis of energy poverty in the Netherlands. Finally, in section 5 we discuss which policy consequences arise from the results and suggest opportunities for future research.

2. Three I's of poverty

2.1. Poverty orderings and axioms

As noted before, since the seminal contributions of Sen (1976), it is widely believed that poverty measurement should be decomposable into three orderings: incidence, intensity, and inequality. This paragraph describes their use and the extent to which they satisfy axioms from development economics (see Table 1).

The first ordering, *incidence*, refers to the 'headcount', the most used measure to represent poverty. Typically, it is illustrated by a ratio or 'headcount index' that simply indicates the proportion of a population (e.g. a neighbourhood or country) that is classified as living in poverty. Ravallion (2016) described how this satisfies the focus axiom (independence from changes among the non-poor) and scale invariance axiom (stability when incomes and poverty line increase by the same proportion). The headcount index received criticism from Sen (1976), who pointed out that the headcount index would not increase when an already poor household becomes poorer. Despite this flaw, which makes it an inadequate measure to analyse the impact of specific policies on poverty alleviation, it gained widespread popularity because of its intuitive explanation.

The second ordering, *intensity*, corresponds to the poverty gap. Instead of counting households, it counts shortfalls of income or

Table 1
Characteristics of various poverty orderings, based on Foster et al. (1984).

Poverty ordering	Numeric expression	Focus axiom	Scale invariance	Monotonicity axiom	Transfer axiom
Incidence	Usually a proportion (0–100%) of population living in poverty	Satisfied	Satisfied	–	–
Intensity	Poverty gap as sum per household, index as ratio between 0 (non-existent) and 1 (extremely intense)	Satisfied	Satisfied	Satisfied	Partially satisfied[a]
Inequality	Ratio between 0 (equal poverty) and 1 (completely unequal poverty)	Satisfied	Satisfied	Satisfied	Satisfied

[a] This index satisfies the axiom with transfers from poor to non-poor households but not with transfers from poor to *less* poor households.

consumption, usually presented in monetary terms. It represents the minimal means needed to eliminate poverty if progressive transfers would be costless and perfectly targeted, and while this is only theoretically possible it enables a prompt evaluation of the extent of deprivation (Morduch, 2005). Besides the focus and scale invariance axioms, measuring the poverty gap also satisfies the (subgroup) monotonicity axiom: when already poor households become poorer, the outcome of the measure increases (Kakwani, 1980).

To arrive at the third ordering of the poverty measurement, *inequality*, it must comply with the transfer axiom (Foster and Shorrocks, 1988). This axiom, first introduced over a century ago by Dalton (1920), indicates that regressive welfare transfers from households below the poverty line to richer (or *less* poor) households must affect the outcome. This way, the index penalises the worsening of inequality to the detriment of the most impoverished households, giving greater weight to the deficit of the poorest households than that of the relatively less poor ones.

2.2. Conventional energy poverty indicators

Given the complex nature of the concept, a variety of rather different energy poverty indicators have emerged. Most scholars agree that measurement should focus on the three most important drivers of energy poverty: a household's lack of financial means, a home's low energy efficiency, and high energy prices (Walker and Day, 2012).[1]

An important distinction in the literature is the difference between 'consensual' and 'income/expenditure'- based indicators'. Consensual indicators stem from self-reporting, and indicate the share of the population that is not able to afford adequate heating or cooling at home, while income/expenditure- and more recently 'income/efficiency'-based indicators rely on administrative data (Romero et al., 2018).[2] As national governments are generally opting for the latter school of indicators to monitor energy poverty and inform resource allocation, we focus on those in this section (complemented with less prevalent ones in Table 2).[3]

2.2.1. Boardman's 10% and 2M

The most-used energy poverty indicator is often credited to Brenda Boardman, while she built on the first attempt to quantify 'the fuel poor' in England from Isherwood and Hancock (1979). They suggested to calculate each household's share of income spent on 'fuel, light and power', the so-called 'burden', and focus on those spending over twice the national median. Boardman (1991) adopted the twice the median (2M) approach, which amounted to 10% in England at the time she published her pioneering work. Despite her own concerns, that exact proportion was embraced by policymakers and even institutionalised by governments abroad without context-specific contemplation (Tirado Herrero, 2017).

Besides the arbitrary threshold, there is a more fundamental difference between the two interpretations. While 2M is a 'relative' indicator with flexible thresholds that increase when most households are spending more on energy, the 10% approach is far more dependent on market dynamics. When prices are unusually high, it may classify a large majority of households as being energy poor, which undermines the indicator's 'prioritising function'. In a way, it presents energy poverty as a cyclical problem rather than a structural one (Imbert et al., 2016). This complicates the evaluation of policy interventions and the commitment of governments to alleviate or even eradicate energy poverty (Charlier and Legendre, 2021).

Moreover, simply looking at a proportion of income has another practical disadvantage. It could label high-income households who live in large energy-inefficient homes as energy poor (Hills, 2012). This effect could be mitigated by applying an income correction, shown by Heindl (2015) who filtered out all incomes above the median, although this remains rather uncommon. Nevertheless, variants of this indicator remain the most important energy poverty statistic, as they are still dominant across the European academic and policy literature.

2.2.2. Low Income High Cost (LIHC)

The UK government commissioned John Hills in 2011 to enhance expenditure-based energy poverty measurement and replace the 10% metric. Hills developed the residual Low Income High Cost (LIHC) indicator, an expenditure-based metric that considers households energy poor if they "*have required fuel costs that are above the median level*" and if they "*would be left with a residual income below the official poverty line*" (Hills, 2012, p. 9).[4] Hills (2012, p.32) thus suggested two threshold values: one for high (above-median) expenditure and one for low (60% of median equivalised) income after deducting housing and required energy costs.

While the UK government adopted and institutionalised the LIHC indicator in 2013, its practical implications were not without controversy. Walker et al. (2014) pointed out that choosing the median as a threshold would overlook smaller homes, while these are often occupied by 'vulnerable, lower income households'. In fact, by opting for the median energy expenditure, half of all households would always remain above the threshold – no matter how low the prices – and eliminating

[1] Resident behaviour is sometimes referred to as the 'fourth driver' of energy poverty (Kearns et al., 2019).

[2] Increasingly, the 'multi-indicator' approach is advocated in the literature, as a combination of indicators can capture the diverse drivers of energy poverty (Best et al., 2021; Castaño-Rosa et al., 2019; Thomson et al., 2017). This approach identifies a household as being in energy poverty when at least one out of two or more indicators confirms this. It differs from the 'multi-criteria' or 'composite' school of energy poverty measurement, which integrates a relatively large number of variables and assesses their relative importance based on expert weighting (Nussbaumer et al., 2012). While these analyses appreciate the local context, the variable-selection and weight-allocation process is sometimes also regarded as overly value-driven and somewhat arbitrary (Nussbaumer et al., 2012; Simoes et al., 2016).

[3] We do not go into the 'hidden energy poverty' branch of expenditure-based indicators that focuses on curiously low rather than high energy expenditures, as it assumes some low-income households consistently ration their energy use because of wider financial problems (Betto et al., 2020; Meyer et al., 2018). Other less-used indicators are described by Heindl (2015).

[4] The income threshold is sloping rather than straight in Fig. 1 because lower energy expenditure would also decrease the income threshold (as energy expenditure is used to calculate disposable income in this residual approach).

Table 2
Characteristics of several expenditure- and efficiency-based energy poverty indicators.

EP indicator	Focus point	Energy-related threshold	Nature of threshold	Price sensitivity	Means tested	Official statistic (institutionalised)
10%	Ratio of energy expenditure to income signalling high burden	10% of disposable income	Absolute	High	–	Belgium, England (dropped), France (dropped), Ireland
2M	Ratio of energy expenditure to income signalling high burden	Twice the median energy burden	Relative	Low	–	EU, France [a], Spain
M/2	Low energy expenditure signalling rationing	Half the median energy expenditure	Absolute	Low	–	EU, Spain
MIS	Residual income falls below minimum income standard	Disposable income after energy cost (AEC)	Absolute	Low	Yes	–
LIHC	Residual income and energy expenditure	National median energy expenditure	Relative	Low	Yes	England (dropped), France (dropped)
LILEE	Residual income and energy efficiency	National efficiency target (or median efficiency)	Absolute or Relative	Low	Yes	England

[a] But only of the 30% lowest-income households.

energy poverty would become practically impossible (Moore, 2011). Housing quality and energy efficiency improvements would hardly decrease the calculated incidence of energy poverty. Moore (2012) therefore suggested to complement or replace the energy expenditure threshold with one based on energy efficiency.

2.2.3. Low Income Low Energy Efficiency (LILEE)

The suggestion by Moore (2012) to concentrate on energy efficiency was welcomed by policymakers, as evidenced by the UK government's proposal of the new Low Income Low Energy Efficiency (LILEE) indicator, which replaced the LIHC indicator (Department of Business Energy and Industrial Strategy [BEIS], 2021a). The rationale behind this shift was that this indicator would better allow the government to track its progress in achieving energy poverty targets.

As with all indicators, the LILEE indicator received critical reflections, although there have not been empirical studies in the literature yet. Deller et al. (2021) argued that a shift from expenditure to efficiency would classify fewer elderly households as energy poor, while it does not consider their significantly higher energy needs compared to other household types. The same argument applies to other situations in which a household typically requires more energy – for instance because of physiological or social reasons – and thus represents a more fundamental difference: household characteristics lose importance to housing quality.

2.3. Energy poverty gap indices

While the use of poverty gaps remains rare in energy poverty research and policy, the initial impetus was given at the turn of the century by World Bank economists. Foster et al. (2000) defined energy poverty as energy consumption not meeting basic energy needs, and the gap as the distance separating the energy poor from the energy poverty line.[5] Sefton (2002) first applied the energy poverty gap to policy evaluation and defined it as the difference between what households can afford to spend, set at 10% of income, and what they would need to spend to 'heat their homes satisfactorily'.

The gap was first introduced in the wider policy arena by Hills (2012) in his LIHC indicator. He believed that the indicator would gradually lose its primacy to the poverty gap in assessing policy impact, as it is sensitive to prices, policies, and programmes (Bogaars, 2020). However, Boardman (2012) foresaw that Hills' poverty gap could be neglected when presented as a subsidiary element of the indicator, while she acknowledged its benefit of combining both extent and depth of energy poverty.

Fig. 1 illustrates the various definitions of energy poverty incidence and poverty gaps considered in this study. The proportional Boardman's 2M indicator is visualised in the first panel, by plotting (household) energy expenditure on the vertical axis versus income on the horizontal axis. Therefore, the energy burden (e_i), i.e. the share of energy expenditure as percentage of income, is represented by an arrow pointing to the bottom left (as the direction of increasing energy expenditure on the y-axis points 'downwards'). The dashed diagonal line marks 2M's energy poverty line, that is set to twice the median energy burden (z_{2M}). The grey area below the line represents all energy poor households. By counting the number of households that fall within this area we can obtain a measure of energy poverty incidence, while their distance from the line yields an estimate of the energy poverty gap (g_i). Consequently, if a household's energy burden is 15%, and twice the median energy burden is 10%, the energy poverty gap represents 5% of the household's income.

On the other hand, LIHC and LILEE in the bottom two panels are residual indicators with two thresholds. First, they share a low-income threshold (z_{LI}) with a sloping line, because income (I_i) is considered after deducting energy expenditure and a household would need more income (horizontal axis) to be able to afford increasing energy expenditure or decreasing energy efficiency (vertical axis). Households only classify as energy poor if their income I_i does not exceed the low-income threshold z_{LI}. Second, the horizontal thresholds or energy poverty lines of LIHC and LILEE differ, with the former line depicting the national median energy expenditure (z_{HC}) and the latter as the energy costs needed to properly heat a house with a reference energy efficiency quality standard (z_{LEE}). While e_i is defined as a household's energy burden in 2M, it represents a household's energy expenditure in LIHC, and energy costs needed to properly heat a household's home with the current energy efficiency in LILEE. The presence of two thresholds explains why for most households – such as Household A in Fig. 1 – the energy poverty gap represents the distance to the regular energy poverty line, but since some households – such as Household B – already surpass the low-income threshold (z_{LI}) with a more modest decrease in energy costs a household's energy poverty line could also be lower than Z_{HC} or Z_{LEE}. Yet again, the grey area represents all energy poor households, while deviation from the horizontal line yields the energy poverty gap (g_i).

The methodological roots of the notion of energy poverty gaps can be found in the so-called class of Foster, Greer and Thorbecke indices, henceforth FGT indices. The various FGT indices to measure poverty are decomposable into their underlying contributing factors: incidence, intensity, and inequality. Also, these indicators are sub-group-consistent and (thus) satisfy the key invariance, dominance, and subgroup axioms (see Table 1). Conventionally, the FGT class is based on the income poverty gap, which is the shortfall of income as compared to the poverty line.

In parallel, the energy poverty gap is defined as the reduction in energy costs that is needed to lift a household out of energy poverty

[5] As they focused on underconsumption of Guatemalan households, Foster et al. (2000) set the energy poverty line on 2154 kWh per year.

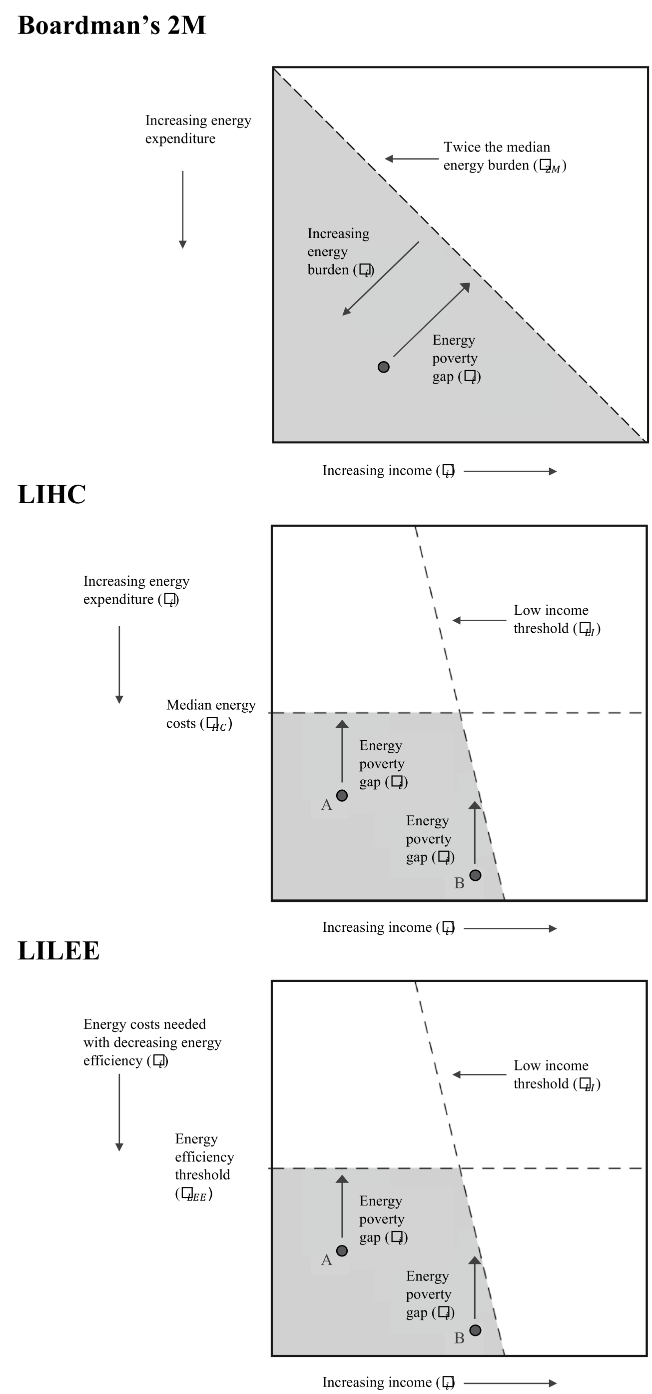

Fig. 1. Illustration of incidence (grey) and intensity (arrows) of energy poverty in terms of three commonly institutionalised energy poverty indicators, inspired by the UK Department of BEIS.

(Hills, 2012). Formulated differently, a households' energy poverty gap is defined as the energy cost surplus as compared to the energy poverty line. Hence, the energy poverty gap of an energy poor household i can be formulated as:

$$g_i = e_i - z_i \tag{1}$$

in which the household's energy poverty line (z_i) is deducted from the household's energy costs (e_i). In sum, whereas conventional income poverty metrics are defined in terms of income falling short of a certain threshold, the energy poverty metrics are defined in terms of high energy costs, i.e. excess energy consumption above a threshold energy consumption level. To arrive at the normalised energy poverty gap, the remainder is divided by the energy poverty line. Normalisation is crucial as it allows for thorough comparison between households with different energy poverty lines (2M would for instance have yield different energy poverty lines for households with varying levels of disposable income), and thus implies expressing the energy poverty gap as a share of the energy poverty line.

Within the class of FGT indices, various individual energy poverty indices can be derived by substituting different values of the parameter α into the following poverty metric:

$$P_\propto = \frac{1}{N}\sum_{i=1}^{H}\left(\frac{g_i}{z_i}\right)^{\alpha} \tag{2}$$

where N is the number of all households under consideration, H is the number of energy poor households, g_i is the energy poverty gap, z_i is the energy poverty line that is used to normalise the energy poverty gap, and α is a parameter that essentially defines the implicit social welfare function underlying the poverty metric P. The higher the value of P, the more energy poverty there is in an area. When α is set at a low value, the poverty metric weights all households with energy costs above z roughly the same. The higher the value of α, the greater the weight placed on the poorest households.

With$\alpha = 0$, equation (1) reduces to the headcount ratio, measuring energy poverty *incidence*: the fraction of the population that is energy poor:

$$P_0 = \frac{H}{N} \tag{3}$$

With$\alpha = 1$, equation (3a) measures energy poverty *intensity*, expressed in terms of the energy poverty gap index:

$$P_1 = \frac{1}{N}\sum_{i=1}^{H}\left(\frac{g_i}{z_i}\right) \tag{4}$$

which equals the average normalised energy poverty gap of all households. In contrast to the head count ratio poverty indicator P_0 , which considers all energy poor households equally poor, the poverty gap index indicator P_1 estimates the depth of energy poverty by considering how far, on average, energy poor households are from the poverty line.

With$\alpha \geq 1$, equation (1) measures energy poverty *inequality* along with energy poverty. With $\alpha = 2$, equation (1) becomes:

$$P_2 = \frac{1}{N}\sum_{i=1}^{H}\left(\frac{g_i}{z_i}\right)^2 \tag{5}$$

The 'squared poverty gap index' P_2 does satisfy the transfer axiom, allocating exponentially more weight to the most intense energy poverty. Watts (1968) was the first to develop a poverty metric that satisfied the transfer axiom, by dividing income over the poverty threshold and taking the logarithm of the result. However, log values make his index less intuitively applicable to energy poverty gaps as these gaps, in contrast to income gaps exceed the poverty thresholds (since they are defined as an energy costs surplus) rather than falling short of a threshold.[6]

As hinted at before, the various energy poverty metrics P defined by the value of α, each imply an energy poverty ordering that links to a certain aggregation of individual welfare functions (Foster and Shorrocks, 1988a). The energy poverty P_0, which measures energy poverty incidence in terms of the headcount ratio, corresponds to symmetric welfare functions that are increasing in energy costs reductions of each energy poor household ("first degree" welfare dominance). The energy

[6] Using ordinal energy poverty indicators would allow for the Watts index to be applied, as proposed by Best et al. (2021).

poverty ordering P_1, which measures energy poverty intensity in terms of an energy poverty gap, corresponds to symmetric welfare functions that exhibit both monotonicity and equality preference; the latter implies that all progressive transfers to energy poor households improve welfare ("second degree" welfare dominance). Finally, the energy poverty ordering P_2, which measures energy poverty inequality along with energy poverty, corresponds to symmetric welfare functions that are not only monotonic and equality preferring but also "transfer sensitive"; the latter implies that welfare increases disproportionally with transfers to households with highest energy poverty gaps ("third degree" welfare dominance). In other words, for $\alpha \geq 1$, greater value is given to the 'poorest energy poor' households, while $\alpha \rightarrow \infty$ makes it into a 'Rawlsian' maximin measure that focuses solely on the 'energy poorest' household (Foster et al., 1984, p. 763).[7]

2.3.1. TIP curves

Following equation (1), we can develop various energy poverty metrics that concentrate on the incidence, the intensity, and the inequality of energy poverty, respectively. To graphically represent these "*three 'I's of poverty*", Jenkins and Lambert (1997) introduced the 'TIP curves' in the literature on measuring income poverty. This method of representation (illustrated in Fig. 2 below) works as follows. First, all households in the population are ranked from poorest to richest. Then, the cumulative share of the population is plotted against the cumulative poverty gaps of the population. Households that are not in poverty represent a poverty gap of zero. Therefore, the line becomes horizontal when it reaches non-poor households, meaning that the x-coordinate of the point where the curve becomes horizontal represents the incidence (P_0 in Fig. 2) of poverty. At the same time, the y-coordinate of the point where the curve becomes horizontal depicts the intensity (P_1 in Fig. 2) of poverty among the population, i.e. the aggregate poverty gap. Finally, the line increases in curvature when the (poor) population becomes more unequal, in similar but mirrored fashion when compared to the one from Lorenz (1905).

As they represent all poverty orderings in one visual summary, the TIP curves provide an excellent instrument to describe the distribution of poverty in a single population, but also to test whether one distribution of poverty dominates another. When populations A and B are graphed together, and line A lies completely above line B without intersecting, one can unambiguously conclude that population A suffers from more severe poverty than population B. However, this conclusion cannot be drawn when the lines cross, as this implies a trade-off between the incidence, intensity, and inequality of poverty in the two populations. Therefore, the TIP curves allow for robust and complete comparison between regions, time periods and subgroups, given that the same indicator or combination of indicators is used.

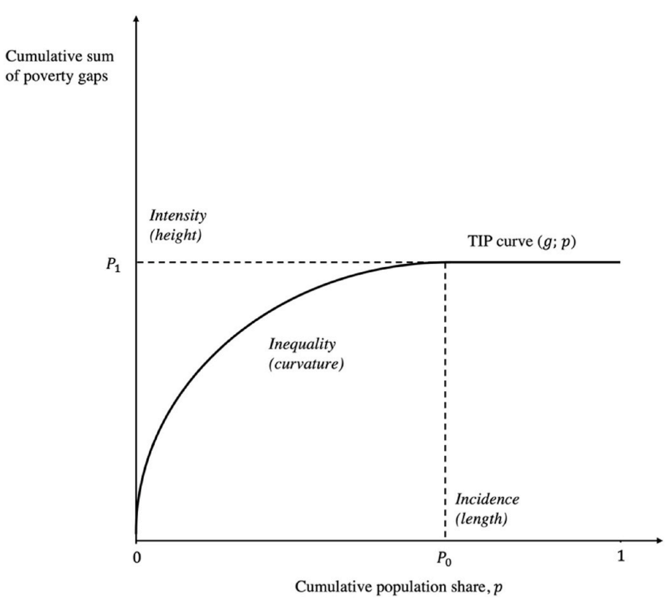

Fig. 2. TIP curves from Jenkins and Lambert (1997) representing incidence, intensity, and inequality of poverty.

3. Data and methods

In the remainder of this paper we illustrate the use of the FGT indices in measuring welfare trade-offs of different energy poverty policies, using a microdata assessment of energy poverty patterns in the Netherlands. In this section we describe the data set used, and data corrections, classifications, and transformations that we opted for (see the Appendix for a flow chart illustrating the method).

3.1. Dataset

This study makes use of household-level microdata from 2019. The dataset from Statistics Netherlands (2021), referred to in Dutch as CBS, covers all Dutch municipalities and 78 per cent of the households, which amounts to approximately 5.7 million households.[8] For most households excluded from this dataset there is no reliable data on energy consumption, for instance because they are connected to district heating or because they have unconventional housing arrangements.[9] Descriptive statistics for several key variables are given in Table 3.

3.2. Analysis and transformations

3.2.1. Income and energy expenditure

While researchers from the UK often use their national definition of a 'low-income' – which is 60% of the median income – we opt for the Dutch definition from Statistics Netherlands: 130% of the 'social minimum'. The social minimum threshold is different per household, as it is based on household characteristics, benefits, and living conditions.[10]

In line with previous studies, energy expenditure was deducted from net income to arrive at a household's disposable income for LIHC and LILEE. However, our method differs from some of those studies since housing costs were not deducted. This is mainly because Statistics Netherlands does not yet provide the data. While we acknowledge that future research into the driving characteristics of energy poverty must include housing cost as it is of increasing importance to purchasing power (Burlinson et al., 2018), its inclusion remains contested. Moore (2012) states that it could overvalue underoccupied housing, inner cities with high housing cost, or households who simply prefer more expensive

[7] Kanbur (1987, p.111) states that "*government's aversion to inequality can be continuously varied from one extreme where no particular attention is paid to the poor, to the other where it cares only about the welfare of the very poorest, the so-called Rawlsian maximin outcome*".

[8] *Under* certain conditions, this microdata is accessible for statistical and scientific research. For further information. microdata@cbs.nl

[9] Unconventional housing arrangements could for instance refer to houseboats or homes partially functioning as shops.

[10] Statistics Netherlands provided the authors with an extra variable named 'BMNORMH2019', which considers social assistance benefits, state pensions, student grants, child benefits, child-related budgets, health care allowances, nominal health care premiums, allowances for disabled people (formerly known as Wtcg), rent allowances, and government grants for owner-occupied home.

Table 3
Descriptive statistics for several key variables.

Household variable (per annum)	Sample	Mean	Min	Max	Standard deviation
Income (euros)	5,679,529	49,853	−2,722,540[c]	50,776,410[c]	57,549
Low-income threshold (euros)	5,628,774	20,441	15,171	77,952	4437
Gas consumption (m^3)	5,680,162	1256	0	8559	686
Electricity consumption (kWh)	5,680,162	2769	0	11, 250	1534
Energy expenditure (euros) [a]	5,680,162	1819[b]	237	9281	753
Energy efficiency threshold (expenditure in euros of same-sized band C housing) [a]	5,669,195	1807	1096	3577	495

[a] Estimation based on the average supply tariffs of 2019.
[b] The median expenditure is 1,697, which is the high-cost threshold of the LIHC indicator.
[c] As described in 3.2.1, we also consider capital gains (and losses) as income, which explains these considerable income extremes.

housing.[11]

To enhance the low-income threshold we add a correction term that accounts for a household's financial capital, calculated by annuitising households' financial assets (Mulder et al., 2023).[12] We include this correction term to properly account for households in our dataset that have no income, but do have capital at their disposal. This method prevents misclassification of households living off financial wealth in large homes in affluent neighborhoods as energy poor. Moreover, it was demonstrated by Best et al. (2021) that household wealth has a decisive but often neglected impact on energy poverty.

Regarding energy expenditure, we use 'actual' instead of 'required' costs. This involves advantages and disadvantages. The main critique is that expenditure-based indicators (2M and LIHC) do not detect households in hidden energy poverty that restrict energy use due to limited budgets (Roberts et al., 2015; Tirado Herrero, 2017). Due to behavioural patterns like rationing before thermal retrofit ('prebound' effects) and increased consumption afterwards ('rebound' effects), predicted energy savings based on aggregated statistics (LILEE) may over- or underestimate savings of individual households (Sunikka-Blank and Galvin, 2012). On the other hand, relatively high energy needs of elderly, disabled and unemployed people are reflected in higher actual energy expenditure but not in 'required' expenditure, which is modelled solely based on household size, referred to by Snell et al. (2015) as 'one-size-fits-all'. A lack of data has also caused other researchers to use actual energy expenditure (Heindl, 2015; Legendre and Ricci, 2015; Roberts et al., 2015).

We estimate energy expenditure based on average fixed costs and proportional tariffs in 2019 and the gas and electricity consumption of households. The dataset from Statistics Netherlands only considers gas and electricity consumption that households have procured from their energy suppliers, which means self-produced electricity is excluded. This effectively lowers energy poverty lines for households without renewable energy installations that are not shielded from price surges. To assess the response of different indices to varying market conditions, we introduce a price shock that sets the variable supply tariffs of gas and electricity to the levels of January 2022 (see Appendix Table 1).[13] This is however not an attempt to assess energy poverty in 2022, as consumption patterns can wildly differ, but rather to explore the indices' theoretical nature and behaviour. Furthermore, we do not equivalise energy expenditure based on household size to avoid that specific household types are overweighted (single-person households) or underweighted (large families) using income/expenditure based indicators (Heindl, 2015).

3.2.2. *Data correction, classification, and transformation*

As Mulder et al. (2023) already demonstrated, the Dutch energy burden was 4% in 2019, which implies a 2M threshold of 8% (15.6% after the price shock). In addition to the conventional 2M indicator, we also calculate the poverty orderings for a means-tested 2M* indicator. This would respond to critique that 2M labels high-income households who live in large energy-inefficient homes as energy poor. Means-testing was previously done in this context by Heindl (2015), who filtered ('truncated' in his own words) all income groups above the median. We use our own 'low-income-and-wealth-test' that is described above.

Since far from all Dutch homes have been allocated a reliable energy efficiency index, we estimate energy efficiency based on housing characteristics. We categorise all homes in the dataset into 440 housing classes based on a conventional approach from Van Middelkoop and Kremer (2020).[14] This approach differentiates between construction period, typology, and size category (see Appendix Table 2). We then calculate the median expenditure of each housing class and compare it to the median expenditure of homes with EPC Band C in the same size category.[15] When the median expenditure of a household's housing class is higher than that amount, the home is classified as energy inefficient. An obvious limitation of this approach is that we use measures of central tendency, and therefore neglect differences that exist within these housing classes. To arrive at the LILEE poverty gap, we deduct the median expenditure of same-sized homes with EPC Band C from the median expenditure of the household's housing class. This means that resulting poverty gaps vary; not only between size categories, but also among same-sized housing classes.

As described in 3.3, we first normalise the poverty gaps by dividing them by the poverty lines, and subsequently normalise the results to avoid high gaps to be capped at 1.

[11] Considering 'user cost' is a conventional method to calculate housing cost of homeowners and tenants in way that allows for comparison, but it is also much debated in the Netherlands (Haffner and Heylen, 2011). Not considering housing cost is a way to avoid this complexity.

[12] The annuity is predicated on the estimation of the remaining lifespan of the longest-living member within a household, in conjunction with long-term interest rates provided by the De Nederlandsche Bank (DNB), which are also utiliSzed for pension computations by prominent Dutch pension funds. It is important to note that this approach is contingent upon various assumptions such as interest rates, life expectancy and the absence of inheritance, which could result in the misclassification of certain households. The decision to only consider financial assets of a household and exclude other forms of assets such as property value, business capital and substantial investments, is due to their inability to be easily converted into funds for paying energy bills. A more accurate estimate of 'salary from assets' could contribute to future energy poverty research.

[13] The average fixed cost and tariffs for 2019 can be found here: https://opendata.cbs.nl/#/CBS/nl/dataset/84672NED/table.

[14] These housing classes are publicly available (albeit in Dutch) on the website of Statistics Netherlands: https://www.cbs.nl/nlnl/maatwerk/2020/13/energielevering-woningen-naar-energielabel-en-pv-2018.

[15] As mentioned before, we use EPC Band C as threshold because this aligns with the aims of the Dutch government. It also matches the LILEE threshold set by the UK government. As mentioned earlier, we deliberately try to come as close to the institutional context as possible in this paper.

4. Results and discussion

In this section we present the results of calculating the various FGT indices for energy poverty statistics in the Netherlands. In doing so, we identify the three I's of poverty (incidence, intensity, and inequality) for different energy price levels (2019 'base' prices plus a hypothetical price shock) and across geographies (Dutch municipalities). These aspects are explored in the following sections, respectively.

4.1. Poverty orderings before and after price shock (APS)

The macrolevel statistics in Table 4 demonstrate that the same dataset provides significantly different outcomes for the four energy poverty indicators. This is true both across poverty orderings as well as in different market conditions, although the underlying distributions cause minor variations. The incidence of energy poverty ranges between 4.5% and 8.3% according to these indicators, with higher proportions based on energy expenditure than on energy efficiency. The same applies to annual poverty gaps which vary between €131.57 and €484.19 among those in energy poverty. An important reason for this is that we estimate energy efficiency of housing classes based on measures of central tendency, hence excluding 'extreme' values.

As hinted at by Rademaekers et al. (2016), the resulting expenditure-based poverty gaps seem to be higher in the Netherlands than in other countries, such as Italy, Spain, and Slovakia. One possible explanation is that energy prices are generally higher in the Netherlands compared to those countries. The same distribution would therefore yield higher poverty gaps. The high poverty gaps in the Netherlands need to be studied more in-depth to answer this question. However, we do emphasise the need to normalise poverty gaps (see *Intensity* in Table 4) when comparing between regions or contexts, which is something that has been hardly done in previous studies.

While the average poverty gap of energy poor households represents the intensity of energy poverty across the Netherlands in 2019, the average poverty gap of all households shows the average shortfall of the total population as compared to the energy poverty line. The aggregate energy poverty gap represents the total sum of money that would be needed to lift all households from energy poverty in a particular year. Despite the unrealistic assumption of perfectly targeted transfers, this is useful information for government authorities wishing to compensate specific households for high energy burdens. The untargeted alternative – supporting all households – conflicts with energy saving reduction goals in the context of climate policies, as it discourages homeowners to invest in energy efficiency improvements and reduces the incentive for all households to reduce their energy consumption.

Following this rationale, the choice of a particular energy poverty indicator and poverty gap index by policymakers makes their implicit welfare considerations and policy preferences explicit. In turn, the FGT indices can be used to evaluate effectiveness of energy poverty policies, as function of the targets and preferences chosen by policy makers. Would 2M be the preferred indicator, perfectly targeted support reduces the energy burden of households to twice the median share (under APS conditions this would have costed 493 million for all households and 344 million for low-income households). With LIHC, alleviation efforts would focus on subsidising expenditure of low-income households to median levels (under APS conditions this would have costed 308 million). Alternatively, a LILEE support package would give low-income households a discount on their energy bills based on the estimated inefficiency of their home (under APS conditions this would have costed 85 million).[16] While it must be stressed that perfect targeting is impossible, and despite the existence of arguments favouring the implementation of universal relief schemes, these figures seem incredibly low when compared to the untargeted billions that the Dutch government spent on lowering energy taxation and duties in 2021 and 2022 (Rijksoverheid, 2022).

Let us provide a simple example in the context of our dataset for the Netherlands, to illustrate how using poverty gaps in quantitative policy evaluations and simulations can inform about the impact of policy decisions. Imagine that, given the APS situation (see Table 4), the Dutch government would have chosen to intervene with a generic energy price cap that lowers energy prices for all households back to 2019 levels. An evaluation of this policy in the spirit of Bagnoli and Bertoméu-Sánchez (2022), based on their relative indicator (2M), would lead to the conclusion that it had hardly reduced energy poverty (from 8,7% to 8, 3%). However, when considering average poverty gaps (from €1002 to €484), it would demonstrate that while many households were still identified as energy poor, their overall depth of deprivation was reduced.

Hence, not only policymakers but researchers also implicitly choose welfare functions when designing or evaluating relief schemes. When they would predict or assess their effectiveness in alleviating households from energy poverty, the use of different parameters makes this choice explicit and therefore allow for evaluation on the three poverty orderings Incidence, Intensity, and Inequality. While we mainly focus on Intensity as compared to Incidence in this paper, Inequality, measured here with the squared poverty gap P_2, puts more weight on households with relatively high energy poverty gaps. The higher value for the parameter α, the more 'Rawlsian' the targeting or evaluation of a relief scheme becomes – thus reflecting a choice to put higher weight on supporting the 'energy poorest'. However, this is not the case when opting for $\alpha =\leq 1$ and thus for first- or second-degree welfare dominance.

Another observation regarding the poverty orderings is that while the non-corrected 2M returns the highest energy poverty Incidence, Intensity, and Inequality of all indicators, the relative difference with the corrected 2M* is smaller for intensity and even more so for inequality. Since we normalised, we can therefore state that, energy burdens of low-income households are higher than those of higher income households. Compared to other indicators, LILEE intensity and inequality are much lower than its incidence. This is because the design of this indicator is based on medians, and therefore neglects outliers (excessively high consumption translated into immense poverty gaps). LIHC results are similar to 2M*, which again stresses the high energy burden of low-income households.

As described theoretically in 2.4.2, the TIP curves in Fig. 3 illustrate the incidence vertically, the intensity (average and aggregated poverty gaps) horizontally, and the inequality – less intuitively – based on the curvature of the first part of the line. They also visually demonstrate earlier mentioned observations, such as the stochastic dominance of 2M. Better yet, the TIP curves reveal the distributional build-up of poverty gaps (see the Appendix for frequency graphs). Therefore, one could for instance immediately determine what the minimal cost would be of compensating the 1% 'energy poorest' households, and how much this would be under different (APS) market conditions. According to 2M, this would be almost 100 million euros in 2019, and above 200 million euros APS.

4.2. Spatial patterns

The three LILEE poverty orderings are mapped in Fig. 4 (spatial results for other indicators can be found in the Appendix). The maps show the geographic variance and can therefore be seen as spatial decompositions of energy poverty incidence, intensity, and inequality. While the overall picture is rather similar across the orderings, with high

[16] Designing relief schemes based on a combination of indicators would align best with the current consensus in the literature that a multi-indicator approach best suits the complex problem that energy poverty is.

Table 4
Energy poverty orderings for four indicators in the Netherlands in 2019 and after a hypothetical price shock.

	2019				After Price Shock (APS)			
	2M	2M[a]	LIHC	LILEE	2M	2M[a]	LIHC	LILEE
Headcount energy poverty x 1000	473.96	308.72	248.57	253.72	492.24	337.778	299.60	296.39
Headcount energy poverty ratio in % (*Incidence*)	8.34	5.44	4.38	4.47	8.67	5.95	5.27	5.22
Aggregate annual energy poverty gap in euros x 1,000,000	229.49	148.52	113.67	33.38	493.40	343.82	307.85	85.25
Average annual energy poverty gap of *energy poor* households in euros	484.19	481.07	457.31	131.57	1002.35	1017.88	1027.54	287.62
Average annual energy poverty gap of all households in euros	40.40	26.15	20.01	5.88	86.86	60.53	54.20	15.01
Energy Poverty Gap Index x 1000 (*Intensity*)	24.62	19.01	11.66	3.82	26.32	20.07	15.98	5.05
Squared Energy Poverty Gap Index x 1000 (*Inequality*)	13.91	11.04	5.75	0.63	15.13	12.75	8.71	0.95

[a] Corrected to include only low-income households, with after-energy-cost (AEC) corrected income below social minimum.

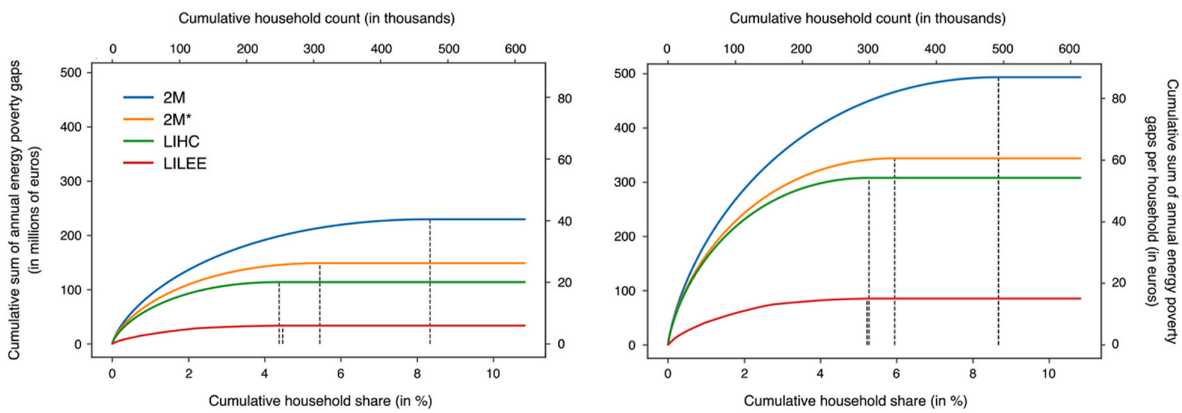

Fig. 3. TIP curves illustrating energy poverty incidence, intensity, and inequality according to our four indicators, with the left graph illustrating the 2019 situation and the right graph the situation after a hypothetical price shock.

levels in the northeast of the Netherlands, a closer look demonstrates significant differences between the orderings.[17]

First, the number of municipalities with above-average scores for energy poverty tend to decrease across orderings (from about a quarter in 4a, to one in ten in 4b, and only about one in twenty in 4c). Upon closer examination, this elucidates a crucial lesson: many municipalities with high incidence rates exhibit relatively higher poverty gaps on average, whilst also accommodating the most significant gaps. This phenomenon can be attributed to the fact that the measure of intensity provides a normalised average, whereas inequality, in contrast, assigns greater importance to relatively high gaps. Consequently, the map depicting intensity values provides a more accurate portrayal of energy deprivation than the map displaying incidence values, whereas the map depicting inequality scores illuminates the effect if policymakers intend to specifically target the most disadvantaged households. Ultimately, these maps could prove useful in informing policy decisions, resource allocation, and policy evaluations.

Second, the distinctions between various poverty orderings imply that resource allocation would inevitably diverge in the event of deploying different (gap) indices. To illustrate this, we normalised the values for LILEE intensity and inequality per municipality and compared them (see Fig. 4d). The findings indicate that if the Dutch government were to allocate funding based on intensity instead of incidence, funding for *Purmerend* would experience an almost threefold increase (185% increase), whereas *Zeewolde's* funding would undergo an approximate halving (79% decrease). This suggests that in Zeewolde, most households experiencing energy poverty inhabit homes that only slightly surpass the inefficiency thresholds we established, resulting in relatively low intensity values. In contrast, energy poor households in *Purmerend* live in considerably inefficient homes. Resource allocation based on incidence instead of intensity would thus underestimate their deprivation.[18] While larger municipalities generally demonstrate less significant disparities, *Eindhoven* would lose 33.9% of its funds due to similar dynamics as in *Zeewolde*.[19] This shows that the choice of a certain poverty ordering in resource allocation directly affects spatial welfare outcomes.

Third, energy poverty seems to be relatively more prevalent and severe in rural than in urban areas according to the LILEE indicator (while the picture is less straightforward according to the expenditure-based indicators, see Appendix). This apparent uran-rural divide in Fig. 4 corresponds with the conclusions from Roberts et al. (2015), who conclude, based on the 10% indicator, that rural households are more vulnerable due to the nature of the rural housing stock, while urban households generally live in energy poverty for longer periods of time. The former aligns with our results, although our picture is likely to change when housing cost is used to calculate disposable income. The latter remains to be studied in the Netherlands.

5. Conclusion and policy implications

In this paper we drew from the literature on income poverty evaluation (Foster and Shorrocks, 1988a, 1988b, 1988c; Sen, 1976) to argue that the use of carefully designed energy poverty gap indices can substantiate the design and monitoring of energy poverty policies. To date, most researchers and policymakers have focused on the 'headcount' ratio or incidence of energy poverty, but this approach neglects the

[17] This picture would most probably differ when housing cost would be deducted from disposable income before calculating incidence and intensity.

[18] Purmerend merged with Beemster into a new municipality on January 1st, 2022, retaining its historic name.

[19] Furthermore, the population size of the four biggest cities in the Netherlands would still account for a significant resource shift in absolute terms, despite more subtle variations (*Amsterdam* −7.6%, *Rotterdam* +6.1%, *Utrecht* +7.0%, *The Hague* −3.5%).

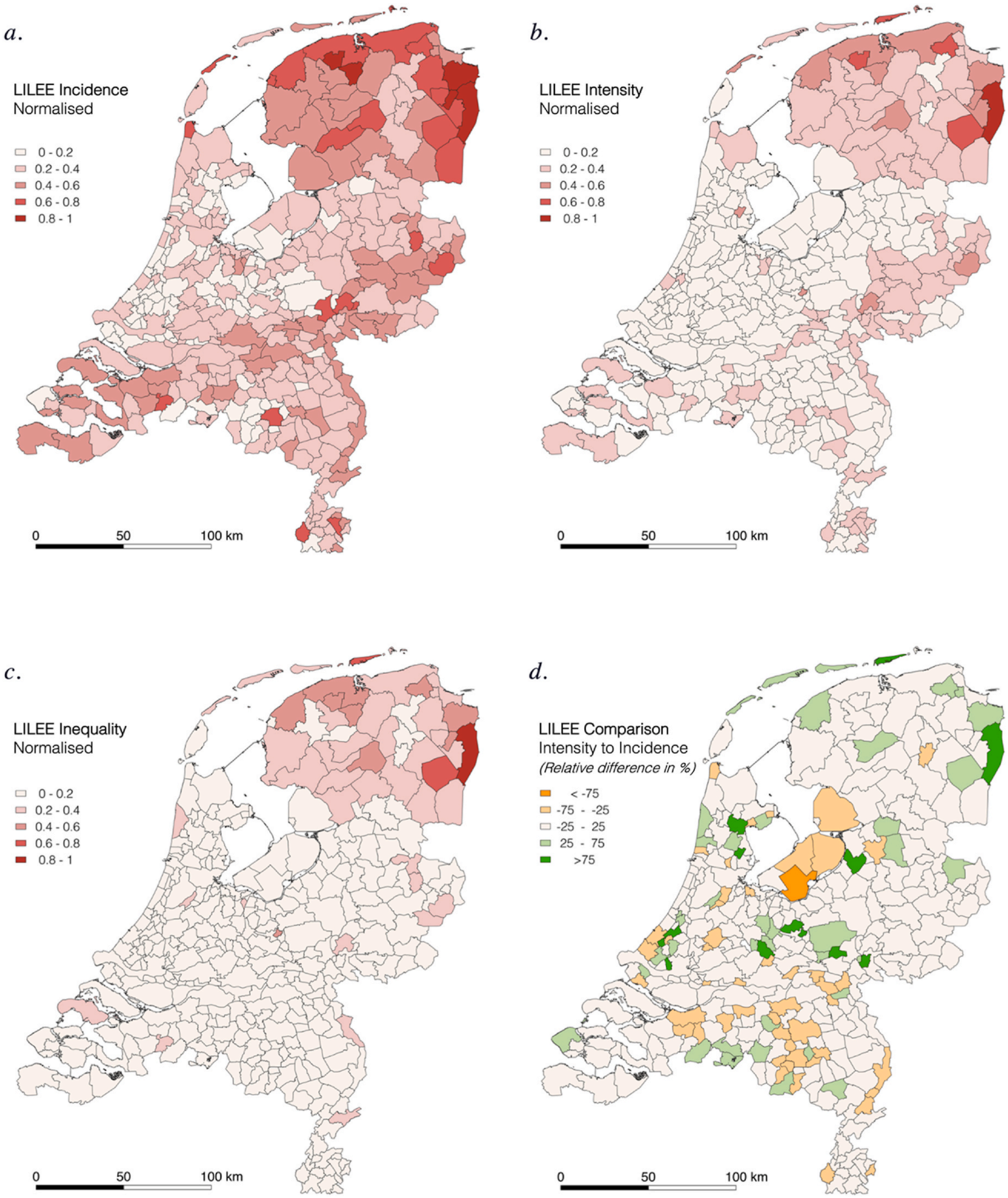

Fig. 4. Four maps depicting energy poverty per Dutch municipality according to the LILEE indicator, with normalised scores for a.) incidence, b.) intensity, c.) inequality, and d.) relative intensity set against incidence to illustrate how national resource allocation to municipalities would differ when substantiated by another poverty ordering.

intensity of deprivation and therefore the degree of inequality among households in energy poverty. Considering poverty gaps would fill this desideratum, and allow for robust comparison between regions, time periods, and subgroups (Foster and Shorrocks, 1991). We also showed that the choice for a particular energy poverty (gap) indicator or index makes the implicit welfare choices of energy poverty policies explicit. We argued that complementing energy poverty Incidence metrics with its associated Intensity and Inequality metrics could greatly benefit the design of effective energy poverty reduction strategies, by improving the accuracy of policy design, resource allocation, and policy evaluation.

We illustrated our arguments for the case of the Netherlands, using recently developed microdata statistics on energy poverty, and the use of an imposed energy price shock. Using these data, we calculated the aggregate energy poverty gap - the total sum of money that is needed to lift all households from energy poverty in a particular year - for different indicators of energy poverty, implying different poverty orderings and (thus) welfare functions. In line with these results, we identified differences in spatial targeting of relief funds based on Incidence versus Intensity and Inequality.

The numerical results underline that more elaborate energy poverty metrics may help to decide on the type of government intervention. While a situation of low incidence and high intensity implies the need for more targeted policies, the reverse situation suggests broader relief schemes. The aggregate poverty gap is indicative of the minimal amount of money needed to lift households from energy poverty (according to the indicator in use). Understanding its distribution helps to target policies on the most deprived households and therefore to substantiate future responses to energy crises. It therefore poses the question whether a government wants to distribute its resources evenly across all households in energy poverty or prioritise the most severe cases. Moreover, these investments aimed at maintaining purchasing power could be compared to the cost and benefits of large-scale insulation programmes. The insights therefore not only help to compare policy approaches, but also to weigh short- and long-term objectives.

In addition, evaluating policies across poverty orderings may expose implicit social welfare choices behind relief schemes. The more weight an energy poverty indicator allocates to the welfare of the ‘energy poorest’, the more ‘Rawlsian’ policy design or evaluation becomes. While the statistics put forward in this paper are decomposable and therefore allow for straightforward comparison between subgroups, one could also choose to allocate higher weight to the poverty gaps of certain subgroups. Since the literature demonstrates that various characteristics increase health risks for households in energy poverty, policymakers and researchers may decide to differentiate between subgroups by means of using different social welfare functions.

This study also introduces the TIP curves from Jenkins and Lambert (1997) to an energy poverty context. This visualisation technique serves as a rather effective depiction of poverty distributions, intuitively representing all three orderings or ‘I’s of poverty: Incidence, Intensity, and Inequality. While we use the TIP curves in this paper to compare conventionally institutionalised indicators (2M, 2M*, LIHC and LILEE), one could also use the curves to compare energy poverty in different years, regions, or subgroups. When designing a relief scheme targeted at households identified as energy poor, one could also use the curves to compare the theoretical cost – assuming perfect welfare transfers - of ‘compensating’ different segments of the energy poor population.

Measurement could be further improved by deducting households’ housing cost from their disposable income, and arguably also by considering required instead of actual energy expenditure. To measure LILEE more accurately, reliable energy efficiency data is needed. Our approach – based on a categorisation of housing characteristics and the median of this housing class compared to same-sized EPC Band C homes – neglects exceptionally well or badly insulated homes in certain housing classes. Furthermore, while we choose a relative threshold to prioritise those most in need of support, future research must experiment with absolute thresholds and poverty gaps.

Since energy poverty is a complex and multi-faceted problem, indicators can only estimate particular aspects of deprivation. For instance, most institutionalised indicators hardly consider any characteristics that increase vulnerability, such as the presence of elderly, disabled, or infant household members. Roberts et al. (2015) therefore suggest monitoring not only the levels but also the dynamics of energy poverty. Even Hills (2012), a strong advocate of statistics-based policies, preferred governments to also target beyond the results of his indicator. Ultimately, this is a political decision, and the utility of the poverty gap depends on the functioning of a welfare state. While more focus on the ‘energy poorest’ could help to detect and benefit the ‘worst-off’, this must not shift to ‘technocratic efficiency thinking’ (Middlemiss, 2017).

Nevertheless, it is evident that public entities should explore distributional effects of different types of targeting. This contributes to a more climate-friendly and purposeful response to future energy price shocks without adding inflationary pressure. An example is the reform of the British Warm Home Discount which aims to improve targeting efficiency towards households identified as energy poor (BEIS, 2021). It promises to automate rebates by matching data on means-tested benefits and housing characteristics, which is closely aligned with the design of the LILEE indicator in this study. Means- and efficiency-tested discounts would guarantee a certain level of energy consumption in substandard housing while still penalising unsustainable behaviour. It would be interesting to compare the distributional effects of various targeted energy poverty policies, but also compare them to broader progressive fiscal policy (Galvin, 2022).

Further research could also use gap indices to explore the driving characteristics behind energy poverty in various time periods and geographies. While so far, logistic regression techniques have been used to predict a dichotomous distinction between energy poor and non-poor, predicting ratio variables opens the door to other sophisticated predictive models. Furthermore, longitudinal analyses of microdata could provide greater insight into the dynamics of households’ responses to changing housing conditions and energy prices. Lastly, future investigations could even experiment with estimating ‘positive’ poverty gaps that illustrate the distance of non-poor households to the threshold values, hence exploring society’s resilience.

CRediT authorship contribution statement

T.M. Croon: Conceptualization, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **J.S.C.M. Hoekstra:** Supervision, Writing – review & editing. **M.G. Elsinga:** Supervision, Writing – review & editing. **F. Dalla Longa:** Software, Validation. **P. Mulder:** Supervision, Conceptualization, Methodology, Writing – review & editing.

Declaration of competing interest

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Data availability

The authors do not have permission to share data.

Appendix

Table A1
Average fixed energy cost and tariffs in 2019 (Statistics Netherlands, 2022) and after fictional doubling in price

Energy source	Sort of cost	Name of cost	2019	Price shock
Natural gas	*Fixed cost (in Euros)*	*Transport tariff*	177.61	
		Standard supply tariff	66.53	
	Proportional cost (Euros/kWh incl. VAT)	*Variable supply tariff*	0.3505	1.1956
		RE duty	0.06340	
		Energy taxation	0.35469	
Electricity	*Fixed cost (in Euros)*	*Transport tariff*	238.32	
		Standard supply tariff	66.46	
		Annual tax deduction	311.62	
	Proportional cost (Euros/m^3 incl. VAT)	*Variable supply tariff*	0.0803	0.3169
		RE duty	0.02287	
		Energy taxation	0.11934	

Table A-2
Different construction periods, typologies, and size categories that together form 440 housing classes (Van Middelkoop and Kremer, 2020)

Typology	Construction period	Floor area (m^2)
Apartment	<1930	<15
Corner house	1930–1945	15–50
Semi-detached house	1946–1964	50–75
Townhouse (row house)	1965–1974	75–100
Detached house	1975–1991	100–150
	1992–1995	150–250
	1996–1999	250–500
	2000–2005	>500
	2006–2010	
	2011–2015	
	≥2015	

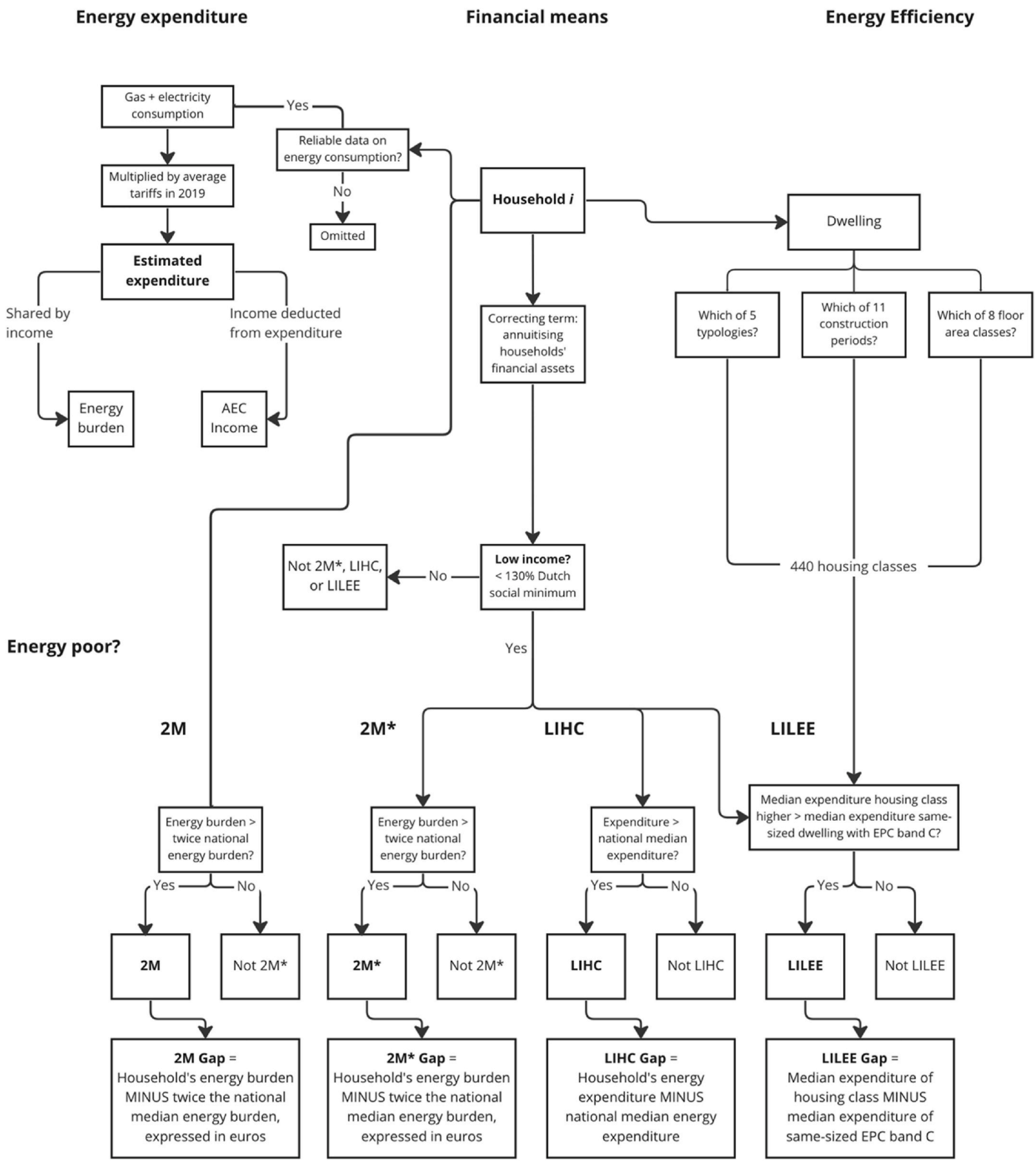

Fig. A1. Flow chart illustrating the methods used to calculate the energy poverty gap for the four indicators used in this study.

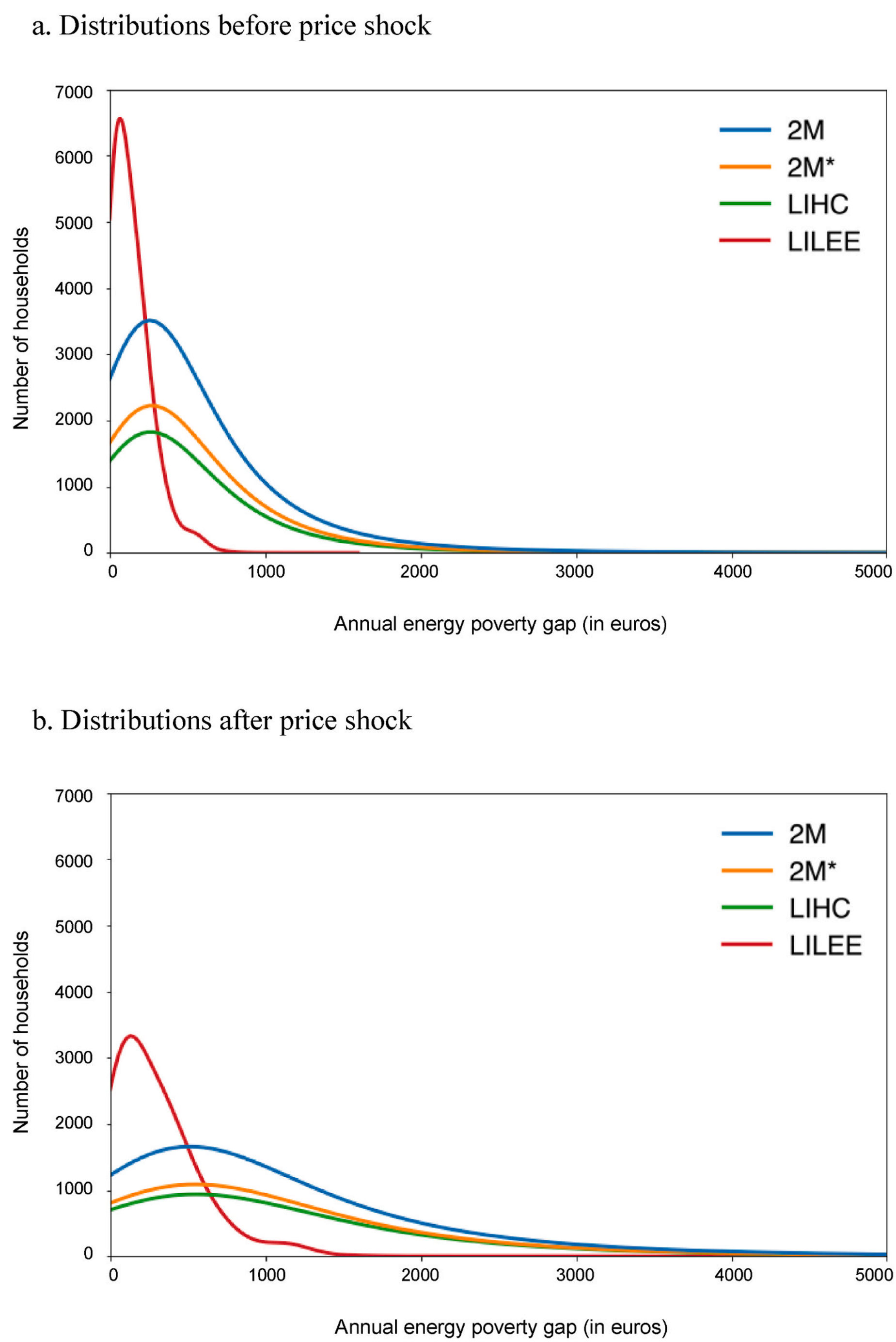

Fig. A2. Two frequency graphs showing the distributions of energy poverty gaps according to the four indicators used in this study, with graph a. depicting distributions before the theoretical price shock, and b. after the price shock.

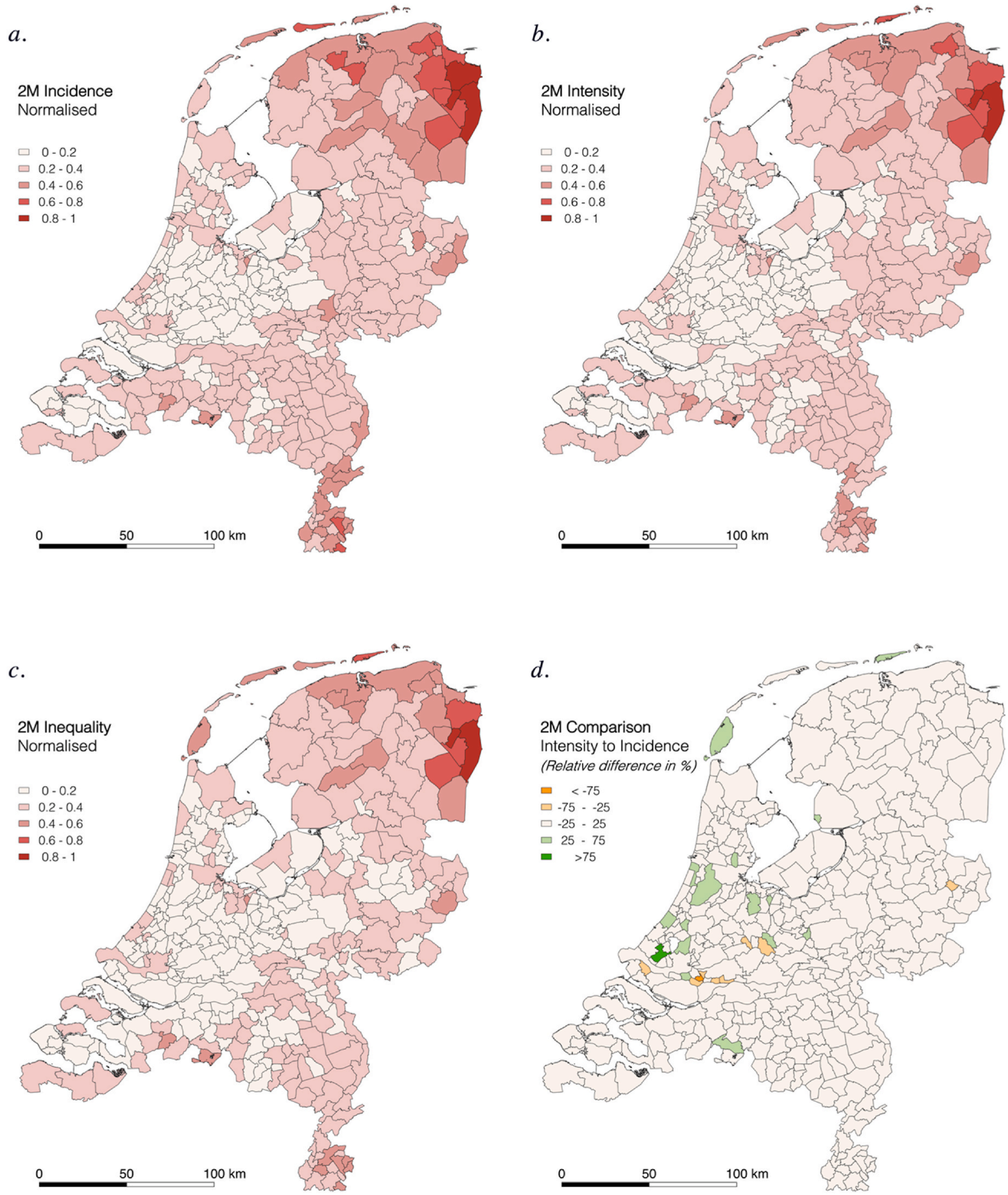

Fig. A3. Four maps depicting energy poverty per Dutch municipality according to the 2M indicator, with normalised scores for a.) incidence, b.) intensity, c.) inequality, and d.) relative intensity set against incidence to illustrate how national resource allocation to municipalities would differ when substantiated by another poverty ordering.

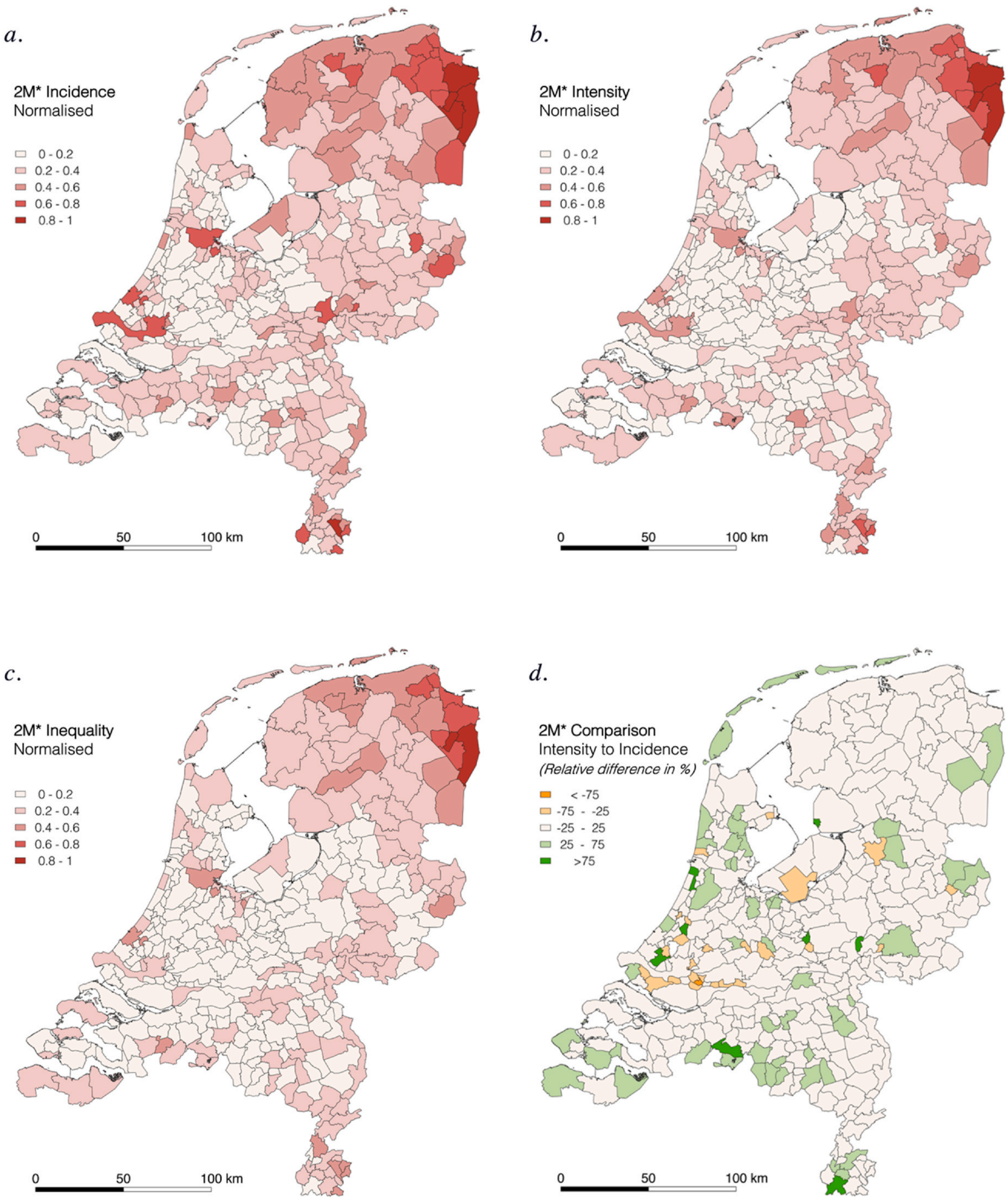

Fig. A4. Four maps depicting energy poverty per Dutch municipality according to the 2M* indicator, with normalised scores for a.) incidence, b.) intensity, c.) inequality, and d.) relative intensity set against incidence to illustrate how national resource allocation to municipalities would differ when substantiated by another poverty ordering.

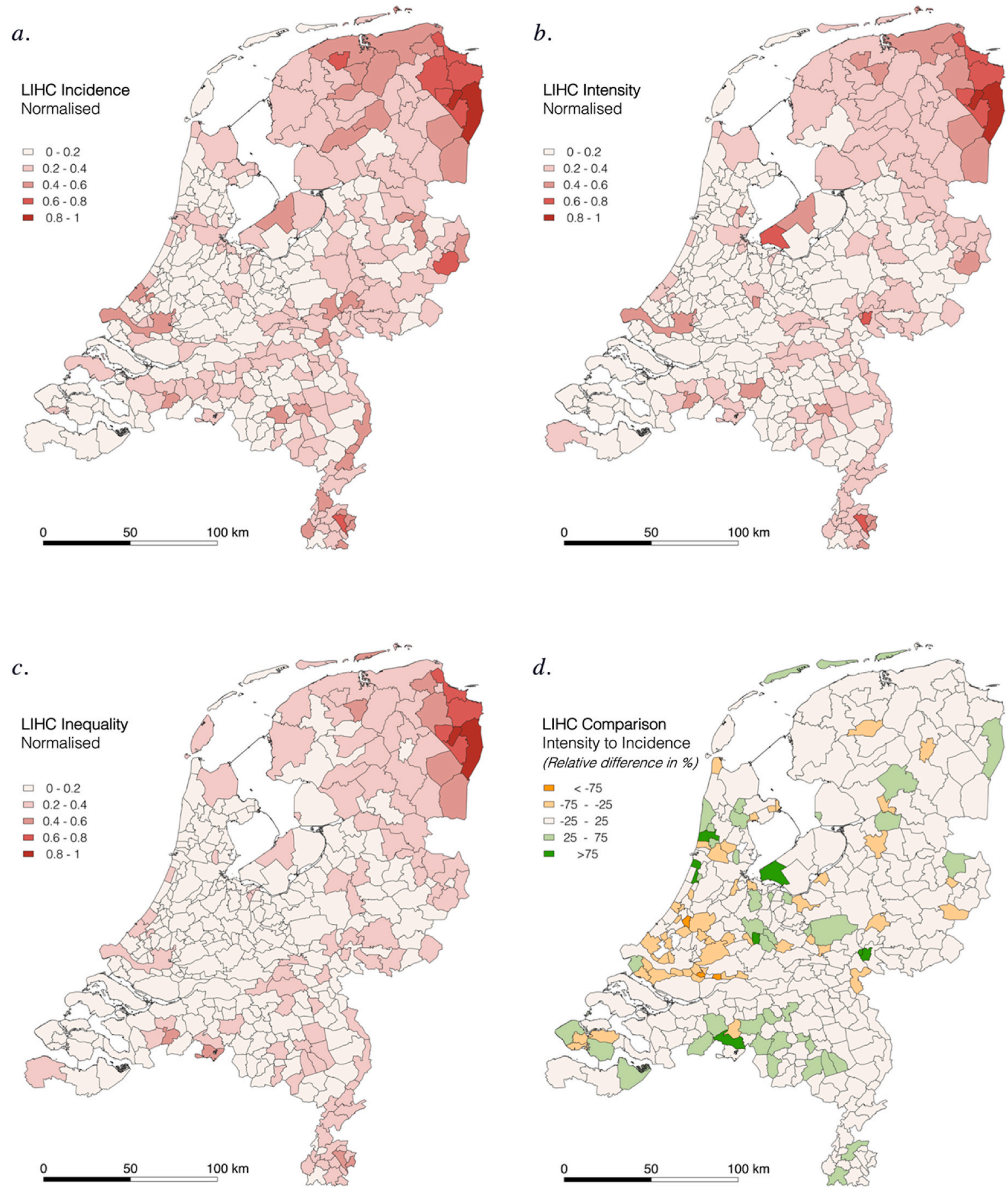

Fig. A5. Four maps depicting energy poverty per Dutch municipality according to the LIHC indicator, with normalised scores for a.) incidence, b.) intensity, c.) inequality, and d.) relative intensity set against incidence to illustrate how national resource allocation to municipalities would differ when substantiated by another poverty ordering.

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