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BRIDGING THE GAP: A NOVEL M2/LIHC HYBRID INDICATOR UNVEILS ENERGY POVERTY DYNAMICS - CASE STUDY OF THE CZECH REPUBLIC

Matej Opatrny
Milan Scasny

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Institute of Economic Studies,
Faculty of Social Sciences,
Charles University in Prague

[UK FSV – IES]

Opletalova 26
CZ-110 00, Prague
E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

Institut ekonomických studií
Fakulta sociálních věd
Univerzita Karlova v Praze

Opletalova 26
110 00 Praha 1

E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

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Bridging the Gap: A Novel M2/LIHC Hybrid Indicator Unveils Energy Poverty Dynamics - Case Study of the Czech Republic

Matej Opatrny[1]
Milan Scasny[1]

[1]Charles University Environment Centre, Institute of Economics Studies

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Abstract:
This paper introduces a novel composite energy poverty indicator, the M2LIHC, which combines elements of the twice-median expenditure share (2M) and Low Income High Cost (LIHC) measures. Using a unique dataset merging the Czech Household Budget Survey and EU-SILC data from 2017-2022, we demonstrate how this hybrid approach provides new insights into energy poverty dynamics. The M2LIHC indicator addresses key limitations of existing metrics, avoiding the LIHC measure's counterintuitive response to income changes in the lowest decile and mitigating the 2M indicator's potential overestimation of energy poverty among higher-income households with high energy costs. Our comparative analysis reveals significant differences in energy poverty rates and household characteristics identified by each indicator. The M2LIHC measure proves more robust to income fluctuations than LIHC while maintaining sensitivity to both income and energy cost components. We find energy poverty in the Czech Republic has increased across all indicators from 2017 to 2022, with the M2LIHC indicator suggesting a rise from 8.9% to 13.5%. To further validate our approach, we employ the DASMOD (Distributional And Social Impact Model) to simulate various energy and climate policy scenarios. These simulations demonstrate the complex effects of compensation policies on energy poverty measures, with M2LIHC providing a more nuanced view of policy impacts. By providing a more comprehensive and theoretically consistent measure of energy poverty, coupled with policy simulation capabilities, the M2LIHC indicator offers policymakers an improved tool for targeting support and assessing the effectiveness of energy poverty alleviation strategies in the context of energy transitions and climate policies.

JEL: D12, D14, D63
Keywords: Energy poverty, LIHC indicator, M2/LIHC Indicator

1 INTRODUCTION

Energy poverty poses a serious challenge to the health and well-being of millions of households worldwide who struggle to attain adequate energy services. Combating this pervasive issue requires robust measurement tools to identify affected populations and effectively target policies. However, existing energy poverty indicators often paint contrasting pictures of who is energy poor, complicating efforts to understand and alleviate the problem (Deller et al., 2021).

This paper introduces a novel composite energy poverty indicator, the M2LIHC, which combines elements of the twice-median expenditure share (2M) and Low Income High Cost (LIHC) measures. Using a unique dataset merging the Czech Household Budget Survey and EU-SILC data from 2017-2022, we demonstrate how this hybrid approach provides new insights into energy poverty dynamics.

The M2LIHC indicator addresses key limitations of existing metrics, avoiding the LIHC measure's counterintuitive response to income changes in the lowest decile and mitigating the 2M indicator's potential overestimation of energy poverty among higher-income households with high energy costs. Our comparative analysis reveals significant differences in energy poverty rates and household characteristics identified by each indicator, building on the findings of Deller et al. (2021).

To further validate our approach and explore its policy implications, we employ the DASMOD (Distributional And Social Impact Model) to simulate the impact of various energy and climate policy scenarios on Czech households. This microsimulation allows us to project how policy-induced changes in prices and incomes may affect the prevalence and severity of energy poverty across different household types and income groups, with a particular focus on our M2LIHC indicator.

By providing a more comprehensive and theoretically consistent measure of energy poverty, coupled with policy simulation capabilities, the M2LIHC indicator offers policymakers an improved tool for targeting support and assessing the effectiveness of energy poverty alleviation strategies in the context of energy transitions and climate policies.

2 LITERATURE REVIEW

2.1 Defining and Measuring Energy Poverty

Conceptually, energy poverty describes a household's inability to secure socially- and materially-necessitated levels of domestic energy services (Bouzarovski, 2018). However, translating this definition into quantitative measures has proven contentious. Existing energy poverty indicators variously concentrate on required energy expenditure shares, absolute or relative energy costs, self-reported ability to afford adequate energy, and proxy measures of energy service deprivation (Herrero, 2017; Deller, 2018).

The two most widely-used expenditure-based metrics are the 10% measure (M1) and the twice-median expenditure share (2M or M2) indicator. A third common approach is the Low Income High Cost (LIHC) indicator. Under M1, a household is energy poor if its energy costs exceed 10% of income (Taylor, 1993). The M2 indicator identifies a household as energy poor if its share of energy expenditure in income is more than twice the national median share (Deller et al., 2021). The LIHC approach, proposed by Hills, identifies a household as energy poor if its required energy costs are above the national median and its residual income after subtracting energy and housing costs falls below the official poverty line (Hills, 2012). Additionally, subjective measures based on households' self-reported assessments of their ability to afford adequate energy services are also commonly used (Waddams Price et al., 2012; Thomson et al., 2017a).

Studies comparing these indicators reveal they often identify distinct populations as energy poor with only partial overlap (Waddams Price et al., 2012; Deller et al., 2021). For example, in the UK from 2001-2009, fewer than 5% of M1 or M2 energy poor households self-reported an inability to afford adequate warmth (Deller et al., 2021). Significant demographic differences also emerge, with older households more likely to be objectively energy poor but less likely to perceive themselves as such compared to younger households (Waddams Price et al., 2012). These divergences suggest current metrics struggle to holistically represent the complex, multidimensional nature of energy poverty (Sareen et al., 2020). Expenditure-based M1 and M2 measures neglect cases of energy rationing where households restrict consumption below notional requirements (Herrero, 2017). Consensual measures rely on individual perceptions of energy needs and affordability that may vary across populations (Petrova and Simcock, 2021). Consequently, some scholars advocate for a multi-indicator approach combining objective and subjective measures (Sareen et al., 2020; Deller, 2018).

2.2 Determinants and Impacts of Energy Poverty

Extensive research documents the sociodemographic risk factors and detrimental impacts of energy poverty. Low income is consistently the strongest predictor, but household size, dwelling efficiency, rural location, and electricity-only energy supply are also associated with elevated risks (Thomson et al., 2016; Belaïd, 2018; Kozulj, 2011). Notably, the role of elderly age status varies by indicator, with older households more vulnerable according to expenditure metrics but not subjective measures in the UK (Deller et al., 2021).

The health consequences of energy poverty are well-established, particularly excess winter mortality and mental illness (Thomson et al., 2017b; Jessel et al., 2019). Energy poor households often face a "heat or eat" dilemma and exhibit greater food insecurity (Lambie-Mumford and Snell, 2015). A growing literature also links energy poverty to social isolation, poor educational outcomes, and reduced subjective wellbeing (Longhurst and Hargreaves, 2019; Aristondo and Onaindia, 2018). These severe and multifaceted impacts underscore the urgency of advancing energy poverty measurement to better identify at-risk groups.

2.3 Policy Implications and Future Directions

Comparative research on energy poverty indicators carries important implications for policy design and targeting. The contrasting risk profiles generated by existing measures lead to divergent assessments of the problem and appropriate interventions (Deller, 2018; Kozulj, 2011). For example, fuel poverty assistance in the UK has historically focused on elderly households based on expenditure metrics, but this conflicts with their lower rates of self-reported energy affordability strain (Deller et al., 2021).

To improve identification, scholars increasingly call for a multidimensional approach combining objective expenditure, consensual, and direct energy service measures (Herrero, 2017; Sareen et al., 2020). Some propose composite indices that integrate multiple dimensions, though determining appropriate weights remains challenging (Martín-Consuegra et al., 2020). Internationally, the EU Energy Poverty Observatory endorses a suite of primary and secondary indicators, underscoring growing recognition of the need for multi-faced measurement (Bouzarovski, 2018).[1]

As climate policies ratchet up household energy costs, better tools to identify the energy poor and target compensatory measures will become increasingly vital (Jessel et al., 2019). Methodologically, researchers emphasize the value of longitudinal data to capture energy poverty dynamics and duration effects (Alem and Demeke, 2020; Barkat et al., 2023; Drescher and Janzen, 2021). Newly available smart meter and energy performance certificate data also promise to improve measurement of energy service levels and quality (Thomson et al., 2017a; Sareen et al., 2020; Ortiz et al., 2021).

Ultimately, further comparative analysis of energy poverty indicators is needed to validate a dashboard of metrics for policymaking. Our paper contributes to this task by developing and testing a novel composite M2-LIHC indicator. While no single metric can perfectly capture all dimensions of energy poverty, triangulating insights from multiple measures, as we propose, offers a way forward. Refinement of energy poverty indicators is critical to produce more accurate, consistent, and policy-relevant assessments of this pervasive yet still under-addressed form of deprivation.

3 DATA

This study utilizes a unique dataset that combines information from two primary sources: the Household Budget Survey (HBS) and the European Union Statistics on Income and Living Conditions (EU-SILC) for the Czech Republic. Both surveys are conducted by the Czech Statistical Office (CZSO) and provide comprehensive information on household income, expenditure, and living conditions.

3.1 EU Statistics on Income and Living Conditions (EU-SILC)

The EU-SILC survey provides data on income, poverty, social exclusion, and living conditions. For example, the Czech implementation of EU-SILC in 2021 covered more than 11,000 private households. Key features of the survey include:

- A systematic random two-stage sampling with a 4-year rotation scheme.

[1] Primary indicators include inability to keep home adequately warm, arrears on utility bills, high share of energy expenditure in income (2M), and hidden energy poverty (HEP). Secondary indicators encompass factors such as presence of leak, damp, or rot in dwellings, inability to keep home adequately cool, and various housing quality metrics.

- Use of the Central Register of Census Districts as the sampling frame.
- Coverage of all regions of the Czech Republic.
- Data collection through personal interviews by specially trained interviewers.

The survey captures the situation of households at the time of the interview (around May 1, 2021) for most socio-demographic characteristics, while income data refer to the entire previous calendar year (2020).

3.2 Household Budget Survey (HBS)

The Household Budget Survey is an annual survey that collects detailed information on household expenditures, income, and consumption patterns. For example, in the year 2022, the survey included 3,428 households, representing approximately 0.08% of all permanently occupied dwellings in the Czech Republic. The sample is based on a two-stage stratified sampling design:

- First stage: Selection of census districts, with small districts (fewer than 20 permanently occupied dwellings) merged within the same municipality.
- Second stage: Selection of 10 permanently occupied dwellings within each chosen census district.

The Czech Household Budget Survey (HBS) employs a sophisticated sampling method derived from the four-year EU-SILC panel survey. This approach ensures comprehensive coverage of household economic dynamics over time. The HBS operates continuously throughout the year across all Czech regions, with households selected from the third wave of EU-SILC participating in two waves of HBS data collection, each spanning two four-week periods. This year-round data collection strategy is crucial as it captures seasonal variations in expenditures, providing a more accurate representation of household spending patterns across different periods of the year.

Data collection involves a combination of personal interviews and detailed expenditure tracking by households. An initial questionnaire updates EU-SILC data and gathers additional household information. Subsequently, households record their expenditures over two separate four-week periods, either by collecting receipts or manually logging expenses in a provided diary. This meticulous methodology yields a rich dataset encompassing household composition, living conditions, and granular expenditure patterns, accounting for seasonal fluctuations and providing a robust foundation for analyzing various economic phenomena, including energy poverty.

3.3 Dataset Construction

To illustrate the methodological integration of our data sources, we focus on the year 2022. Our primary dataset is derived from the 2022 Household Budget Survey (HBS), which is augmented with data from the Survey on Income and Living Conditions (SILC). Given the way how the data are collected by the CZSO we need to use both 2022 and 2021 SILC data sets to have the full merged database.

The 2022 HBS reports expenditures in current prices. However, it's important to note that the HBS data collection spans two years: 2021 and 2022. To ensure temporal consistency, expenditures from 2021 are adjusted to 2022 price levels by the Czech Statistical Office (CZSO). This adjusted HBS dataset, encompassing household expenditure data from both 2021 and 2022, is designed to be representative of the Czech Republic's general population. After applying appropriate weights, the 2022 HBS sample represents 4.49 million households.

Income data in SILC are reported with a one-year lag. Consequently, our analysis requires the adjustment of 2020 incomes (from SILC 2021) and 2021 incomes (from SILC 2022) to 2022 price and real income levels. We employ a wage indexation method based on the nominal average monthly wage per person, as published by the CZSO.[2] This index incorporates both real wage growth and inflationary effects. However, we acknowledge the potential limitations of this approach, particularly its assumption of uniform wage growth across all income categories, which may not accurately reflect income dynamics, especially for higher-income groups.

For example, the final integrated dataset comprises 3,424 households in the year 2022, which, when weighted, represents 4,489,288 households in the Czech Republic, accounting for 99.87% of all households reported in the HBS.

[2]The indicator can be found here: `https://www.czso.cz/csu/czso/pmz_cr`

3.4 Key Variables

The combined dataset includes a wide range of variables, including but not limited to:

- Household composition and characteristics
- Detailed income components (employment, self-employment, social benefits, etc.)
- Expenditure patterns across various categories, with a focus on energy expenditures
- Housing conditions and amenities
- Subjective assessments of financial situation and living conditions
- Health status and access to healthcare
- Education levels and current educational activities
- Employment status and job characteristics

Of particular importance for our study are the variables related to energy expenditure and income, which form the basis of our energy poverty indicators.

3.5 Dataset Overview

Our analysis covers the period from 2017 to 2022, providing a comprehensive view of energy poverty trends in the Czech Republic. Table 1 presents key statistics for each year, including the prevalence of energy poverty according to different indicators (2M, LIHC, and M2LIHC), median income, median energy expenditure, sample size, and the total number of households represented.

As shown in Table 1, the sample size has increased substantially over the years, from 841 households in 2017 to 3,423 in 2022. The table also reveals a general upward trend in energy poverty rates across all indicators, with the 2M indicator showing the most pronounced increase from 10.8% in 2017 to 18.9% in 2022.

Year	2M	LIHC	M2LIHC	Income Median	Energy exp. Median	Sample size	Total HHs
2017	10.8%	12.1%	8.9%	371 723	35 556	841	1 369 420
2018	13.5%	13.0%	10.5%	413 616	36 616	1 848	3 104 783
2019	15.8%	12.7%	11.2%	438 836	33 929	2 897	3 600 412
2020	16.6%	13.0%	11.7%	426 179	30 523	3 660	4 460 924
2021	18.2%	13.9%	13.1%	453 892	31 102	3 487	4 488 216
2022	18.9%	14.4%	13.5%	499 152	34 069	3 423	4 487 055

Note: Net income is not equivalized. Total HHs represents the total number of households in the population, calculated using weights (pkoefp) from the HBS dataset.

Table 1. Energy poverty indicators and related statistics by year

Table 2 delineates the key factors influencing the estimation of energy poverty prevalence among households. A significant methodological shift in the Czech Statistical Office's data collection protocols in 2016 had substantial implications for the Household Budget Survey (HBS) sample construction from 2017 to 2019. This change precluded comprehensive household matching between the HBS and the Survey on Income and Living Conditions (SILC), potentially introducing selection bias in our sample.

The period from 2020 to 2022 was marked by exogenous shocks that significantly perturbed both the magnitude and composition of household income and expenditure patterns. Primarily, the COVID-19 pandemic induced substantial alterations in consumption behaviors and income streams. Concurrently, the geopolitical tensions arising from the Russia-Ukraine conflict precipitated a migration influx, potentially influencing labor market dynamics and, by extension, household incomes. Moreover, the conflict's ramifications on global energy markets have had discernible effects on household energy expenditures.

Data for year	2017, 2018, 2019	2020	2021	2022
HBS (expenditure)	Methodology change in 2016	COVID-19 impact on expenditure for 1/2 of households in sample	COVID-19 impact on expenditure for all households	COVID-19 impact on expenditure for 1/2 of households Impact on energy market due to Russia-Ukraine war on expenditure for 1/2 of households
SILC (income)			COVID-19 impact on income for 1/2 of households (income for 2020)	COVID-19 impact on income for all households (income for 2020 or 2021)
HBS-SILC matching (after weighting)	Matching not possible for entire HBS household sample; after weighting model covers 1.37, 3.11 and 3.60 mil. out of total 4.49 mil. households	Matched 4.46 mil. households	Matched 4.49 mil. households	Matched 4.49 mil. households
Impact on poverty indicator	Indicators not representative for Czech population. Direction of impact unpredictable. Exogenous factors insignificant.	(+) COVID-19 impacted energy consumption due to movement restrictions	(+) COVID-19 impacted energy consumption due to movement restrictions	(+) COVID-19 impacted energy consumption due to movement restrictions
((+) poverty increases; (-) poverty decreases)			(+) COVID-19 led to income reduction in some segments	(+) COVID-19 led to income reduction in some segments

Note: During the pandemic period, there was a significant impact on energy expenditure, as these expenditures were lower due to travel restrictions. On the other hand, incomes were negatively affected by the closure of certain sectors of the economy. These two opposing effects influence the level of energy poverty indicators, and it is difficult to determine, without deeper analysis, which of them prevails.

Table 2. Factors influencing household income and expenditure

3.6 Limitations

While this combined dataset offers a comprehensive view of household economics and living conditions in the Czech Republic, researchers should be aware of potential limitations:

- The 1st and 9th or 10th income deciles are often underestimated, as these groups may include individuals less likely to participate (e.g., very affluent individuals or homeless people).
- The HBS may suffer from underreporting of socially sensitive goods such as alcohol and illicit substances.
- The time lag between income reference periods and current living conditions may not fully capture rapid changes in household circumstances.

Despite these limitations, the merged dataset provides a unique and valuable resource for analyzing energy poverty, offering a multifaceted view of household finances, living conditions, and energy consumption patterns in the Czech Republic.

4 METHODOLOGY

We calculate various energy poverty indicators using the following steps:

4.1 Poverty Line and Median Income

First, we calculate the poverty line and median net household income:

$$\text{Poverty Line} = 0.6 \times \text{Median}(\text{Net Income}) \tag{1}$$

$$\text{Median Income} = \text{Median}(\text{Net Income}) \tag{2}$$

where Net Income represents the net income per household.

4.2 2M Indicator

We calculate the 2M indicator for our dataset:

$$\text{M2}_i = \begin{cases} 1 & \text{if } \frac{E_i}{Y_i} > 2 \times \text{Median}\left(\frac{E}{Y}\right) \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where E_i is the energy expenditure and Y_i is the net income of household i.

4.3 LIHC Indicator

The Low Income High Cost (LIHC) indicator is defined as:

$$\text{LIHC}_i = \begin{cases} 1 & \text{if } (Y_i - H_i - E_i) < \text{Poverty Line and } E_i > \text{Median}(E) \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where H_i represents housing costs.

4.4 M2LIHC Indicator

Finally, we introduce our novel M2LIHC indicator, which combines aspects of the 2M and LIHC approaches:

$$\text{M2LIHC}_i = \begin{cases} 1 & \text{if } (Y_i - H_i - E_i) < \text{Poverty Line and } \frac{E_i}{Y_i} > 2 \times \text{Median}\left(\frac{E}{Y}\right) \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

This indicator identifies households as energy-poor if they have low residual income after energy and housing costs and disproportionately high energy expenditures relative to income. All calculations use appropriate survey weights to ensure the population's representativeness.

5 COMPARATIVE ANALYSIS OF ENERGY POVERTY INDICATORS

5.1 Comparison of indicators

Figure 1 presents a comparative analysis of three energy poverty indicators applied to Czech household data: the 2M indicator, the Low-Income High Costs (LIHC) indicator, and our proposed M2LIHC hybrid indicator.

This comparison illustrates the crucial differences in how various indicators identify energy-poor households:

- The 2M indicator (top) identifies households whose energy expenditure exceeds twice the median share of income spent on energy. This captures households with disproportionately high energy costs relative to their income.
- The LIHC indicator (middle) uses dual thresholds of income and median energy expenditure, focusing on households with both low incomes and high energy costs.

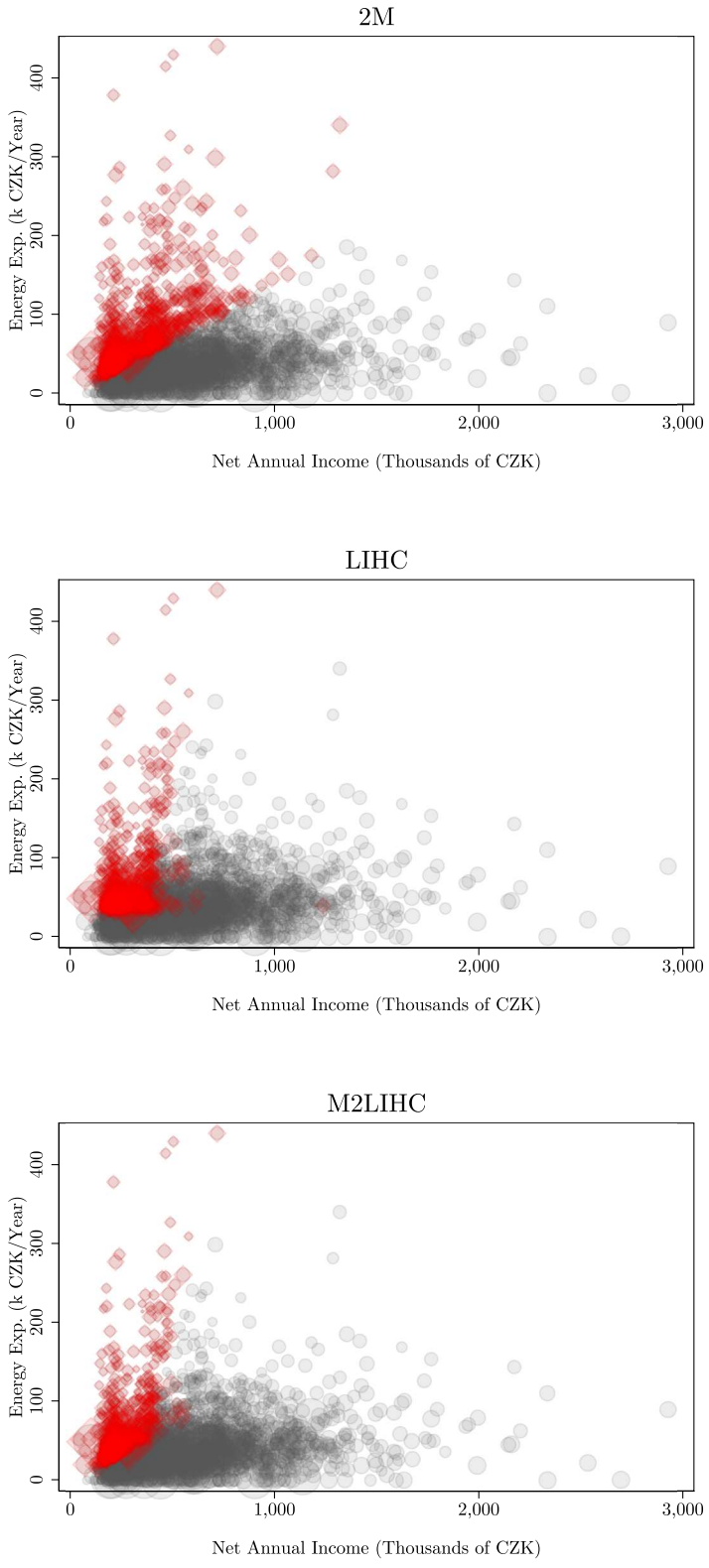

Figure 1. Comparison of different energy poverty measures - data from 2022

- Our proposed M2LIHC indicator (bottom) combines elements of both 2M and LIHC approaches, aiming to provide a more comprehensive identification of energy-poor households.

The scatter plots reveal a wide distribution of household incomes and energy expenditures, underscoring the complexity of energy poverty. This variability highlights why a single indicator may fail to capture all dimensions of the issue.

The M2LIHC indicator addresses this complexity by incorporating the strengths of both 2M and LIHC approaches, while avoiding the potential over-inclusion of higher-income households. As shown in the bottom graph, this hybrid indicator captures households that are identified as energy-poor by either 2M or LIHC, but excludes those considered non-energy-poor by both measures. This approach helps to focus on households that are most likely to be experiencing genuine energy poverty, rather than those who may have high energy costs but also high incomes.

This comparative analysis demonstrates the potential of our M2LIHC indicator to provide a more nuanced and comprehensive identification of energy-poor households. By combining the strengths of established indicators, M2LIHC offers policymakers a tool that can inform more targeted and effective energy poverty alleviation strategies.

5.2 Addressing Limitations of Existing Energy Poverty Indicators

In developing our composite M2LIHC indicator, we identified significant limitations in both the Low Income High Costs (LIHC) and the 2M measures. The LIHC measure exhibits a counterintuitive response to income changes, particularly in the lowest income decile (D1). Conversely, the 2M indicator, while sensitive to income changes, may overestimate energy poverty by including wealthy households with high energy costs.

Our analysis reveals that the LIHC indicator can produce results that are inconsistent with the fundamental principles of poverty measurement. Specifically, we observed that a reduction in income for households in D1, simulated through increased taxation, counterintuitively results in a decrease in LIHC-measured energy poverty. Conversely, income augmentation in D1, modeled as a compensatory payment, leads to an increase in LIHC-measured poverty. This paradoxical outcome stems from the dual criteria structure of the LIHC indicator:

i) Net income minus housing and energy expenditures falls below 60% of the median total income (threshold = 188,930 CZK, median = 499,152 CZK in 2022) **AND**

ii) Energy expenditures exceed the median energy expenditure (median = 34,069 CZK in 2022)

The crux of this paradox lies in the interaction between income changes and energy expenditure patterns. When income decreases, the first condition is consistently met for households already classified as LIHC poor. However, the second condition becomes problematic due to the high-income elasticity of energy demand (estimated at +1.21 by Ministry of Finance of the Czech Republic (2022) for Czech HHs). A 10% reduction in income, for instance, leads to a 12.1% decrease in energy expenditure, potentially pushing households below the energy expenditure threshold and out of LIHC-classified poverty.

Our data reveals approximately 18 households in D1 with annual energy expenditures marginally above the LIHC threshold (between 34,069 and 36,000 CZK). An income reduction shifts their energy expenditures below the 34,069 CZK threshold, effectively removing them from LIHC poverty classification despite their worsened economic situation.

This phenomenon creates a policy paradox where LIHC-measured poverty could theoretically be mitigated by reducing incomes, a clearly counterproductive approach to addressing energy poverty. To genuinely reduce energy poverty as measured by LIHC in D1, policymakers would need to either:

- Implement substantial energy efficiency measures to reduce energy expenditure, or
- Provide significant income supplements to elevate disposable income (after housing and energy costs) above the 188,930 CZK threshold, requiring an average increase of approximately 100,000 CZK per household in D1.

The M2LIHC indicator we propose addresses this limitation by incorporating elements of the 2M indicator, which focuses on the share of income spent on energy. This composite approach provides a

more robust and theoretically consistent measure of energy poverty, avoiding the paradoxical outcomes observed with LIHC alone.

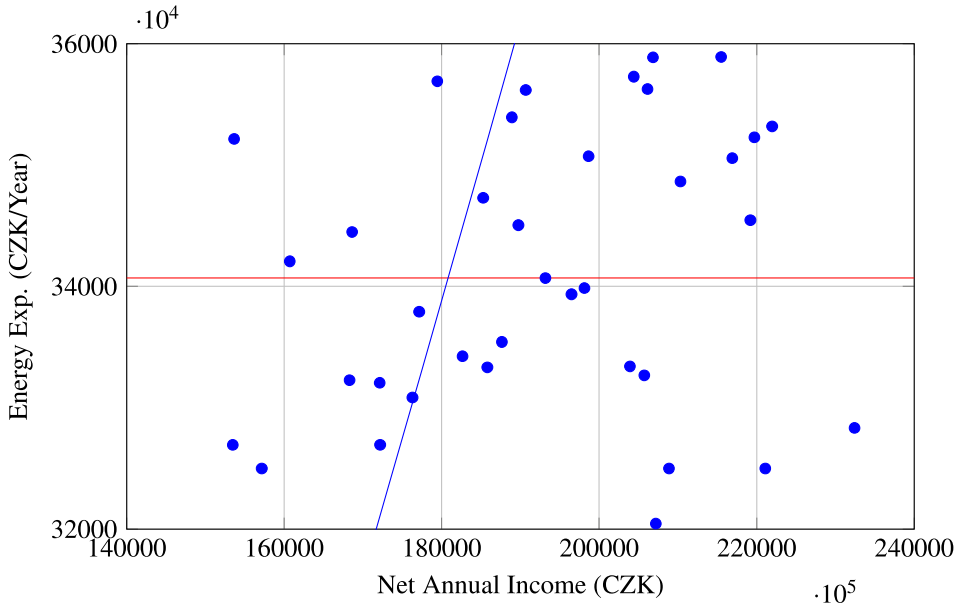

Figure 2. The LIHC Energy Poverty Paradox: As income increases, some households may paradoxically move into LIHC poverty due to increased energy expenditure. The red line represents the median energy expenditure threshold (34,069 CZK). The blue line shows the positive relationship between income and energy expenditure (elasticity of 1.21). Blue dots represent households near the threshold. This graph zooms in on the first decile around the threshold of median expenditure from the merged data sets HBS and SILC from 2022.

The Figure 2 illustrates the counterintuitive aspect of the LIHC indicator. As household income increases, energy expenditure rises at a faster rate due to the high income elasticity (1.21). Consequently, households just below the median energy expenditure threshold may cross it as their income increases, paradoxically classifying them as energy poor under the LIHC definition. Conversely, households experiencing a small decrease in income might fall below the energy expenditure threshold, removing them from LIHC-classified poverty despite their worsened economic situation.

This paradox underscores the necessity of our proposed M2LIHC indicator, which aims to provide a more accurate and economically consistent measure of energy poverty by combining the strengths of both the 2M and LIHC approaches.

6 SIMULATION USING DASMOD TOOL

In this paper, we employ the DASMOD (Distributional And Social Impact Model) to simulate the impact of energy and climate policies on Czech households, with a particular focus on the modified Low Income High Cost (M2LIHC) indicator of transport poverty. The M2LIHC indicator, an adaptation of the LIHC approach, allows us to identify households that face both high energy costs and low residual incomes. By utilizing DASMOD's microsimulation capabilities, we can project how policy-induced changes in prices and incomes may affect the prevalence and severity of transport poverty across different household types and income groups.

The DASMOD model, described briefly below, enables us to estimate changes in household expenditures, incomes, and welfare under various policy scenarios. This analysis provides crucial insights into the distributional effects of proposed energy and climate policies, helping to identify potentially vulnerable groups and inform policy design to mitigate adverse impacts on transport affordability.

The DASMOD is a static microsimulation optimization model used for analyzing the impacts of environmental and other policies on household expenditures and incomes in the Czech Republic. It utilizes household-level microdata from the Czech Statistical Office's Household Budget Survey to simulate

policy effects across the income distribution (Brůha and Ščasný, 2005; Ščasný, 2006, 2007; Ščasný and Brůha, 2007; Brůha and Ščasný, 2006, 2007, 2008).

The core of DASMOD is a demand system that models household responses to price changes. For each good k, the change in consumption is calculated as:

$$q_k^1 = q_k^0(1+\Delta P_k)^{(1+\eta_{kk})} \times \prod_{c \neq k}(1+\Delta P_c)^{\eta_{kc}} \times (1+\Delta Y)^{\eta_k^y} \tag{6}$$

where q_k^0 and q_k^1 are quantities before and after the policy change, ΔP_k is the percentage price change, ΔY is the income change, and η_{kk}, η_{kc}, and η_{yk} are own-price, cross-price, and income elasticities respectively.

The model simulates changes in household expenditures, tax payments, and welfare measures like compensating variation. It also incorporates modules for analyzing income inequality and tax progressivity using indices such as the Gini, Theil, and Suits indices. While static in nature, DASMOD can provide valuable insights into the distributional impacts of policy changes across household types and income groups.

For this study, DASMOD utilizes price change predictions from the Energy-Environment-Economy Global Macro-Economic (E3ME) macro-econometric model to simulate the impacts of the NECP-WAM scenario, which formed the basis for the Czech Republic's National Energy and Climate Plan of September 2023.[3] The analysis focuses on impacts in 2027, providing policymakers with quantitative projections of how climate and energy policies may affect household welfare and transport poverty indicators across the population.

The WAM (With Additional Measures) scenario is a key component of the updated National Energy and Climate Plan of the Czech Republic. This scenario serves as the foundation for projecting the country's progress towards its climate and energy goals. According to the document, the WAM scenario demonstrates the feasibility of meeting several important targets, including reducing overall emissions by 63% compared to 1990 levels by 2030, achieving a 68% reduction in ETS sectors compared to 2005, and a 32% reduction in non-ETS sectors. The scenario also confirms the possibility of completely phasing out coal for heat and electricity production by 2033, with significant decreases expected between 2025 and 2030. Additionally, the WAM scenario projects that the share of renewable energy sources in final energy consumption could reach 30% by 2030, contributing to the broader European target (Ministerstvo průmyslu a obchodu České republiky, 2023). See the following WAM variations used for our purposes. These scenarios represent different annual compensation amounts for households (HHs) in deciles 1 and 2 only:

- **WAM0:** No compensation (CZK 0)
- **WAM7734:** Annual compensation of CZK 7,734
- **WAM10k:** Annual compensation of CZK 10,000
- **WAM20k:** Annual compensation of CZK 20,000
- **WAM30522:** Annual compensation of CZK 30,522

[3] E3ME is a macro-econometric model that covers the entire global economy, linked to energy systems and environmental emissions. It's designed to address policy analysis and forecasting challenges related to the relationships between the economy, energy systems, and the environment. The model is maintained and developed by Cambridge Econometrics, and it's widely used for policy assessment, particularly for analyzing the impacts of energy and climate policies on economies and emissions. E3ME can provide detailed outputs for a range of economic indicators, energy use, and emissions levels, making it a valuable tool for policymakers and researchers studying the intersections of economic, energy, and environmental issues.

	BASE 2022			WAM2027 - 0			WAM2027 - E3ME-7734 (D1,D2)			WAM2027 - 10k (D1,D2)			WAM2027 - 20k (D1,D2)			WAM2027 - 30522 CZK (D1,D2)		
	Modeled Income			CZK2022/YEAR 0 CZK			Total 2027-32 m CZK2022 67,373			Total 2027-32 m CZK2022 87,118			Total 2027-32 m CZK2022 174,235			Total 2027-32 m CZK2022 265,901		
Decile	M2	LIHC	M2LIHC	M2	LIHC	M2LIHC	M2	LIHC	M2LIHC	M2	LIHC	M2LIHC	M2	LIHC	M2LIHC	M2	LIHC	M2LIHC
1	51.89%	36.01%	51.89%	51.89%	36.12%	51.89%	51.22%	36.85%	51.22%	50.86%	37.11%	50.86%	50.68%	37.78%	50.68%	49.73%	38.79%	49.73%
2	33.30%	30.22%	33.30%	34.03%	29.97%	34.03%	33.73%	30.22%	33.73%	33.53%	30.22%	33.53%	33.32%	30.89%	33.32%	32.64%	31.57%	32.64%
3	35.38%	40.88%	32.50%	36.46%	43.87%	36.28%	36.46%	43.87%	36.28%	36.46%	43.87%	36.28%	36.46%	43.71%	36.28%	36.53%	43.49%	36.35%
4	26.91%	21.32%	15.56%	27.09%	20.72%	14.98%	27.09%	20.43%	14.98%	27.09%	20.43%	14.98%	27.09%	20.43%	14.98%	27.24%	19.79%	14.98%
5	22.72%	9.38%	6.64%	23.52%	9.38%	7.04%	23.68%	9.38%	7.04%	23.68%	9.38%	7.04%	23.68%	9.38%	7.04%	23.68%	9.38%	7.04%
6	17.52%	3.60%	2.51%	17.06%	3.23%	2.13%	17.06%	3.23%	2.13%	17.06%	3.23%	2.13%	17.06%	3.23%	2.13%	17.67%	3.23%	2.13%
7	13.16%	0.66%	0.00%	13.16%	0.66%	0.00%	13.16%	0.66%	0.00%	13.16%	0.66%	0.00%	13.16%	0.66%	0.00%	13.16%	0.66%	0.00%
8	6.93%	0.35%	0.35%	6.93%	0.00%	0.00%	6.93%	0.00%	0.00%	6.93%	0.00%	0.00%	7.26%	0.00%	0.00%	7.26%	0.00%	0.00%
9	5.03%	0.00%	0.00%	5.03%	0.00%	0.00%	5.03%	0.00%	0.00%	5.03%	0.00%	0.00%	5.03%	0.00%	0.00%	5.03%	0.00%	0.00%
10	1.97%	0.28%	0.00%	2.34%	0.28%	0.00%	2.72%	0.28%	0.00%	2.72%	0.28%	0.00%	2.72%	0.28%	0.00%	2.72%	0.28%	0.00%
Total	21.48%	14.24%	14.28%	21.75%	14.39%	14.63%	21.70%	14.46%	14.53%	21.65%	14.48%	14.48%	21.64%	14.60%	14.44%	21.56%	14.69%	14.28%

Table 3. Energy Modeling Scenarios Comparison

Note: It is important to note that the BASE 2022 indicator results presented here differ from those shown in Table 1. This discrepancy arises from the methodological distinction in income data sources. The current analysis utilizes modeled income data generated by DASMOD, whereas Table 1 employs self-reported household income figures. This variation in data sources accounts for the observed differences in results between the two tables.

Key findings based on our results from Table 3 include:

1. Persistence of energy poverty: Across all scenarios, the lowest income deciles (1-3) consistently show the highest levels of energy poverty, regardless of the indicator used.

2. Differential impact of compensation: As compensation increases, we observe a slight decrease in the M2 indicator for the lowest deciles. For instance, in decile 1, M2 decreases from 51.89% in the base scenario to 49.73% in the highest compensation scenario (WAM30522).

3. Counterintuitive LIHC trend: Interestingly, the LIHC indicator shows a consistent increase as compensation levels rise, particularly in the lowest deciles. For decile 1, LIHC increases from 36.01% in the base scenario to 38.79% in the highest compensation scenario.

4. M2LIHC insights: The M2LIHC indicator, which combines aspects of both M2 and LIHC, shows a slight decrease in overall energy poverty as compensation increases. This suggests that while the LIHC measure may increase, the overall energy poverty situation as captured by M2LIHC improves marginally with higher compensation.

5. Limited impact on higher deciles: The compensation scenarios have minimal to no effect on households in deciles 5 and above, as expected given the targeted nature of the compensation.

The increase in the LIHC indicator with higher compensation is particularly noteworthy. This counterintuitive result may be due to the relative nature of the LIHC measure, where increased income could push some households above the median expenditure threshold without necessarily alleviating their energy burden.

The M2LIHC indicator provides a more nuanced view, suggesting that despite the increase in LIHC, overall energy poverty situations improve slightly with compensation. This highlights the importance of using multiple indicators to assess energy poverty, as each captures different aspects of the problem.

For policymakers, these findings underscore the complexity of addressing energy poverty. While direct financial compensation can help alleviate some aspects of energy poverty, it may not be sufficient on its own. Complementary policies addressing energy efficiency, housing quality, and energy prices may be necessary for a more comprehensive approach to reducing energy poverty.

Further research is needed to understand the long-term impacts of these compensation scenarios and to explore additional policy measures that could more effectively target and reduce energy poverty across all income deciles.

7 DISCUSSION

The proposed M2LIHC indicator aims to address some of the limitations of existing energy poverty measures by combining elements of expenditure-based and income-based approaches. By incorporating aspects of both the 2M and LIHC indicators, M2LIHC provides a more comprehensive picture of energy poverty that is sensitive to both income changes and energy costs.

Compared to the 10% indicator (Taylor, 1993), M2LIHC avoids the issue of households with high incomes and high energy expenditures being misclassified as energy poor. The 10% measure has been critiqued for this limitation by several researchers (Moore, 2012; Hills, 2012). M2LIHC also improves upon the LIHC indicator (Hills, 2012) by maintaining sensitivity to changes in income levels, addressing the ”LIHC paradox” where income decreases can counterintuitively reduce measured energy poverty.

However, M2LIHC is not without limitations. Like other expenditure-based measures, it relies on actual energy spending rather than required spending to maintain adequate warmth. This may underestimate energy poverty among households that restrict energy use due to affordability concerns (Thomson et al., 2017a). Additionally, the dual threshold approach of M2LIHC adds complexity compared to single-threshold indicators.

In terms of modeling policy scenarios, M2LIHC demonstrates appropriate sensitivity to income changes. Simulations show that increasing household incomes through policies like tax cuts or benefit increases results in decreases in M2LIHC-measured energy poverty. Conversely, policies that reduce disposable income lead to increases in the M2LIHC rate. This aligns with the intuitive expectation that higher incomes should reduce energy poverty, addressing a key limitation of the LIHC approach.

However, M2LIHC remains less sensitive than a pure income-based measure like 2M to small changes in income. This reflects its dual criteria, where households must meet both an income and an expenditure condition to be classified as energy poor. While this reduces volatility in measured energy poverty rates, it may also mute the apparent impacts of some income-based policy interventions.

Overall, M2LIHC represents a step forward in energy poverty measurement by balancing sensitivity to both the income and energy cost components of affordability. However, like all indicators, it involves trade-offs and cannot capture every aspect of this complex phenomenon. Further research comparing M2LIHC to other composite indicators like those proposed by Faiella and Lavecchia (2021) (derived from the heating expenditure needed to achieve a minimum comfort level) and Charlier and Kahouli (2019) (suggest focusing on income heterogeneity by considering different groups of households separately when defining energy efficiency measures) would be valuable to assess its relative strengths and limitations.

8 CONCLUSION

This study introduces the M2LIHC indicator, a novel composite measure of energy poverty that combines elements of the 2M and LIHC approaches. Our analysis of Czech household data from 2017 to 2022 demonstrates the potential of this hybrid indicator to provide a more nuanced and comprehensive assessment of energy poverty. The M2LIHC indicator shows that energy poverty in the Czech Republic has increased from 8.9% to 13.5% during this period.

The M2LIHC indicator addresses key limitations of existing metrics, avoiding the counterintuitive response to income changes observed in the LIHC measure and mitigating the potential overestimation of energy poverty among higher-income households with high energy costs. By balancing sensitivity to both income and energy cost components, it offers a more robust tool for identifying energy-poor households.

Our DASMOD simulations of various policy scenarios further validate the utility of the M2LIHC indicator. The simulations reveal that while direct financial compensation can help alleviate some aspects of energy poverty, its effects are complex and not uniformly beneficial across all indicators. The M2LIHC measure provides a more nuanced view of these policy impacts, suggesting slight improvements in overall energy poverty situations with compensation, even as the LIHC measure counterintuitively increases.

These findings underscore the importance of using multiple indicators to assess energy poverty and highlight the complexity of addressing this issue through policy interventions. The M2LIHC indicator, combined with microsimulation tools like DASMOD, provides policymakers with a more comprehensive framework for evaluating and designing energy poverty alleviation strategies.

However, we acknowledge that no single indicator can capture all dimensions of energy poverty. Future research should focus on comparing the M2LIHC with other composite indicators, exploring its applicability in different national contexts, and further investigating the long-term impacts of various policy scenarios.

In conclusion, the M2LIHC indicator represents a significant step forward in energy poverty measurement and policy analysis. By providing a more accurate and theoretically consistent measure, coupled with policy simulation capabilities, it contributes to the ongoing refinement of methodologies crucial for addressing this pressing socio-economic challenge. As countries navigate complex energy transitions and implement climate policies, tools like the M2LIHC and DASMOD will be essential in guiding evidence-based policies to alleviate energy poverty and ensure a just transition to sustainable energy systems.

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Univerzita Karlova v Praze, Fakulta sociálních věd
Institut ekonomických studií [UK FSV – IES] Praha 1, Opletalova 26
E-mail : ies@fsv.cuni.cz http://ies.fsv.cuni.cz