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Review article

Income and price elasticities of household electricity demand: A comparative systematic review of aggregated and disaggregated data studies

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ABSTRACT

This systematic review investigates disparities in research coverage and assesses the implications of income and price elasticities on household electricity demand. By analyzing studies across various regions and income groups, it aims to uncover imbalances in research distribution and understand their impact on energy policy development. The review employs a systematic approach, analyzing peer-reviewed and gray literature from Scopus, Web of Science, and Google Scholar databases from 1980 to 2023. It addresses four research questions: regional and income group classifications, differences in income elasticities, variations in price elasticities, and the accuracy and variability of household electricity demand elasticity estimates between aggregated and disaggregated data studies. The review reveals significant imbalances, with the Middle East, North Africa, and Sub-Saharan Africa underrepresented, while Europe and Central Asia exhibit robust research. Consistent inelasticity in electricity demand is observed across contexts and timeframes. High-income countries dominate this research, leading to a lack of empirical studies in low-income regions, hindering tailored interventions. Understanding short- and long-run elasticities is crucial for effective demand forecasting and policy design. This review uniquely compares income and price elasticities from aggregated and disaggregated data studies, highlighting regional research disparities and their implications for energy policy. It emphasizes the need for inclusive, context-specific investigations to foster sustainable development and equitable energy access globally.

1. Introduction

Electricity is vital for modern households, powering essential appliances and systems (Ofetotse et al., 2021). With economic growth and urbanization, understanding household electricity demand determinants is crucial for policymakers, energy suppliers, and environmental planners (Akil et al., 2020; Ali et al., 2021). Key economic factors are income and price elasticities, which measure the responsiveness of electricity demand to changes in household income and electricity prices, respectively (Ahmed and Nisar, 2019; Al-Mosawy et al., 2021). These elasticities are essential for crafting effective energy policies, managing supply-demand balance, and promoting energy efficiency (Taghvaee et al., 2023, 2022; Wakashiro, 2019). Higher household income typically increases electricity consumption due to more appliances and larger living spaces (Nguyen et al., 2021; Singh et al., 2022). Conversely, higher electricity prices can reduce consumption, though responsiveness varies across sectors and households (Zohuri et al., 2019).

This study distinguishes itself from previous research by conducting a systematic and comparative analysis of income and price elasticities derived from both aggregated and disaggregated data. While earlier studies have explored the elasticities of household electricity demand, they have predominantly focused on either aggregated macro-level or disaggregated micro-level data without considering the implications of the data structure (Aslam and Ahmad, 2023; Auffhammer and Rubin, 2017; Gao et al., 2021a; Li, 2024; Liddle and Hasanov, 2022). This

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research is novel in that it explicitly compares the elasticity estimates obtained from these two approaches, thereby offering nuanced insights that are critical for policymakers (Alberini et al., 2019; Liddle and Hasanov, 2022). The implications of this study are particularly significant for low-income regions, such as Sub-Saharan Africa and the Middle East, where empirical studies are sparse (Díaz and Medlock, 2021a; Krishnamurthy and Kriström, 2015). By providing evidence-based elasticity estimates, this research contributes to the development of region-specific energy policies that address the unique challenges faced by these regions (Rahmati et al., 2019).

This systematic review compares and synthesizes aggregated and disaggregated data studies, it aims to clarify how income and price changes impact electricity consumption. Furthermore, it highlights that higher electricity prices can reduce spending on essential goods like food, thereby affecting household welfare (Jin and Kim, 2022). Integrating these findings, the review seeks to inform nuanced and targeted energy policies tailored to the needs and behaviors of different household groups and regions, promoting equitable and efficient energy consumption patterns (Charlier and Kahouli, 2019; Han and Wei, 2021).

The study's importance stems from its capacity to guide energy policy. Elasticity estimates are used by policymakers to forecast economic shifts and develop interventions (DOGAN, 2023; Mohammed et al., 2023). Recognizing differences between aggregated and disaggregated data enables more precise predictions and impactful policies (Sun et al., 2023). Furthermore, energy suppliers and environmental planners can utilize these findings to streamline supply strategies and encourage sustainable energy consumption, promoting environmental preservation and energy security (Jalilzadehazhari et al., 2021; Tan et al., 2022).

This study contributes to the existing literature by systematically reviewing and comparing the income and price elasticities of household electricity demand derived from aggregated and disaggregated data. Specifically, this comparative review aims to answer the following research questions:

i. What are the regional and income group classifications in studies that utilize aggregated and disaggregated data?
ii. How do the income elasticities of household electricity demand differ between studies that utilize aggregated and disaggregated data?
iii. What are the variations in the price elasticities of household electricity demand observed across the different levels of data aggregation?
iv. How does the use of disaggregated compared to aggregated data, affect the accuracy and variability of household electricity demand elasticity estimates?

2. Literature review

Existing literature on household electricity demand has predominantly focused on two distinct approaches: aggregated and disaggregated data. Studies using aggregated data, provide macro-level insights that encompass broad regional or national trends in electricity consumption (Li, 2024; Liao et al., 2020). However, these studies often overlook granular details that may be captured through micro-level (disaggregated) data analysis (Seebauer and Wolf, 2017; Vetter-Gindele et al., 2023). Disaggregated studies, like those by focus on individual household consumption patterns, revealing variations that aggregated data may conceal (Hino et al., 2013; Malmodin, 2023). Despite the importance of these approaches, a systematic comparison between them is notably absent from the literature (Morley and Hazas, 2011; Rauf and Adekoya, 2023). This is especially crucial for low-income regions, where electricity consumption patterns may vary significantly from those in high-income countries (Abaravicius et al., 2006; Pelz and Urpelainen, 2020). By addressing this gap, the present study aims to offer a comprehensive understanding of how household electricity demand elasticity is influenced by the data level used in analysis (Hino et al., 2013; Seebauer and Wolf, 2017).

2.1. Theoretical literature

Sen's Capability Theory, emphasizing individual freedoms and the ability to lead a life one values, provides a nuanced framework for understanding household electricity demand dynamics, particularly regarding income and price elasticity. This approach, which extends beyond traditional economic measures to encompass broader human welfare and capabilities, can be used to analyze how economic factors affect household electricity consumption in the context of well-being and social development (Nainggolan, 2022).

Econometric estimates from Indonesia reveal that residential electricity is price and income-inelastic, indicating that changes in income and electricity prices have minimal impact on consumption (Naz, 2016). Sen's framework suggests that households prioritize electricity to meet basic capabilities, becoming less responsive to price and income variations once these are satisfied (Fayard et al., 2021). This is especially pertinent in urban areas, where higher electricity consumption indicates a broader range of fulfilled capabilities compared to rural areas (Rauhut and Hatti, 2021).

Sen critiques traditional economic theory for neglecting the complexity of poverty and well-being, reinforcing the idea that income alone doesn't sufficiently indicate electricity demand or general well-being (Fayard et al., 2022; Liddle and Huntington, 2021). The capability approach emphasizes individual freedoms and capabilities, suggesting that policies influencing electricity demand should not rely solely on economic incentives or disincentives (León Tamayo and Moreno, 2017). An international perspective on household electricity demand shows diverse responses to income, weather, and prices across countries, indicating that capability-enhancing policies need to be context-specific (Naz, 2016). This supports Sen's call for policies addressing immediate suffering and enhancing capabilities, including improvements in education and public health.

Applying Sen's Capability Theory to the analysis of income and price elasticities in household electricity demand highlights the need to consider a wide array of human capabilities and well-being in policy formulation. This indicates that managing electricity demand effectively necessitates understanding the intricate relationship between economic variables and the capabilities they facilitate or limit.

2.2. Empirical literature

2.2.1. Disaggregated data studies

Studies using disaggregated data to analyze household electricity demand are crucial for effective energy policy design. John Anderson Parulian Nainggolan's research on Indonesia, utilizing SUSENAS panel data from 2011 to 2013, revealed that residential electricity is price and income-inelastic. Urban residents consume more electricity than rural ones, indicating a need for increased capacity or higher tariffs to encourage savings (Nainggolan, 2022). Similarly, research by Daniel de Abreu Pereira Uhr and André Luis Squarize Chagas in São Paulo, Brazil, showed price elasticity between −0.26 and −0.64 and income elasticity between 0.11 and 0.32, confirming inelastic demand (Tiedemann et al., 2023).

In Europe, Jin and Kim's analysis indicated higher income elasticities in lower quantiles and uniform price elasticities across all quantiles, showing a greater impact of income changes on electricity demand among lower-income households (Tiedemann et al., 2023). Li et al. found that low-income groups have lower price elasticity due to consumption focused on basic needs, while high-income groups exhibit higher elasticity (Jin and Kim, 2022). A meta-analysis by Marques, Pereira Uhr, and Ziero Uhr across Latin America and the Caribbean reported income elasticity of approximately 0.20 in the short term and 0.92 in the long term, with price elasticity around −0.37 and −0.46,

respectively, indicating significant regional variations (Zhang et al., 2023).

Byrne, Nauze, and Martin's field experiment revealed significant rigidity in household electricity demand in response to substantial price shocks, indicating higher inelasticity than previously observed (de Abreu Pereira Uhr and Chagas, 2017). Supriadi and Falianty demonstrated that Indonesian households with a 900 VA installed capacity are particularly sensitive to electricity price changes, emphasizing the need for targeted subsidy policies (Marques et al., 2024). Schulte and Heindl, analyzing German expenditure data from 1993 to 2008, found an expenditure elasticity for electricity of 0.3988 and a price elasticity of −0.4310, showing that low-income households exhibit a weaker response to energy price changes compared to higher-income households (Byrne et al., 2021).

These studies collectively highlight the complexity of household electricity demand elasticity, influenced by income, regional variations, and electricity tariff structures. They emphasize the need to consider these factors in policymaking for effective energy savings and efficiency (Taghvaee et al., 2023, 2022).

2.2.2. Aggregated data studies

The theoretical and empirical literature on the income and price elasticities of household electricity demand, especially studies using aggregated data, reveals the complexities of household responses to electricity price and income changes. Tiedemann and Sgarlato highlight the difficulties in estimating electricity demand elasticity due to price endogeneity and autocorrelation in high-frequency data, pointing out the limitations of estimators like Ordinary Least Squares (OLS) and Instrumental Variable (IV) regressions in capturing short-term demand elasticity (Tiedemann et al., 2023). This complexity is also observed in regional studies, which show varying elasticity degrees. For example, in Indonesia, household electricity demand is price- and income-inelastic, with urban households consuming more electricity than rural ones, suggesting the need for increased capacity or higher tariffs to encourage savings (Tiedemann et al., 2023). In contrast, research on 18 European Union countries finds higher income elasticities at lower quantiles and consistent price elasticities across all quantiles, with long-run elasticities significantly higher than short-run elasticities, indicating potential for policy measures to enhance electricity efficiency and market transparency (Nainggolan, 2022; Taghvaee et al., 2023, 2022).

A meta-analysis for Latin America and the Caribbean identifies short- and long-term income and price elasticities, noting the influence of data structure, estimation method, and sampling period (Jin and Kim, 2022). Similarly, a study on Brazil's residential electricity consumption using household data revealed elasticities that stress the importance of considering household and family characteristics (Marques et al., 2024). Liddle and Hasanov's dynamic panel models for high- and middle-income countries highlight significant differences in output and price elasticities, crucial for energy planning and climate policies (de Abreu Pereira Uhr and Chagas, 2017). Supriadi and Falianty's analysis of potential savings from removing electric subsidies in Indonesia underscores household sensitivity to electricity price changes (Liddle and Hasanov, 2022). Liddle and Huntington's international perspective on household electricity demand shows varying responses to income, weather, and prices between high- and middle-income countries, emphasizing the challenges of future electricity demands in a warming world (Supriadi and Falianty, 2019). Lastly, Schulte and Heindl's study on Germany, using a quadratic expenditure system, reveals that increases in real energy prices disproportionately impact low-income households, highlighting the importance of considering behavioral responses in energy taxation (Liddle and Huntington, 2021).

3. Materials and methods

This study employs a systematic review to examine income and price elasticities of household electricity demand. A systematic review ensures the transparent and reproducible identification, assessment, and synthesis of relevant literature (Tranfield et al., 2003). It involves: (1) formulating research questions, (2) identifying keywords, synonyms, limits, and exclusion criteria, (3) selecting resources and databases for evidence, (4) determining study inclusion based on criteria, and (5) critically appraising studies for quality, bias, and data extraction. Peer-reviewed articles and gray literature from Scopus, Web of Science, and Google Scholar databases from 1980 to 2023 were used. These databases provide access to multidisciplinary scientific literature and customized searches. Google Scholar also offers access to major publishers' databases and gray literature for additional information.

3.1. Identification of relevant literature (identification)

When choosing the appropriate databases, we placed emphasis on those that offer advanced capabilities for searching and analyzing literature that cannot be achieved through basic keyword searches. These databases maintain records of the authors included in the reference lists of their publications. For this study, we utilized three citation indices: (1) Scopus, a comprehensive database of peer-reviewed journals, books, and conference proceedings from a variety of fields. It includes features such as author and affiliation searches, citation impact analysis, and analytical tools. (2) Web of Science, which indexes high-impact journals through ISI's citation indexes, including the Science Citation Index Expanded (1956-present), Social Sciences Citation Index (1956-present), and Arts and Humanities Citation Index (1975-present). (3) Google Scholar, a resource that provides access to scholarly literature from publishers and gray literature from organizations such as governments, educational institutions, and business and industry associations outside of commercial publishing channels. While gray literature is typically not peer-reviewed, it may still be a valuable and reliable source of information on the review topic.

Journals for our study were selected using the Clarivate (WoS) Master Journal List (MJL), an essential tool for a systematic literature review across multiple indices on the Web of Science platform. The Web of Science Core Collection, curated by expert editors, includes only journals with high editorial standards and best practices. Search filters enabled navigation through over 24,000 journals across 254 subject disciplines. Journal profile pages provided comprehensive information, including journal metrics, peer review details, and open-access information. Table IV presents the metrics for the selected journals. The selection process followed PRISMA guidelines to ensure transparency and replicability.

The process of selecting journal articles began with defining key Boolean search expressions. The search employed the following expressions: "Household electricity demand"; "Energy demand AND households"; "Residential electricity demand"; "Electricity demand" AND "residential"; and "Electricity demand in households." To capture a broader range of articles, "Allintext" and "Allintitle" search operators were used. Fig. I illustrates the search results up to March 29, 2024, yielding 6915 records.

3.2. Inclusion and exclusion criteria (Screening)

Decisions on which studies to include in a review are crucial and require judgment. This review employed two individuals working independently to assess each study's eligibility. Ideally, the initial screening of titles and abstracts to exclude irrelevant articles was conducted in duplicate by two independent reviewers. The criteria were confined to titles, abstracts, and keywords of articles published between 1980 and 2023. The search criteria revealed that significant articles on household electricity demand began in 1980, with 2023 being the latest, indicating ongoing debate on factors influencing household electricity demand growth. The authors initially included a broad range of articles to ensure comprehensiveness, excluding conference abstracts, regulatory documents, and nonpublic sources. Mendeley reference manager

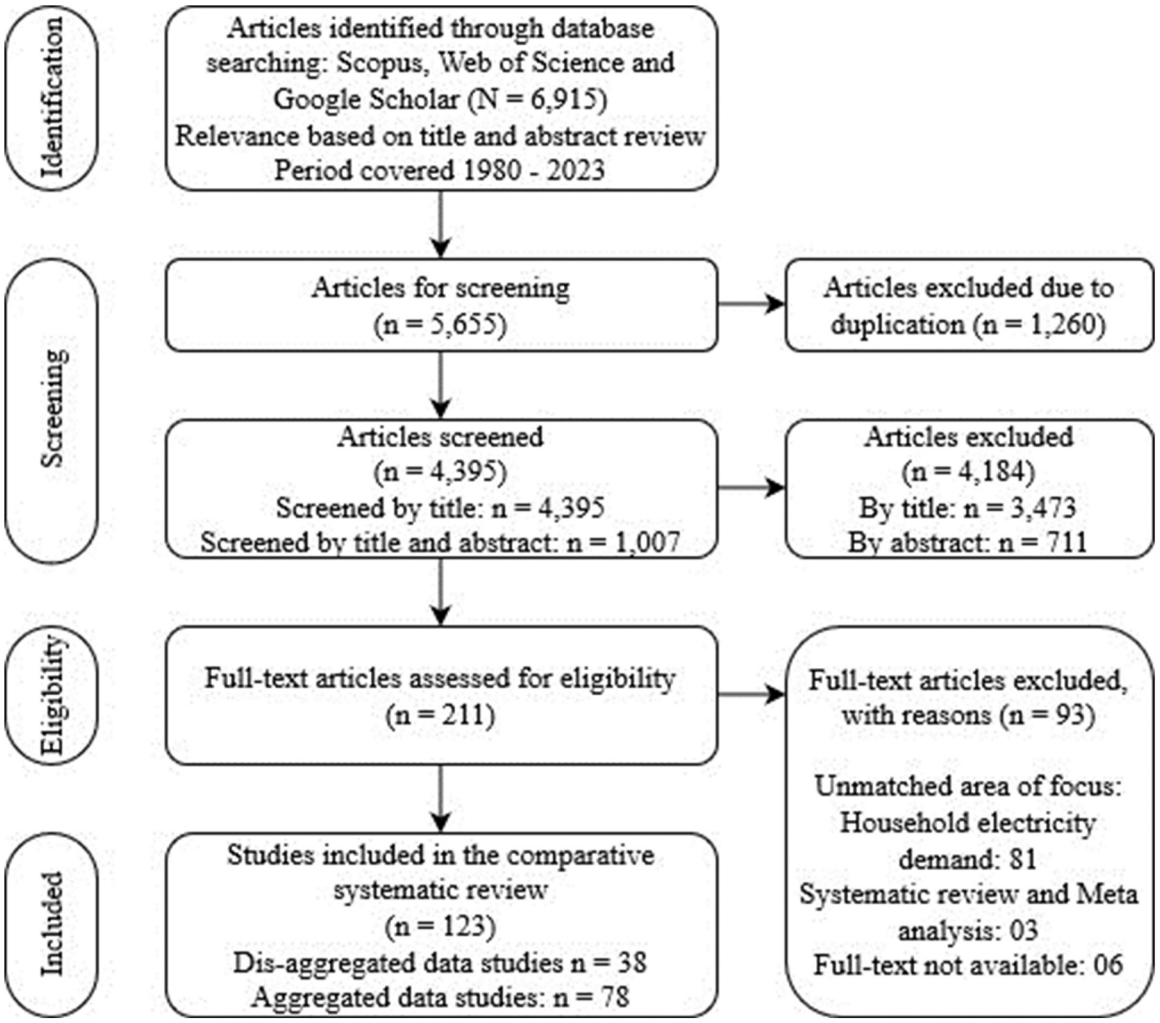


Fig. I. Flow chart for the systematic literature review.

was utilized to organize the articles and remove duplicates. Of the 4395 studies initially identified, 4184 were excluded because their titles or abstracts did not explicitly reference income or price elasticities of household electricity demand. For example, studies focused solely on broader energy consumption patterns or environmental impacts were excluded. This approach ensured that only relevant studies were included.

3.3. Data extraction and synthesis (eligibility)

Two independent reviewers extracted data using a standardized form, gathering details such as authorship, publication year, research design, sample size, key findings, and methodologies. This systematic approach aimed to minimize bias and ensure consistency. The extracted data underwent thematic analysis to identify patterns and themes related to barriers to electricity consumption demand growth in Uganda. This analysis categorizes and interprets key findings, providing a refined understanding of the challenges. The synthesized information offers a comprehensive overview of the barriers and their implications for Uganda's electricity consumption growth. Summarized data categories are presented in Table 1.

3.4. Data charting

After identifying relevant articles through a systematic literature review, a structured data-charting approach was used to organize and synthesize the extracted information systematically and transparently. Comprehensive data extraction forms were designed and iteratively refined before data charting. These forms included categories like authorship, publisher, publication year, study country, study region, income group, study period, study method, income elasticity, price elasticity, and barriers to electricity consumption demand growth in Uganda. The forms were developed based on research questions and study objectives to ensure all relevant information was captured. An Excel file was created to detail each study, including all information in Table 1.

Two independent reviewers maintained consistency and reliability in

Table 1
Study Categories.

Categories	Category description
Authorship	Author of the Article
Publisher	Name of the journal or organization where the article was published
Publication year	Year in which article was published
Study country & region	Country and region where the study was conducted
Income group	Income group category of the country where the study was undertaken
Study period	Annual time series coverage of the study
Study method	Data analysis techniques employed in considered studies
Income elasticity	Income elasticity of demand for household electricity
Price elasticity	Price elasticity of demand for household electricity

data charting, having undergone training for a shared understanding of extraction forms and research objectives. Regular meetings addressed discrepancies and refined the charting process, enhancing data synthesis reliability. The charted data underwent rigorous thematic analysis to identify recurring patterns, themes, and barriers. This involved systematically reviewing and coding information to uncover commonalities and variations in reported barriers to growth in electricity consumption demand in Uganda. Thematic analysis synthesized qualitative and quantitative data, refining the understanding of complexities surrounding these barriers. Data charting was iterative, with continuous refinement of extraction forms and analysis techniques as new insights emerged, ensuring a dynamic and responsive synthesis, contributing to the findings' depth and richness. The study maintained rigor in data charting by adhering to systematic literature review guidelines, specifically the PRISMA framework, thus enhancing transparency and replicability.

3.5. Analysis of price and income elasticities of household electricity demand

The price elasticity of electricity demand measures the responsiveness of electricity consumption to changes in electricity prices. It is typically expressed as:

$$Price\ Elasticity(PE) = \frac{\%Change\ in\ Quantity\ Demanded}{\%Change\ in\ Price}$$

The income elasticity of electricity demand measures the responsiveness of electricity consumption to changes in household income. It is expressed as:

$$Income\ Elasticity(IE) = \frac{\%Change\ in\ Quantity\ Demanded}{\%Change\ in\ Income}$$

The Quadratic Expenditure System (QES), developed by (Pollak and Wales, 1978), is a flexible consumer demand model that allows for the derivation of price and income elasticities of demand for disaggregated data studies. This model is particularly useful for analyzing household electricity demand, as it can accommodate varying consumer preferences and budget constraints. The QES is an extension of the Almost Ideal Demand System (AIDS) and is characterized by its ability to capture non-linear relationships between expenditure and consumption. Below, we derive the price and income elasticities of household electricity demand using the QES framework.

The QES model specifies the expenditure share of a good as a quadratic function of total expenditure and prices. The expenditure share equation for electricity can be expressed as:

$$w_i = \propto_i + \beta_i \ln x + \sum_j \gamma_{ij} \ln p_j + \delta_i (\ln x)^2 \quad (I)$$

where w_i is the expenditure share of electricity, x is total expenditure, p_j are prices, and $\propto_i$, β_i, γ_{ij}, δ_i are parameters to be estimated.

The price elasticity of demand for electricity, *HHPE*, is derived from the partial derivative of the expenditure share with respect to the price of electricity, adjusted by the expenditure share:

$$HHPE = \frac{\partial w_i}{\partial \ln p_j} \bullet \frac{x}{w_i} = \left(\gamma_{ij} - \beta_i \frac{\partial \ln x}{\partial \ln p_j}\right) \bullet \frac{x}{w_i} \quad (II)$$

This elasticity captures how a change in the price of electricity affects its demand, holding other factors constant (Aslam and Ahmad, 2023).

The income elasticity of demand, *HHIE*, is derived from the partial derivative of the expenditure share with respect to total expenditure:

$$HHIE = \frac{\partial w_i}{\partial \ln x} \bullet \frac{x}{w_i} = (\beta_i + 2\delta_i \ln x) \bullet \frac{x}{w_i} \quad (III)$$

This elasticity measures the responsiveness of electricity demand to changes in household income (Jin and Kim, 2022; Nainggolan, 2022).

A descriptive analysis was conducted on household income (HHIE) and price (HHPE) elasticity of household electricity demand, considering disaggregated data studies. While for aggregated data studies, short-run (SRIE) and long-run (LRIE) income elasticity, and short-run (SRPE) and long-run (LRPE) price elasticity were analyzed. This analysis examines variations in these elasticities through measures of central tendency and dispersion.

3.5.1. Common sample descriptive analysis of income and price elasticities of demand

The study used sample descriptive analysis methods to understand the distribution and characteristics of income and price elasticities of demand. The mean, the average elasticity, is calculated by dividing the sum of all elasticity values by the number of observations. The median, the middle value in an ordered set, provides a measure less affected by outliers. Standard deviation quantifies the dispersion around the mean, calculated as the square root of the variance. Skewness indicates distribution asymmetry, with positive skewness showing right-skewness and negative skewness showing left-skewness. Kurtosis measures the "tailedness" of the distribution, with high kurtosis indicating heavy tails. The Jarque-Bera test is a goodness-of-fit test that checks whether the sample data have skewness and kurtosis matching a normal distribution, calculated using the formula

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \quad (IV)$$

where n is the sample size, S is skewness, and K is kurtosis.

3.5.2. Test for equality of means and variances between income and price elasticities of demand

ANOVA F-test and Welch F-test were used to test the equality of means, whereas Bartlett's test and Levene's test were used to test the equality of variances. The ANOVA F-test compares the means of three or more groups, assuming the homogeneity of variance and normality.

$$\text{The test statistic is} F = \frac{MS_{between}}{MS_{within}} \quad (V)$$

where $MS_{between}$ is the mean square between groups and MS_{within} is the mean square within groups (Hasalem and Jitthavech, 2018; Yılmaz et al., 2017). However, the ANOVA F-test is not robust to the violations of these assumptions. Welch's F-test, on the other hand, was designed to handle heteroscedasticity (unequal variances) and nonnormality.

It uses a modified test statistic,

$$F_w = \frac{\sum_{i=1}^{k} \frac{n_i(\overline{X}_i - \overline{X})^2}{s_i^2}}{1 + \frac{2(k-2)}{k^2-1} \sum_{i=1}^{k} \frac{1}{n_i - 1}} \quad (VI)$$

where $\overline{X}_i$ and s_i^2 are the sample mean and variance of the *i-th* group, respectively (Jan and Shieh, 2014, 2020).

Bartlett's test was used to test the equality of variances, under the assumption of normality. The test statistic was

$$\chi^2 = \frac{(N-k)\ln(S_p^2) - \sum_{i=1}^{k}(n_i - 1)\ln(S_i^2)}{1 + \frac{1}{3(k-1)}\left(\sum_{i=1}^{k} \frac{1}{n_i - 1} - \frac{1}{N-k}\right)} \quad (VII)$$

where S_p^2 was the pooled variance (Almeida et al., 2008; Gastwirth et al., 2009).

Levene's test, which is robust to non-normality, uses absolute deviations from the group means.

The test statistic is

$$W = \frac{(N-k)\sum_{i=1}^{k} n_i (Z_i - Z)^2}{(k-1)\sum_{i=1}^{k}\sum_{j=1}^{n_i} (Z_{ij} - Z_i)^2} \quad \text{(VIII)}$$

where $Z_{ij} = |X_{ij} - \overline{X}_i|$ and Z_i is the mean of Z_{ij} (Almeida et al., 2008; Gastwirth et al., 2009). These tests are crucial for comparing the income and price elasticities of demand, ensuring that the assumptions of homogeneity and normality are met or appropriately adjusted, thus providing reliable statistical inferences.

4. Results

The literature survey in Tables 2 and 3 aligns with the categories in Table 1, detailing the author, publication year, research country, time period, methods used, and income and price elasticities of household electricity demand. This thematic analysis emphasizes aggregated versus disaggregated data studies, consistent with the objectives.

4.1. Thematic analysis

4.1.1. Analysis of studies by year of publication

Fig. 2 illustrates trends in studies on household electricity demand growth, with the earliest articles published in 1980 (disaggregated) and 1984 (aggregated). Until 1997, publications fluctuated between zero and one annually. From 1997–1999, and consistently from 2002 to 2018, aggregated studies outnumbered disaggregated ones. The peak for aggregated data studies was in 2011 with four articles, while both aggregated and disaggregated studies peaked at four articles in 2011 and 2021, respectively. This indicates a notable disparity, with fewer studies using disaggregated data.

4.1.2. Analysis of studies by regional classification

The regional analysis of household electricity demand studies used the World Bank's country classifications by region. The Middle East and North Africa had the fewest studies, with only 5 % involving aggregated data. Europe and Central Asia led with 26 % aggregated and 37 % disaggregated studies. East Asia and the Pacific followed with 16 % and 24 %, while Latin America and the Caribbean had 11 % and 22 %, respectively. Sub-Saharan Africa had 8 % disaggregated and 5 % aggregated studies. Significant disparities in research distribution were evident, indicating a need for more comprehensive studies in the Middle East and North Africa. In contrast, Europe and Central Asia's extensive studies reflect a strong research infrastructure and interest in household energy demand.Fig. 3.

4.1.3. Analysis of studies by income group classification

We utilized the World Bank's income-based country classification to examine studies by income group. The distribution highlights a significant lack of empirical research on household electricity demand in low-income countries. As depicted in Fig. 4, only 3 % of disaggregated studies and none of the aggregated data studies were conducted in low-income countries. Conversely, high-income countries accounted for 58 % of disaggregated and 50 % of aggregated studies. There is a clear ordinal increase in the number of publications across income groups from low- to high-income economies for both aggregated and

Table 2
Income and price elasticities of household electricity demand for disaggregated data studies.

Study	Country	Period	Method	Income Elasticity		Price Elasticity	
(Parti and Parti, 1980)	USA	1975	CDF	0.15		−0.58	
(Dennerlein, 1987)	Germany	1977–1984	DCCM	0.42		−0.38	
(Baker and Blundell, 1991)	UK	1972–1988	AIDS	0.17	to 0.28	−0.67	to −1.04
(Branch, 1993)	USA	1985	GLS	0.23		−0.20	
(Nesbakken, 1999)	Norway	1990–1992, 1994–1995	DCCM	0.01	to 0.28	−0.24	to −0.66
(Metcalf and Hassett, 1999)	USA	1984, 1987, 1990	OLS, IV, FD			−0.27	to −1.11
(Halvorsen and Larsen, 2001)	Norway	1975–1994	DCCM	0.06	to 0.13	−0.43	to −0.42
(Filippini and Pachauri, 2004)	India	1993–1994	OLS	0.06	to 0.64	−0.29	to −0.51
(Reiss and White, 2005)	USA	1993–1997	OLS, GMM			−0.29	to −0.49
(Labandeira et al., 2006)	Spain	1973–1995	QUAIDS	0.53	to 1.01	−0.44	to −0.80
(Yoo et al., 2007)	South Korea	2005	OLS	0.06		−0.25	
(Alberini et al., 2011)	USA	1997–2007	GLS, FE, GMM	0.01	to 0.02	−0.67	to −0.86
(Bernard et al., 2011)	Canada	1989–2002	PP, FE	0.08	to 0.20	−0.51	to −1.32
(Ngui et al., 2011)	Kenya	2009	AIDS	0.85		−0.63	to −0.88
(Wiesmann et al., 2011)	Portugal	2005–2006	OLS	0.05	to 0.12		
(Asamoah et al., 2012)	Mozambique	2002–2003	Deaton	0.52	to 0.69	−0.49	to −0.66
(Zhou and Teng, 2013)	China	2007–2009	OLS	0.14	to 0.33	−0.35	to −0.50
(Çetinkaya et al., 2015)	Turkey	2003–2012	Deaton, QR	0.23	to 0.20	−0.60	to −0.74
(Huang, 2015)	Taiwan	1981–2011	QR	0.37	to 0.55		
(Sun and Ouyang, 2016)	China	2013	AIDS	0.62		−0.39	
(Khanna et al., 2016)	China	2012	OLS, QR	0.15		−0.51	
(Silva et al., 2017)	Portugal	1993–2008	QR	0.28	to 0.33	−0.54	to −0.77
(Schulte and Heindl, 2017)	Germany	1993–2008	QUAIDS	0.40	to 0.41	−0.43	to −0.50
(Silva et al., 2018)	Portugal	1989–2011	FE, RE	0.30	to 0.35	−0.67	to −0.90
(Ye et al., 2018)	South Africa	2010–2011	2PM	0.13	to 0.43	−0.19	to −1.16
(Athukorala et al., 2019)	Sri Lanka	2011–2015	OLS, FE, RE	0.02	to 0.71	−0.02	to −0.14
(Chindarkar and Goyal, 2019)	India	2005–2012	OLS, FE	0.59		−0.31	to −0.46
(Pereira Uhr et al., 2019)	Brazil	1988–1989, 2008–2013	QR	0.20	to 0.32	−0.46	to −0.56
(Balarama et al., 2020)	Bangladesh	2017	FE, RE, QR			−0.57	
(Bardazzi and Pazienza, 2020)	Italy	1997–2016	PP, FE	0.15	to 0.46	−0.53	to −0.88
(Kostakis, 2020)	Greece	2017	QR	0.14	to 0.21		
(Belaïd et al., 2021)	France	2006–2016	PP, FE	0.22			
(Díaz and Medlock, 2021b)	Mexico	1992–2014	SUR, QUAIDS			−0.21	to −3.19
(Inoue et al., 2021)	Japan	1989–2014	OLS	0.36	to 0.45		
(Carrasco-Gutierrez and Ehrl, 2023)	Brazil	2003–2015	VAR	0.31	to 0.70	−0.12	
(Martins et al., 2023)	Brazil	2004–2021	ECM	0.31	to 0.32	−0.05	to −0.11

Table 3
Income and price elasticities of household electricity demand for aggregated data studies.

Study	Country	Period	Method	Short-run Income Elasticity		Long-run Income Elasticity		Short-run Price Elasticity		Long-run Price Elasticity	
(Modiano, 1984)	Brazil	1963–1981	OLS	0.33		1.13		−0.12		−0.40	
(Donatos and Mergos, 1991)	Greece	1961–1986	OLS	1.50		0.53		−0.58		−0.21	
(Ang et al., 1992)	Singapore	1971–1990	OLS			1.00				−0.35	
(Bentzen and Engsted, 1993)	Denmark	1960–1981	ECM			1.21				−0.47	
(Andrade and Lobão, 1997)	Brazil	1963–1995	VAR, VECM	0.21		0.21		−0.06		−0.05	
(Christodoulakis and Kalyvitis, 1997)	Greece	1970–1990	OLS	1.85		1.33				−0.25	
(Silk and Joutz, 1997)	USA	1949–1993	ECM	0.39		0.52		−0.63		−0.48	
(Hunt et al., 1999)	Honduras	1973–1995	ARDL	1.57				−0.23			
(Beenstock et al., 1999)	Israel	1973–1994	CM	1.00		1.00	to 1.09	−0.52		−0.58	to −0.21
(Bose and Shukla, 1999)	India	1985–1994	OLS	0.88				−0.65	to −1.35		
(Filippini, 1999)	Switzerland	1987–1990	PAM			0.33				−0.30	
(Fatai et al., 2003)	New Zealand	1960–1999	ECM, ARDL	0.24	to 0.46	0.81	to 1.24	−0.24	to −0.18	−0.59	to −0.44
(Berkhout et al., 2004)	Netherlands	1994–1999	OLS	0.61				−0.55			
(Holtedahl and Joutz, 2004)	Taiwan	1955–1995	ECM	0.23		1.04		−0.15		−0.16	
(Hondroyiannis, 2004)	Greece	1986–1999	ECM	0.20		1.56		−0.41		−0.41	
(Kamerschen and Porter, 2004)	USA	1973–1998	SEM	0.65	to 0.69			−0.94	to −0.85		
(Narayan and Smyth, 2005)	Australia	1969–2000	ARDL	0.01	to 0.04	0.32	to 0.41	−0.27	to −0.26	−0.05	to −0.47
(Rapanos and Polemis, 2005)	Greece	1965–1999	PAM	1.54		0.79		−0.60		−0.31	
(De Vita et al., 2006)	Namibia	1980–2002	ARDL			1.27				−0.34	
(Siqueira et al., 2006)	Brazil	1970–2003	VECM	0.18		1.40		−0.30		−0.41	
(Halicioglu, 2007)	Turkey	1968–2005	ECM, ARDL	0.37	to 0.44	0.49	to 0.70	−0.46	to −0.33	−0.63	to −0.52
(Narayan et al., 2007)	G7 countries	1978–2003	DOLS, FMOLS			0.25	to 0.31	−0.11		−1.56	to −1.45
(Zachariadis and Pashourtidou, 2007)	Cyprus	1960–2004	ECM			1.17				−0.43	
(Amarawickrama and Hunt, 2008)	Sri Lanka	1970–2003	ECM, STSM	1.82	to 1.96	0.99	to 1.96			−0.06	to −0.02
(Dergiades and Tsoulfidis, 2008)	USA	1965–2006	ARDL	0.10		0.27		−0.39		−1.07	
(Irffi et al., 2008)	Brazil	1970–2003	DOLS	0.01		0.68		−0.21		−0.69	
(Ziramba, 2008)	South Africa	1978–2005	ARDL	0.30		0.31		−0.02		−0.04	
(Amusa et al., 2009)	South Africa	1960–2007	ARDL			1.67				−0.29	
(Paul et al., 2009)	USA	1990–2006	PAM	0.11				−0.40		−0.13	
(Sa'ad, 2009)	South Korea	1973–2007	STSM	1.33				−0.27			
(Inglesi, 2010)	South Africa	1980–2005	ECM			0.42				−0.56	
(Nakajima and Hamori, 2010)	USA	1993–2008	PAM	0.33	to 1.00			−0.34	to −0.12		
(Nakajima, 2010)	Japan	1975–2005	DOLS	0.60	to 0.65			−1.20	to −1.13		
(Alberini and Filippini, 2011)	USA	1995–2007	PAM, GMM	0.05				−0.15	to −0.08	−0.75	to −0.45
(Azevedo et al., 2011)	USA	1990–2004	SPAM							−0.25	to −0.21
(Dergiades and Tsoulfidis, 2011)	Greece	1964–2006	ARDL	0.80		0.64		−0.61		−0.09	
(Dilaver and Hunt, 2011)	Turkey	1960–2008	STSM	0.38		1.57		−0.09		−0.38	
(Inglesi-Lotz, 2011)	South Africa	1980–2005	TVP			0.79				−0.08	
(Jamil and Ahmad, 2011)	Pakistan	1961–2008	ECM	0.49		1.97		−0.07		−1.22	
(Lee and Chiu, 2011)	Greece	1972–2004	PSTR			0.47				−0.23	
(Shi et al., 2012)	China	2008–2009	OLS	0.06				−2.48			
(Blázquez et al., 2013)	Spain	2000–2008	PAM	0.23		0.61		−0.07		−0.19	
(Blázquez Gomez et al., 2013)	Spain	2001–2010	SAR	0.27				−0.04			
(Okajima and Okajima, 2013)	Japan	1990–2007	GMM					−0.40		−0.49	
(Pourazarm and Cooray, 2013)	Iran	1967–2009	ECM			0.58				−0.11	
(Polemis and Dagoumas, 2013)	Greece	1970–2011	VECM	4.45		0.19		−0.29		−0.08	
(Sun and Lin, 2013)	China	2000–2007	OLS	0.47				−0.12			
(Arisoy and Ozturk, 2014)	Turkey	1960–2008	TVP			0.98				−0.01	
(Lim et al., 2014)	South Korea	1970–2011	ECM			1.09				−1.00	
(Casarejos et al., 2014)	Brazil	1975–2006	VAR, VECM			1.79				−0.71	
(Agostini and Plottier, 2015)	Chile	2006	NLS	0.11	to 0.12			−0.38	to −0.40		
(Ivy-Yap and Bekhet, 2015)	Malaysia	1978–2013	ARDL			1.42				−0.94	
(Moshiri, 2015)	Iran	2001–2008	SURE	0.99	to 1.02			−0.02			
(Zaman et al., 2015)	Pakistan	1972–2012	ECM			1.03				−0.16	
(Miller and Alberini, 2016)	USA	1997–2009	OLS, IV, FE	0.06	to 0.18			−0.20	to −0.80		
(Villareal and Moreira, 2016)	Brazil	1985–2013	OLS			0.19				−0.23	
(Liao et al., 2017)	China	1996–2015	GMM	0.21							
(Uhr et al., 2017)	Brazil	2004–2014	GMM	0.08	to 0.12	0.32	to 1.09	−0.13	to −0.18	−0.62	to −1.47
(Wang and Mogi, 2017)	Japan	1989–2014	TVP	0.86	to 1.59			−0.46	to −0.68		
(Zhang et al., 2017)	China	2011–2012	FRDD					−0.90			
(Campbell, 2018)	Jamaica	1970–2014	ARDL			0.26				−0.82	
(Filippini et al., 2018)	USA	1995–2011	PAM					−0.18	to −0.09	−0.31	to −0.21
(Moshiri and Martinez Santillan, 2018)	Mexico	2002–2012	SURE	0.75				−0.36			
(Su, 2018)	China	1998–2015	FE, RE, GMM	0.08		0.47		−0.14		−0.82	
(Tiwari and Menegaki, 2019)	India	1975–2013	TVP			0.42				−0.21	
(Zin and Moradi, 2019)	Australia	2015	RSM					−0.24		−0.60	
(Alfalah et al., 2020)	Kuwait	1972–2017	ECM			0.04				−1.22	
(Kostakis, 2020)	Greece	2017	QR	0.14	to 0.21						
(Jia and Xu, 2021)	China	2016	PAM	0.37		1.59		−0.20		−0.85	
(Martins et al., 2021)	Brazil	2004–2011	ECM	0.33		0.33		−0.31		−0.62	
(Othman and Hariri, 2021)	Malaysia	1980–2020	ARDL			0.38				−0.71	
(de Souza et al., 2022)	Brazil	1974–2016	ARDL			1.39		0.00		−0.30	
(Kostakis and Lolos, 2022)	Greece	2009–2018	PAM, QR	0.25		0.35		−0.48		−0.80	
(Carrasco-Gutierrez and Ehrl, 2023)	Brazil	2003–2015	VECM	0.31		0.70				−0.12	

Abbreviations for the methods used are defined as follows: Almost Ideal Demand System (AIDS) Conditional Demand Functions (CDF) Difference-in-differences (DD) Discrete Continuous Choice Model (DCCM) Dynamic Ordinary Least Squares (DOLS) Dynamic Partial Adjustment Model (DPAM) Error Correction Model (ECM) First Difference (FD) Fixed Effects (FE) Fully Modified OLS (FMOLS) Fuzzy regression discontinuity DD (FRDD) Generalised Least Squares (GLS) Generalised Method of Moments (GMM) Instrumental Variable (IV) Least Squares Dummy Variable (LSDV) Non Linear Least Squares (NLS) Ordinary Least Squares (OLS) Panel Smooth Transition Regression (PSTR) Partial Adjustment Model (PAM) Pooled Mean Group (PMG) Pseudo-panels (PP) Quadratic Almost Ideal Demand System (QUAIDS) Quantile Regression (QR) Random Effects (RE) Response Surface Methodology (RSM) Seemingly Unrelated Regression (SURE) Spatial-autoregressive (SAR) Static Partial Adjustment Model (SPAM) Structural Equation Model (SEM) Structural Time Series Model (STSM) Time-Varying Parameter (TVP) Two-part Model (2PM) Vector Auto-Regression (VAR) Vector Error Correction Model (VECM)

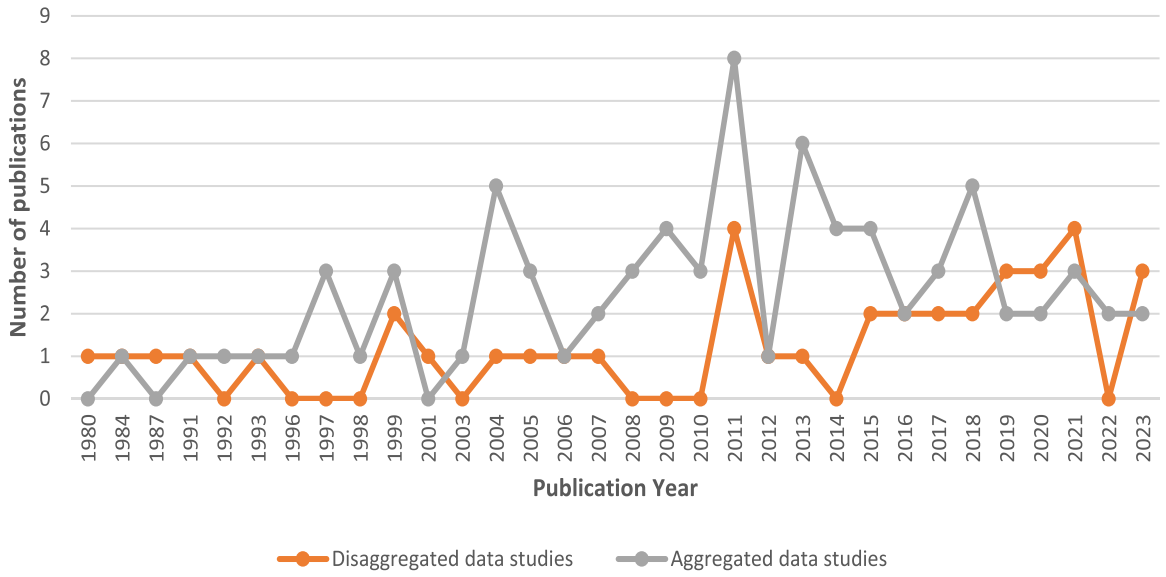


Fig. 2. Distribution of Studies by year of publication.
Author's compilation

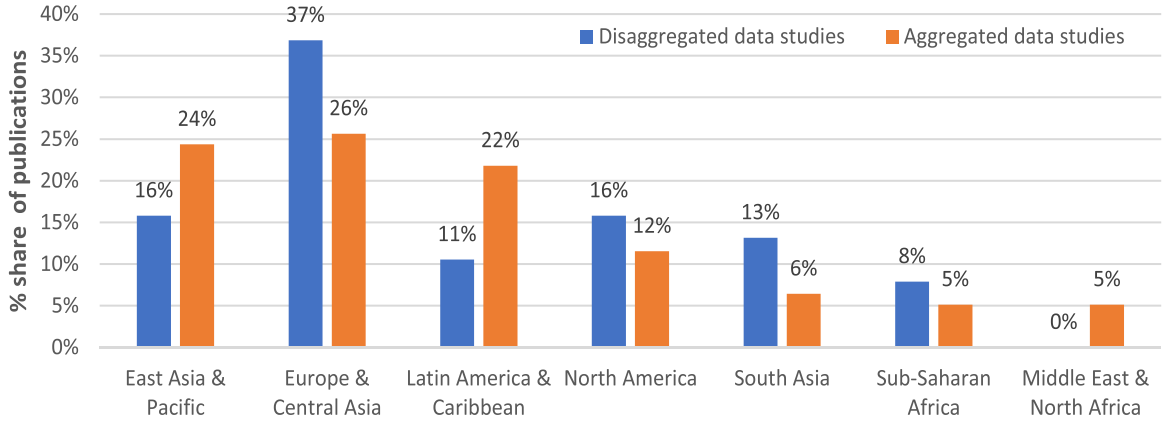


Fig. 3. Distribution of Studies by Region.

disaggregated data studies. This analysis underscores a substantial research gap in low-income countries, with only 3 % representation in disaggregated studies and no aggregated data studies, indicating an urgent need for more studies on electricity consumption patterns in these economically disadvantaged regions.

4.1.4. Sources of data (publishers)

The articles in this study were published in 39 journals, with aggregated studies appearing in 29 journals and disaggregated studies in 17. Half of the aggregated data studies were published in energy policy and energy economics journals, comprising 25.6 % and 24.4 %, respectively. Similarly, energy policy and energy economics journals led in disaggregated data studies, making up 29.0 % and 15.8 %, respectively. Other notable journals for aggregated data studies included the International Journal of Energy Economics and Policy (9 %) and The Energy Journal (6.4 %). For disaggregated data, The Energy Journal of IAEE and the Energy Journal of Elsevier each contributed 7.9 % of the publications throughout the study period.

4.1.5. Analysis of studies by country classification

Table 5 presents the research locations. The USA led in disaggregated data studies with 13.2 %, whereas Brazil dominated aggregated data studies at 15.4 %. Following the USA in disaggregated studies were China, Portugal, and Brazil, each with 7.9 %. For aggregated studies, the USA, Greece, and China followed Brazil, contributing 11.5 %, 12.8 %, and 9.0 %, respectively.

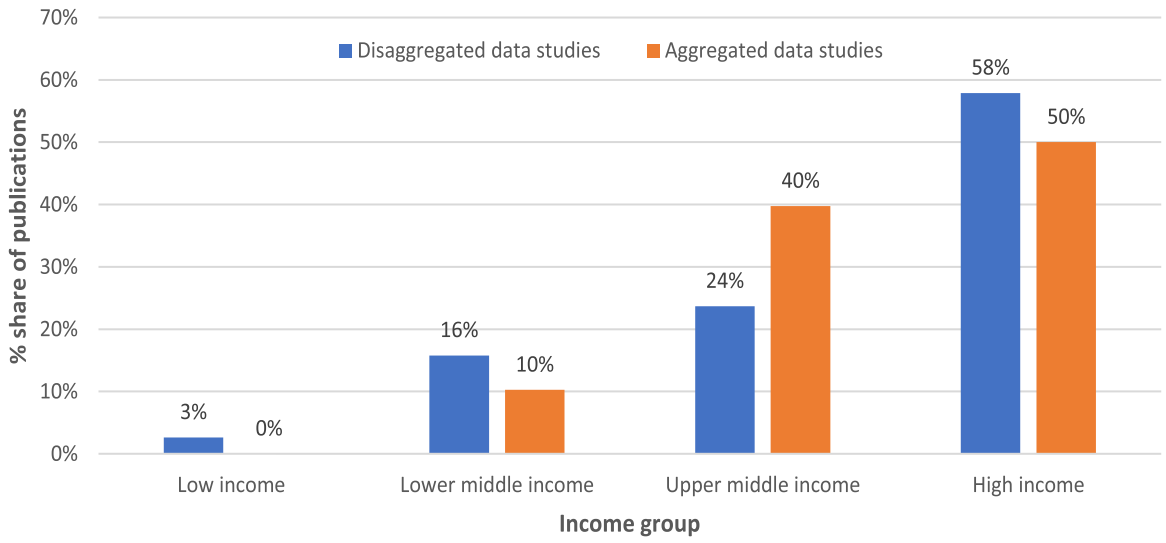


Fig. 4. Distribution of studies by Income group.
Author's compilation

4.2. Analysis of income and price elasticities of household electricity demand

This section thoroughly discusses the results of the income and price elasticities obtained from the reviewed articles, incorporating both macro- and micro-level analyses. Table 6 shows that, on average, the income and price elasticity of electricity demand for disaggregated data studies are inelastic at 0.314 and −0.573, respectively. Elasticities for aggregated data studies are provided for both short and long runs. The income elasticity of household electricity demand is, on average, inelastic in both the short and long run at 0.555 and 0.773, respectively, while the price elasticity of electricity demand is also inelastic in the short and long run at −0.408 and −0.509, respectively.

HHIE and HHPE denote the income and price elasticity of household electricity demand, while SRIE and LRIE refer to the short- and long-run income elasticity, and SRPE and LRPE represent the short- and long-run price elasticity, respectively.

Our dual-perspective analysis of household electricity demand, using both aggregated and disaggregated data, refines insights into income and price elasticities shaping consumption. Disaggregated studies show average inelastic household electricity demand, highlighting consumption's relative insensitivity to income and price changes. Aggregated data studies confirm persistent income and price inelasticity, indicating stable demand responses in both the short and long run.

We examine the equality of means and variances between income and price elasticities of household electricity demand using ANOVA and Welch F-tests for means, and Bartlett, Levene, and Brown-Forsythe tests for variances. Table 7 indicates that the mean elasticities and variances of household electricity demand are significantly different.

Statistical tests for equality of means and variances (Table 7) confirmed heterogeneity in elasticities across studies, highlighting the need for refined, context-specific analyses. This variability underscores the importance of tailored policies that consider the unique dynamics influencing household electricity demand in various contexts. These findings enhance the dialogue on energy consumption, aiding policymakers and researchers in crafting targeted strategies for sustainable and efficient electricity use.

4.3. Analysis of microdata (disaggregated) vs. macrodata (aggregated) in elasticity estimates

Table 8 provides a detailed breakdown of how income and price elasticity estimates differ across regions and data types, alongside the various econometric models used. This analysis critically examines these differences, highlighting the statistical disparities between disaggregated and aggregated data, and how the choice of model and data affects the resulting elasticity estimates.

In Sub-Saharan Africa, aggregated data shows a mean income elasticity of 0.79 (ranging from 0.30 to 1.67), reflecting overall economic growth that stimulates higher electricity consumption. In contrast, disaggregated data for the same region yields a lower mean income elasticity of 0.52 (ranging from 0.13 to 0.85), highlighting that at the household level, some consumers, particularly wealthier ones, may have reached a saturation point in electricity demand. This suggests that while regional economic growth can boost electricity consumption on a larger scale, the incremental increase at the household level is more limited. Similarly, in South Asia, the income elasticity for aggregated data is significantly higher, with a mean of 1.28 (ranging from 0.42 to 1.97), compared to disaggregated data with a mean of 0.40 (ranging from 0.02 to 0.71). This large difference underscores how macroeconomic factors drive electricity demand at the national level, while household-level data reveals more tempered consumption increases with rising income.

In Latin America & the Caribbean, disaggregated data reveals a high mean price elasticity of −0.67 (with a range of −3.19 to −0.05), indicating that many households in the region reduce their electricity consumption significantly when prices increase. Aggregated data, however, reports a much lower mean price elasticity of −0.33 (ranging from −1.47 to −0.05). This suggests that regional averages obscure the substantial price sensitivity of lower-income households, who are more likely to cut back on electricity use when prices rise.

In Sub-Saharan Africa, a similar pattern emerges, where disaggregated data reports a mean price elasticity of −0.67 (with a range of −1.16 to −0.19), compared to −0.22 in aggregated data (ranging from −0.56 to −0.02). This indicates that household-level data better captures the substantial price sensitivity of low-income consumers, who may face difficult choices between reducing electricity consumption or cutting other essential expenses.

In East Asia & Pacific, disaggregated data shows an income elasticity range of 0.06–0.62, while aggregated data shows a wider range of 0.01–1.52. This difference suggests that aggregated data captures broader economic cycles that affect electricity demand across the region. Similarly, the price elasticity in disaggregated data ranges from −0.51 to −0.25, while aggregated data ranges from −2.43 to −0.05, indicating that disaggregated data provides a more precise understanding of household-level responses to price changes, while

Table 4
Analysis of studies by publisher.

Journal	Aggregated		Disaggregated	
	Freq.	%	Freq.	%
Applied Economics Letters	1	1.3		
Applied energy	1	1.3		
Current Research in Environmental Sustainability	1	1.3	1	2.6
Economic Modelling	1	1.3		
Empirical Economics	1	1.3		
Energy	5	6.4	3	7.9
Energy & the Economy	1	1.3		
Energy Economics	19	24.4	6	15.8
Energy Efficiency	3	3.9		
Energy Policy	20	25.6	11	29.0
Energy Research & Social Science			1	2.6
Energy, Ecology and Environment	1	1.3		
Environmental Science and Pollution Research	1	1.3		
EPGE Brazilian School of Economics and Finance	1	1.3		
Institute of Applied Economic Research	1	1.3		
International Conference on PMAPS	1	1.3		
International Journal of Business and Social Science			1	2.6
International Journal of Economic Policy Studies			1	2.6
International Journal of Energy Economics and Policy	7	9.0	2	5.3
International Journal of Energy Sector Management	1	1.3		
Journal of Asian Economics	1	1.3		
Journal of Evolutionary Economics			1	2.6
Journal of Innovation and Entrepreneurship			1	2.6
National Technical University of Athens	1	1.3		
Oxford Review of Economic Policy			1	2.6
PUC Economics Department	1	1.3		
Renewable and Sustainable Energy	1	1.3		
Resource and Energy Economics	1	1.3	2	5.3
Review of economics and statistics			1	2.6
SSRN Electronic Journal	1	1.3		
Sustainability	1	1.3		
The Bell journal of economics			1	2.6
The Electricity Journal	1	1.3		
The empirical Economics letters	1	1.3		
The energy journal	1	1.3	3	7.9
The Journal of Energy and Development	1	1.3		
The Review of Economic Studies			1	2.6
The Scientific World Journal	1	1.3		
Utilities Policy			1	2.6
Total	**78**	**100.0**	**38**	**100.0**

Author's Compilation

aggregated data captures the broader price sensitivity of the entire economy.

For disaggregated data, models such as Quantile Regression (QR) and Fixed Effects (FE) are commonly used. These models are designed to account for household-level heterogeneity, making them ideal for analyzing how different income groups or household characteristics affect electricity demand. For example, in Sub-Saharan Africa, the use of FE models allows researchers to control for unobserved household characteristics, resulting in higher price elasticity estimates for lower-income households. On the other hand, aggregated data is often analyzed using models such as Autoregressive Distributed Lag (ARDL) and Error Correction Models (ECM), which are better suited for capturing long-run relationships and the dynamics of electricity demand at the regional or national level. In Europe & Central Asia, for instance, the use of ARDL and ECM models with aggregated data yields lower price elasticity estimates of −0.35, compared to the higher elasticity of −0.61 observed in disaggregated data analyzed using more flexible models such as QR. These differences highlight how model choice interacts with data type to influence the resulting elasticity estimates.

5. Discussion of results

5.1. Regional and Income group classification of studies

An analysis of household electricity demand studies across various regions, classified by World Bank standards, reveals notable disparities in research distribution. The Middle East and North Africa (MENA) regions are particularly underrepresented, with only 5 % of studies using aggregated data and none using disaggregated data (Ramnath et al., 2022). This research gap underscores the need for a more thorough investigation into household electricity consumption patterns in these areas. The lack of region-specific research limits policymakers' ability to design effective energy policies that account for MENA's unique socio-economic conditions, such as extensive energy subsidies and high per capita consumption. Aggregated data can obscure critical variations between different household types, while disaggregated data provides granular insights into how individual households respond to price and income changes, which is essential for shaping equitable policies. Without studies that explore household-level consumption patterns, MENA risks adopting one-size-fits-all policies that may not address the region's diverse energy needs, and may miscalculate the effects of subsidy reforms or energy efficiency programs.

Europe and Central Asia accounted for 26 % and 37 % of publications in both aggregated and disaggregated studies, respectively. This significant representation indicates a robust research infrastructure and a strong academic and policy interest in household electricity demand (Khanna et al., 2021). Extensive research in these areas enhances understanding of consumption patterns, price sensitivity, and income elasticities, leading to more informed and effective energy policies (Fatourehchi et al., 2022).

East Asia and the Pacific show moderate research activity, contributing 16 % of aggregated and 24 % of disaggregated studies. Latin America and the Caribbean contribute 11 % and 22 %, respectively. This moderate representation indicates increasing research efforts to understand household electricity demand in these economically dynamic regions. These studies offer critical insights into regional consumption behaviors and elasticity, aiding in the creation of targeted energy policies and initiatives.

Sub-Saharan Africa accounted for 8 % of disaggregated and 5 % of aggregated studies in research coverage. This paucity highlights a significant gap in understanding household electricity consumption patterns and their sensitivity to income and price changes (Babayomi et al., 2023). Such underrepresentation challenges policymakers aiming to improve electricity access, affordability, and sustainability in a region where electricity access is a critical developmental issue (Olanrele and Fuinhas, 2024; Sackey et al., 2022).

Studies on income and price elasticities of household electricity demand, categorized by World Bank income groups, show notable disparities in geographic focus. Empirical research is significantly skewed, with low-income countries severely under-represented. Only 3 % of the studies address these regions, and none use aggregated household electricity demand data for low-income countries. This research gap hinders understanding of unique consumption patterns and elasticities in economically challenged areas, complicating the formulation of effective energy policies for low-income households (Nguyen et al., 2023).

High-income countries dominate the research landscape, contributing 58 % of disaggregated and 50 % of aggregated studies. This substantial research output indicates strong infrastructure and significant academic and policy interest in exploring household electricity demand in economically advanced regions (Wen et al., 2022). The extensive research on these countries offers detailed insights into consumption behavior, price responsiveness, and income effects, essential for crafting effective energy policies (Moya et al., 2023).

The data reveals an ordinal increase in publications across income groups, from low-income to high-income economies. Lower middle-

Table 5
Analysis of studies by country.

Country	Disaggregated		Aggregated		Country	Disaggregated		Aggregated	
	Freq.	%	Freq.	%		Freq.	%	Freq.	%
Australia			2	2.6	Mexico	1	2.6	1	1.3
Bangladesh	1	2.6			Mozambique	1	2.6		
Brazil	3	7.9	12	15.4	Namibia			1	1.3
Canada	1	2.6			Netherlands			1	1.3
Chile			1	1.3	New Zealand			1	1.3
China	3	7.9	7	9.0	Nigeria				
Cyprus			1	1.3	Norway	2	5.3		
Denmark			1	1.3	Pakistan	1	2.6	2	2.6
France	1	2.6			Seoul				
Germany	2	5.3			Singapore			1	1.3
Greece	2	5.3	10	12.8	South Africa				
Honduras			1	1.3	Portugal	3	7.9		
India	2	5.3	2	2.6	South Africa	1	2.6	4	5.1
Indonesia					South Korea	1	2.6	2	2.6
Iran			2	2.6	Spain	1	2.6	2	2.6
Israel			1	1.3	Sri Lanka	1	2.6	1	1.3
Italy	1	2.6			Switzerland			2	2.6
Jamaica			1	1.3	Taiwan	1	2.6	1	1.3
Japan	1	2.6	3	3.8	Turkey	1	2.6	3	3.8
Kenya	1	2.6			UK	1	2.6		
Kuwait			1	1.3	USA	5	13.2	9	11.5
Malaysia			2	2.6	**Total**	**38**	**100.0**	**78**	**100.0**

Table 6
Common sample descriptive analysis of income and price elasticities of demand.

	Disaggregated data studies		Aggregated data studies			
	HHIE	**HHPE**	**SRIE**	**SRPE**	**LRIE**	**LRPE**
Mean	0.314	−0.573	0.555	−0.408	0.773	−0.509
Median	0.280	−0.505	0.305	−0.300	0.700	−0.380
Maximum	1.010	−0.020	4.450	−0.004	1.970	−0.014
Minimum	0.010	−3.190	0.010	−2.480	0.040	−2.266
Std. Dev.	0.226	0.460	0.695	0.401	0.467	0.449
Skewness	0.895	−3.522	3.053	−2.403	0.679	−1.449
Kurtosis	3.495	20.582	15.885	11.85	2.753	5.045
Jarque-Bera	7.905	807.182	576.032	291.756	5.549	43.497
Probability	0.019	0.000	0.000	0.000	0.062	0.000
Observations	54.00	54.00	54.00	54.00	54.00	54.00

Table 7
Test for Equality of Means and Variances Between income and price Elasticities of demand.

Test for Equality of Means Between Elasticities				Test for Equality of Variances Between Elasticities			
Method	df	Value	Probability	Method	df	Value	Probability
Anova F-test	(5, 393)	104.983	0.000	Bartlett	5	67.826	0.000
Welch F-test*	(5, 178)	117.477	0.000	Levene	(5, 393)	5.834	0.000
*Test allows for unequal cell variances				Brown-Forsythe	(5, 393)	3.220	0.007

income countries surpass low-income countries in studies, and upper middle-income countries exceed these numbers further, culminating in the highest concentration in high-income nations. This trend highlights the correlation between a country's economic status and the volume of academic research it attracts.

5.2. Income and price elasticities of household electricity demand

The analysis of income and price elasticities from the reviewed articles elucidates electricity demand dynamics, distinguishing between disaggregated and aggregated data approaches. Table 6 reveals the generally inelastic nature of electricity demand across different dimensions and periods.

The average income elasticity of electricity demand in disaggregated data studies was 0.314, meaning a 1 % income increase leads to a 0.314 % rise in electricity demand. This inelastic response suggests electricity consumption does not significantly grow with income, classifying it as a household necessity (Jia et al., 2022; Tiedemann et al., 2023). The average price elasticity of −0.573 indicates that a 1 % rise in electricity prices causes a 0.573 % reduction in demand. Despite being relatively inelastic, demand is more sensitive to price changes than income changes (Jin and Kim, 2022; Liddle and Hasanov, 2022; Marques et al., 2024). This shows households moderately adjust their electricity usage in response to price hikes (Conway and Prentice, 2020; Deryugina et al., 2020).

In the short run, the income elasticity of household electricity demand was 0.555, indicating a moderate but inelastic increase in demand with rising income. Households slightly adjust their electricity usage based on immediate income changes (Boehm et al., 2023). In the long run, income elasticity increased to 0.773, showing that households more substantially adjust their electricity consumption over time as their income changes (Tiedemann et al., 2023). Nevertheless, the demand remains inelastic, emphasizing electricity's essential nature.

The short-run price elasticity of −0.408 indicates a modest decline in

Table 8
Income and Price Elasticity of household electricity demand by Region, Data Type, and Model Choice.

Region	Data type	Income Elasticity (Mean)	Income Elasticity (Range)	Price Elasticity (Mean)	Price Elasticity (Range)	Model Choice
East Asia & Pacific	Microdata	0.34	0.06–0.62	−0.40	−0.51 to −0.25	AIDS, OLS, QR
	Macrodata	0.63	0.01–1.52	−0.56	−2.43 to −0.05	ARDL, DOLS, ECM, FE, FRDD, GMM, OLS, PAM, PMG, RE, RSM, STM, TVP
Europe & Central Asia	Microdata	0.28	0.01–1.01	−0.61	−1.04 to −0.24	AIDS, DCA, DCCM, Deaton, FE, OLS, PP, QR, QUAIDS, RE
	Macrodata	0.84	0.14–4.47	−0.35	−0.80 to −0.01	ARDL, DPAM, ECM, LSDV, OLS, PAM, PSTR, QR, SAR, SPAM, STSM, TVP, VECM
Latin America & Caribbean	Microdata	0.36	0.32–0.70	−0.67	−3.19 to −0.05	ECM, OLS, QR, QUAIDS, SUR, VAR
	Macrodata	0.56	0.01–1.79	−0.33	−1.47 to −0.05	ARDL, DOLS, ECM, GMM, NLS, OLS, SURE, VAR, VECM
North America	Microdata	0.12	0.01–0.23	−0.63	−1.32 to −0.20	CDF, FD, FE, GLS, GMM, IV, OLS, PP
	Macrodata	0.36	0.05–1.00	−0.41	−1.07 to −0.08	ARDL, DPAM, ECM, FE, GMM, IV, OLS, PAM, SEM, SPAM
South Asia	Microdata	0.40	0.02–0.71	−0.33	−0.57 to −0.02	FE, OLS, POLS, QR, RE
	Macrodata	1.28	0.42–1.97	−0.47	−1.35 to −0.02	ECM, OLS, STSM, TVP
Sub-Saharan Africa	Microdata	0.52	0.13–0.85	−0.67	−1.16 to −0.19	2PM, AIDS, Deaton
	Macrodata	0.79	0.30–1.67	−0.22	−0.56 to −0.02	ARDL, ECM, TVP
Middle East & North Africa	Microdata	N/A	N/A	N/A	N/A	N/A
	Macrodata	0.82	0.04–1.09	−0.44	−1.22 to −0.02	CM, ECM, SURE

Abbreviations for the methods used are defined as follows: Almost Ideal Demand System (AIDS) Conditional Demand Functions (CDF) Difference-in-differences (DD) Discrete Continuous Choice Model (DCCM) Dynamic Ordinary Least Squares (DOLS) Dynamic Partial Adjustment Model (DPAM) Error Correction Model (ECM) First Difference (FD) Fixed Effects (FE) Fully Modified OLS (FMOLS) Fuzzy regression discontinuity DD (FRDD) Generalised Least Squares (GLS) Generalised Method of Moments (GMM) Instrumental Variable (IV) Least Squares Dummy Variable (LSDV) Non Linear Least Squares (NLS) Ordinary Least Squares (OLS) Panel Smooth Transition Regression (PSTR) Partial Adjustment Model (PAM) Pooled Mean Group (PMG) Pseudo-panels (PP) Quadratic Almost Ideal Demand System (QUAIDS) Quantile Regression (QR) Random Effects (RE) Response Surface Methodology (RSM) Seemingly Unrelated Regression (SURE) Spatial-autoregressive (SAR) Static Partial Adjustment Model (SPAM) Structural Equation Model (SEM) Structural Time Series Model (STSM) Time-Varying Parameter (TVP) Two-part Model (2PM) Vector Auto-Regression (VAR) Vector Error Correction Model (VECM)

electricity demand due to price increases (Rouhani et al., 2022). Households show limited immediate responsiveness to price changes, maintaining consumption due to electricity's necessity (Byrne et al., 2021; Jin and Kim, 2022). Long-run elasticity slightly increases to −0.509 (Conway and Prentice, 2020), suggesting a more notable adjustment in consumption as households find ways to reduce usage over time in response to sustained price hikes (Byrne et al., 2021; Hofmann and Lindberg, 2019). Despite this, the demand remains inelastic, underscoring the challenge of significantly reducing electricity consumption (Burke and Abayasekara, 2018; Matar, 2019; Sun and Yu, 2017).

Electricity demand remains consistently inelastic to both income and price across different data approaches and timeframes (Barkhordar et al., 2022; Franco et al., 2023), highlighting its essential role in daily life and its relative insensitivity to economic changes (Jin and Kim, 2022). Disaggregated data studies reveal nuanced household behaviors and slight variations, offering detailed insights (Franco et al., 2023; Liddle and Hasanov, 2022), while aggregated data studies capture average responses and general trends over time (Rawal and Ahmad, 2022; Tiedemann et al., 2023). Comparing short- and long-run elasticities in aggregated data shows that households exhibit limited immediate responses to economic changes but gradually adjust consumption more noticeably over time (Tiedemann et al., 2023), which is crucial for understanding and predicting long-term demand patterns (Anvari et al., 2022).

Significant ANOVA and Welch F-test results indicate that average income and price elasticities of electricity demand vary considerably across the examined groups, suggesting different populations, time periods, or contexts exhibit varied responsiveness to income and price changes (Jia et al., 2022; Tiedemann et al., 2023). Bartlett's, Levene's, and Brown-Forsythe tests show non-uniform variability of elasticities across groups, indicating some groups experience more variability in their responsiveness to income and price changes (Jin and Kim, 2022; Tiedemann et al., 2023). Understanding these variances is crucial for policymakers and researchers, emphasizing the complexity and diversity of factors affecting electricity demand elasticity.

5.3. Microdata (disaggregated) and macrodata (aggregated) in elasticity estimates

A key finding is that aggregated data tends to show higher income elasticity compared to disaggregated data, particularly in developing regions. This is because aggregated data captures broader economic trends where income growth leads to increased energy consumption at a national or regional level (Brookes, 1972; Gao et al., 2021; Liddle, 2022; Liddle and Huntington, 2020; Oberfield and Raval, 2021). In contrast, disaggregated data often reflects more stable consumption behavior as households reach income thresholds beyond which additional income does not significantly increase electricity demand (Rahmati et al., 2019)

One of the most notable distinctions between disaggregated and aggregated data is the higher price elasticity observed in disaggregated data. Disaggregated data captures the behavior of individual households, particularly lower-income groups, who are more sensitive to price changes due to fewer energy alternatives or tighter budgets (Tilov and Weber, 2023). Aggregated data, on the other hand, tends to show lower price elasticity, as it averages the consumption patterns of both price-sensitive and less price-sensitive households across a broader region (Franco et al., 2023)

This difference in elasticity is attributed to the aggregation of diverse household behaviors in aggregated data, which masks the heterogeneity observed in disaggregated data (Oberfield and Raval, 2021). The use of disaggregated data allows for a more nuanced understanding of consumer behavior, revealing significant variations in price sensitivity across different household segments (Tilov et al., 2020; Zhou and Teng, 2013). In contrast, aggregated data provides a more generalized view, which can be useful for broad economic analysis but may overlook specific behavioral patterns (Chetty et al., 2013). The implications of these differences are critical for policy-making, as they suggest that interventions based on aggregated data might not effectively address the needs of more price-sensitive groups (Baker et al., 1989; Oberfield and

Raval, 2021; Yilmaz et al., 2019; Zhou and Teng, 2013)

The statistical differences between disaggregated and aggregated data are evident in the wider ranges of elasticity estimates observed in disaggregated data. This is because disaggregated data captures the heterogeneous responses of different households to changes in income and price, leading to greater variability in the results. Aggregated data, on the other hand, tends to smooth out these variations, resulting in more moderate and stable estimates (Chetty et al., 2013; Oberfield and Raval, 2021).

The choice of econometric models also plays a significant role in shaping elasticity estimates, particularly when comparing disaggregated and aggregated data (Carlos Córdoba and Ripoll, 2019). Different models are employed depending on the level of data aggregation and the specific research question (Cooley, 1974; Klein, 1947). Disaggregated data often requires models that account for individual-level variations, while aggregated data is analyzed using models that capture long-term economic trends and relationships between variables (Stigum, 2014).

6. Conclusions and policy implications

6.1. Conclusions

A regional analysis of household electricity demand studies reveals significant research imbalances, with the MENA region and sub-Saharan Africa notably underrepresented. In contrast, Europe and Central Asia benefit from extensive research due to well-developed infrastructure. Addressing these gaps is crucial for fostering sustainable and inclusive energy policies globally.

The distribution of studies on household electricity demand by income level reveals a significant imbalance, with scant research in low-income countries. This underrepresentation hampers understanding of electricity consumption patterns in these regions. Conversely, the abundance of studies in high-income countries offers detailed insights and policy developments, highlighting the need for a more balanced research focus. Bridging this gap through targeted empirical studies in low-income countries is crucial for crafting effective energy policies that promote sustainable development and equitable energy access across all income groups.

Analysis of household electricity demand by income group highlights the urgent need for more empirical research in low-income countries. The underrepresentation of these regions in current literature constrains our understanding of electricity consumption patterns and the creation of effective, context-specific energy policies. Addressing this research gap is essential for promoting equitable and sustainable energy solutions globally, especially in economically challenging contexts where access to electricity is critical. While high-income countries benefit from extensive research, there is an urgent need to focus academic and policy attention on low-income countries. This approach ensures that energy policies and interventions are inclusive and effectively address the needs of all income groups.

Analyzing the income and price elasticities of electricity demand with both disaggregated and aggregated data reveals consistent inelasticity, emphasizing electricity's essential role in households and the minimal influence of income and price changes on consumption. These insights are vital for formulating informed policies and effective energy management strategies to ensure a stable, sustainable energy future.

An analysis of tests for equality of means and variances identified significant differences in the income and price elasticities of electricity demand among different groups. The mean elasticities and their variances vary considerably, indicating the complex and heterogeneous nature of electricity demand responsiveness. These results have crucial implications for policy design and future research, underscoring the necessity for context-specific approaches and a deeper understanding of factors influencing electricity demand elasticity.

The analysis highlights significant differences in elasticity estimates across regions, influenced by both the type of data used and the underlying socio-economic conditions of each region. Disaggregated data provides a more detailed and nuanced understanding of household behavior, particularly in regions with significant income inequality, where lower-income households are more sensitive to both income and price changes. Aggregated data, while useful for capturing broader economic trends, tends to smooth out these variations, leading to lower estimates of price elasticity and higher estimates of income elasticity. Policymakers should take these regional differences into account when designing energy policies, ensuring that interventions are tailored to the specific needs and behaviors of households in different income brackets and regions.

6.2. Policy implications

Regional disparities in household electricity demand research have significant implications. The scarcity of studies in the MENA region and sub-Saharan Africa indicates these areas may miss out on evidence-based policies suited to their consumption patterns and economic conditions. Conversely, extensive research in Europe and Central Asia has allowed these regions to create refined and effective energy policies. Bridging these research gaps is essential for promoting equitable energy solutions and enabling all regions to optimize electricity consumption and achieve developmental goals efficiently.

The significant research gap in low-income countries profoundly affects policymakers, who lack essential data to understand household electricity demand accurately. This deficit hinders the creation of targeted interventions to improve access, affordability, and efficiency. In such contexts, where households are more sensitive to price changes, understanding elasticity is crucial for designing subsidies and pricing strategies that do not worsen poverty or restrict energy access.

The limited research in low-income regions impedes understanding unique electricity consumption patterns and demand elasticity, essential for effective pricing strategies and policy interventions. This gap hampers tailored solutions for better electricity access, affordability, and infrastructure in economically challenged areas, highlighting the urgent need for more academic and policy attention to promote equitable energy solutions and support global sustainable development goals.

Policymakers must account for the inelastic nature of electricity demand when designing price-based interventions or subsidies. Since demand remains relatively stable despite income or price changes, policies should prioritize efficiency improvements and alternative energy sources. Detailed disaggregated data can inform targeted interventions for specific household groups, addressing unique consumption patterns and economic sensitivities. Understanding the differences between short- and long-run elasticities is crucial for long-term energy planning. These insights enable policymakers to forecast future demand and develop strategies for gradual consumption changes. Considering the heterogeneous nature of electricity-demand elasticities is vital, as uniform policies may be ineffective across different groups due to significant differences in elasticity means and variances.

A clear pattern emerges from the data: regions with lower income levels and greater economic inequality tend to exhibit higher price elasticities, especially when disaggregated data is used. This suggests that poorer households in these regions are more vulnerable to price changes, and any increase in electricity prices could disproportionately impact their energy consumption. In contrast, wealthier regions tend to show lower price elasticities, reflecting the ability of households to absorb price increases without significantly reducing their electricity use.

Income elasticity, on the other hand, tends to be higher in developing regions where economic growth is driving increased electricity demand. Aggregated data often amplifies this trend, as it captures the overall rise in consumption at the national level. However, disaggregated data reveals that at the household level, income gains do not always translate into proportional increases in electricity demand, particularly among wealthier households who have already saturated their electricity needs.

The differences in elasticity estimates between disaggregated and aggregated data have important implications for both policymakers and researchers. Policymakers who rely solely on aggregated data may underestimate the sensitivity of lower-income households to price changes, leading to energy policies that are less effective at addressing the needs of vulnerable populations. For example, aggregated data may suggest that price increases will have a moderate impact on overall electricity demand, while disaggregated data reveals that low-income households are likely to reduce their consumption dramatically in response to price hikes.

6.3. Further research

Future research should investigate the factors affecting the inelastic nature of electricity demand and potential regional variations. Additionally, examining the impact of technological advancements and energy efficiency measures on these elasticities can yield valuable insights. These findings highlight the importance of context-specific studies and the need to consider variance heterogeneity in analyses, aiming to uncover the causes of these differences for more tailored energy policies.

For researchers, the choice between disaggregated and aggregated data, and the corresponding models used, affects the accuracy and relevance of elasticity estimates. Studies using disaggregated data provide a more detailed understanding of household behavior, which is crucial for designing targeted interventions, such as subsidies or tiered pricing schemes aimed at protecting low-income households. Aggregated data, on the other hand, is valuable for understanding broader economic trends and long-term shifts in electricity demand, making it useful for large-scale policy planning and infrastructure development.

Ethical Approval: Further research

This study never involved human subjects and got ethical clearance from relevant authorities.

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Geoffrey Mubiinzi: Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Twaha Kigongo Kaawaase:** Supervision, Resources, Conceptualization. **Livingstone Senyonga:** Validation, Supervision. **Muyiwa Samuel Adaramola:** Writing – review & editing, Visualization, Validation, Supervision, Conceptualization. **Francis Wasswa:** Writing – review & editing, Validation, Supervision. **Mary Nantongo:** Validation, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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