Economics Development Analysis Journal Vol. 15 (1) (2026)

Economics Development Analysis Journal

http://journal.unnes.ac.id/sju/index.php/edaj

Household Carbon Footprint: How Does Age Structure Affect Emissions?

Meli Nopiyani[1]✉ , [2]Djoni Hartono

[1,2]Department of Economics, Faculty of Economics and Business, Universitas Indonesia

Article Information

History of Article
Received December 2025
Accepted April 2026
Pusblished June 2026

Keywords:
Average age, household carbon emissions,
life cycle

Abstract

This study analyzes the influence of household age structure on carbon emissions in Indonesia using a quantitative approach based on micro-level survey data. Employing an Ordinary Least Squares (OLS) regression model, it introduces the average age of household members and its squared term to capture potential non-linear effects. The results reveal a non-linear, inverted U-shaped relationship between household age and per capita carbon emissions. The turning point occurs at approximately 36 years, suggesting that households with members around this average age tend to have the highest emissions, which then decline as the average age increases further. This finding aligns with the Life-Cycle Hypothesis, which posits that households in their productive years exhibit more energy-intensive consumption patterns. In addition, the study explores variations in emissions across different household age compositions those dominated by children, adults, and elderly structures. By incorporating these classifications, along with relevant socio-economic and physical household characteristics, the analysis provides deeper insights into how demographic profiles shape energy use and emissions. These findings offer valuable input for developing more targeted and equitable low-carbon policy interventions.

✉ Corresponding author :
Address: 2Department of Economics, Faculty of Economics and Business, Universitas Indonesia
E-mail: meli.nopiyani@ui.ac.id,

ISSN 2252-6560

INTRODUCTION

Climate change due to increasing carbon dioxide (CO_2) emissions has become a central issue for global development, mainly driven by human activities such as the burning of fossil fuels and inefficient energy consumption (IPCC, 2021). If this trend continues, global temperatures are projected to rise by more than 2°C by the end of the century. The household sector contributes to emissions both directly (e.g., electricity and fuel use) and indirectly through the consumption of goods and services (Oswald et al., 2020). To achieve net zero emissions, not only technological innovation is needed, but also changes in lifestyle and energy consumption behavior (Ivanova & Wood, 2020; Velenturf & Purnell, 2021; Wiedmann & Allen, 2021). Household energy consumption, including the use of electronic devices, fuels, and consumption of goods, contributes greatly to emissions (Li et al., 2024; Oswald et al., 2020).

In Indonesia, the household sector contributed around 12.97% of national energy consumption in 2022, down from 14% in 2018. However, in absolute terms, household energy consumption is increasing along with the growth of the middle class and urbanization. Household emissions are influenced by energy consumption behavior (Xue, 2020), income (Buchs & Schnepf, 2013), as well as lifestyle factors and interactions between household members. While a study by Alyasa et al. (2023) showed that income and household size have a significant effect on emissions, there remains a critical research gap as the role of age structure in Indonesia's emission dynamics has not been fully considered. Age structure significantly influences consumption patterns (Gough et al., 2011), making it essential to analyze how these demographic changes impact carbon emissions (Hu et al., 2025).

Family Life Cycle Theory explains that households experience life stages from pre-marriage, marriage, childcare, to old age that influence household structure and consumption behavior (Glick, 1955). Wells and Gubar (1966) later developed this theory in the context of consumer behavior, linking each phase of family life to a distinctive consumption pattern.

In the context of energy consumption and carbon emissions, this theory is relevant because each life stage brings changes in family size, income, and consumption preferences (Fritzsche, 1981; Liddle & Lung, 2010). For instance, energy consumption often increases with the presence of children and decreases as they reach adulthood (Fritzsche, 1981), while modern household structures and evolving gender roles introduce new dimensions to these patterns (Murphy and Staples, 1979). Furthermore, the STIRPAT approach indicates that middle-aged households (40–60 years old) often produce the peak emissions, whereas elderly households contribute through the use of less efficient appliances (Liddle & Lung, 2010). This aligns with the Life-Cycle Hypothesis (Modigliani & Brumberg, 1954), which links consumption to lifelong income patterns, and the influence of the social environment on the elderly (Glass and Balfour, 2003). Recent evidence by Hu et al. (2025) further suggests a non-linear relationship, where per capita emissions increase until an average age of 61 before declining.

Departing from the common use of discrete categories, this study implements a non-linear framework using average age and its quadratic term to capture inverted U-shaped effects, following the methodological refinement of Hu et al. (2025). This approach recognizes that as average household age increases, preferences reflect the collective physiological and psychological needs of all members. Consequently, variations in age composition generate differences in consumption behavior across households, which are reflected in differences in emissions and energy use because all activities that produce emissions are not only decided by one head of the family (Hu et al., 2025).

This research framework measures carbon emissions through the integration of household consumption data and the national Input-Output Table using both emission coefficient and input-output methods (Li et al., 2015; Hu et al., 2025). This dual approach allows for the classification of direct emissions originating from generator consumption, cooking fuel and personal transportation. Indirect emissions originate from the consumption of food, clothing, goods and services, housing, and entertainment.

Previous studies such as Buchs & Schnepf (2013) and Gough et al. (2011) also support that demographic variations in households significantly affect carbon footprints. Furthermore, changes in age structure drive behavioral shifts that directly impact emissions (Basso et al., 2023), mediated by socio-economic factors such as education, income, and regional characteristics (Burgess and Whitehead, 2020). By utilizing large-scale micro-data, this study provides an empirical foundation for climate and energy policies that are better aligned with demographic dynamics. Such evidence is particularly important for Indonesia, where rapid urbanization, population ageing, and middle-class expansion are reshaping long term emission dynamics.

This study contributes to the literature by extending the demographic carbon nexus analysis to an emerging economy experiencing simultaneous urbanization and population ageing. Unlike previous studies that primarily focus on aggregate demographic indicators, this research provides micro-foundation evidence on how household age composition influences both direct and indirect carbon footprints. The empirical findings are expected to support the formulation of socially inclusive climate mitigation policies that account for structural demographic change, consumption behavior heterogeneity, and future population ageing risks. Understanding demographic drivers of emissions is essential for designing sustainable development strategies that are aligned with long-term socio-economic transformation.

RESEARCH METHODS

This study aims to analyze the effect of household age structure on carbon emission levels, by combining direct and indirect emission estimation approaches. Household carbon emissions are calculated as dependent variables derived from two main sources, namely direct energy consumption (direct emissions) and indirect consumption (indirect emissions). The unit of analysis is the household, with data sourced from the 2023 National Socioeconomic Survey (Susenas). This data is cross-sectional and provides detailed information on energy consumption, demographic characteristics, and household socio-economics. To further refine the demographic analysis and overcome misleading proportions between age and number of households, this study is still classified into several age categories of children (<15 years), productive adults (15–64 years), and the elderly (≥65 years). This classification aims to capture variations in demographic composition and their implications for energy consumption and carbon emissions.

Following this categorization, the measurement of emissions is carried out using a method referring to the Intergovernmental Panel on Climate Change (IPCC, 2006) guidelines for direct emissions, and the input-output approach from the Asian Development Bank (ADB) for indirect emissions based on 35 household consumption sectors.

Direct emissions are calculated from household fuel consumption such as gasoline, diesel, kerosene, LPG, and firewood, multiplied by the calorific value and emission factor of each fuel based on the IPCC Tier 1 method. Calculation for direct emissions:

$$HCEs_{direct} = EC \times CV \times EF \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where $HCEs_{direct}$ denotes total carbon dioxide (CO_2) produced (kg CO_2), Energy Consumption (EC) represents the amount of energy used (kWh, liters, or kg), Caloric Value (CV) refers to the caloric value per unit of fuel, and Emission Factor (EF) is the CO_2 produced per unit of energy.

For indirect emissions, which include emissions from consumption of food, clothing, housing, education, and services, an input-output model based on the Leontief approach is used. The calculation formula is:

$$HCEs_{indirect} = F(I-A)^{1}Y \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Technically, indirect HCE is calculated by multiplying the carbon emission intensity of the industrial sector *(F)* by the total economic demand factor matrix *$(I-A)^{1}$*, then multiplied by the household expenditure matrix *(Y).* This study first groups the industrial sectors that correspond to each category of household consumption expenditure based on 35 ADB sectors.

Previous research has identified a non-linear (inverted U-shaped) relationship between household age structure and carbon emissions. Several studies consistently show that the relationship between the average age of household members and carbon emissions follows this non-linear pattern. Zhang et al. (2023), in a global study, found that households with a middle average age tend to produce higher carbon emissions compared to both younger and older households. This finding is further supported by Hu et al. (2025), who observed that energy consumption preferences and behaviors shift with age, leading to a non-linear impact on total household emissions. Accordingly, a quadratic regression model is appropriate for capturing this relationship.

$$HCEs_i = \alpha_0 + \beta_1 Mage_i + \beta_2 Mage_i^2 + \gamma X_i + \mathcal{E}_i \text{ ....(3)}$$

The regression model used in this study is specified as follows: $HCEs_i$ represents household carbon emissions per capita for household i, measured in kilograms of CO_2 per person per year. The key explanatory variable is $Mage_i$, the average age of household members, along with its squared term $Mage_i^2$, included to capture potential non-linear effects (such as an inverted U-shaped relationship) between age and carbon emissions. In addition, X_i denotes a set of control variables including household size, education level, income, cooking fuel type, home ownership status, and residential location. All unexplained variation is captured by the error term $\mathcal{E}_i$.

Table 1 presents the operational definitions of variables used in the study. It outlines the dependent variable Household Carbon Emissions (HCEs) and several independent and control variables such as household age structure, size, income, education, home ownership, cooking fuel type, and location. Each variable is described by its definition, data type (continuous or dummy), and unit of measurement, ensuring clarity in how variables are measured and analyzed throughout the research.

Table 1 Definitions Operational Variables

Variables	Definition	Data Types	Unit
Variables Dependent			
Household Carbon Emissions (HCEs)	Consumption conversion use energy House ladder	Continuous (Log)	Kg CO_2 per year
Variables Independent			
Structure Age	Average age of members in House ladder	Continuous	Year
Control			
Size House Ladder	The amount member house ladder	Continuous	Person
Income	Income house ladder	Continuous (Log)	Rupiah per year
Education	Average home education ladder	Continuous	Year
Home Ownership	Ownership status house	Dummy	1: Owned 0: Rent
Cooking Fuel	Type material burn main for cook	Dummy	1: Modern (LPG, Electric) 0: Traditional
Location	Location (Urban, Rural)	Dummy	1 = Urban, 0 = Rural

Source: Susenas Data Processed, 2025

RESULTS AND DISCUSSION

Table 2 presents descriptive statistics on average household carbon emissions based on Susenas data covering 341,802 households in Indonesia. Emissions are calculated in two main components, namely direct emissions and indirect emissions. The average direct emissions per household were recorded at 984.51 kg CO_2, while indirect emissions were higher, at 1245.18 kg CO_2. Overall, the average total household carbon emissions reached 2229.69 kg CO_2 per year. If calculated per capita, this figure is equivalent to 708.72 kg CO_2 per person per year.

The distribution exhibits substantial right skewness, as indicated by a maximum value of 197,902 kg CO_2. This upper tail dispersion likely reflects very high-income households with disproportionately large consumption capacity. Such households typically generate higher emissions through greater energy use, including private vehicle ownership, energy intensive appliances, larger dwelling sizes, and intensive airconditioning use. This interpretation aligns with prior evidence documenting a positive association between income and household carbon emissions (Hu et al., 2025).

To ensure that such outliers do not bias the regression estimates, the dependent variable is log-transformed and robustness checks excluding upper-percentile values are performed. The results remain consistent, indicating that the main findings are not driven by these extreme observations.

In this study, the estimate of household carbon emissions per capita obtained from Susenas data and the IO-ADB approach shows a figure of around 708.72 kg CO_2 per capita per year. This value is considered reasonable and in line with relevant international and domestic literature and data sources. According to references from Wiedenhofer et al. (2017), the average household carbon emissions in developing countries range from 0.5 to 2 tons of CO_2 per capita per year.

The main variables analyzed were the average age of household members and its square, to test for a possible non-linear relationship (inverted U-curve) to carbon emissions, as supported by Hu et al. (2025). The average age was 36.03 years (median 32.25; range 8–97), and the average age square was 1,535.21, indicating a fairly large variation in age structure across households.

The household size had an average of 3.58 people (median 4; range 1-25), which represents the potential for scale efficiency in energy consumption. The average education of 7.04 years was used as an indicator of energy literacy and the ability to choose energy saving technologies. Household income per capita in log form has a mean of 16.52 (SD: 0.65), reflecting higher economic capacity and indirect consumption in high-income households.

Physical characteristics of the house include home ownership (mean 0.85) and use of modern cooking fuels (mean 0.76), indicating that the majority of households have used LPG or electricity. Finally, 42% of households live in urban areas, which is controlled through dummy variables to capture geographic differences in infrastructure access and consumption patterns.

Table 2 Summary of Analysis Variable Statistics

Variables	Amount Observation	Mean	Median	Standard Deviation	Min	Max
Household Carbon Emissions	341.802	2229.689	1633.926	2440.68	14,244	197902.8
Structure Age	341.802	36,032	32.25	15,390	8	97
Structure Age (*Squared)*	341.802	1535.205	1040.063	1344.512	64	9409
Size House Ladder	341.802	3.5791	4	1.5863	1	25
Education	341.802	7.0365	6.75	3.3883	0	22
Income (Log)	341.802	16.5186	16.4621	0.6461	14.211	20,924
Home Ownership	341.802	.849793	1	0.3572	0	1
Cooking Fuel	341.802	.764600	1	0.4242	0	1
Location	341.802	0.41958	0	0.4934	0	1

Source: Susenas Data Processed, 2025

The descriptive analysis in Figure 1 breaks down direct and indirect consumption in more detail to see the proportion or distribution of household emissions based on the average age of household members. Indirect emissions primarily resulting from the consumption of goods and services such as food, housing (including rent and electricity), and other consumables demonstrate an increasing trend with the rise in the average age of household members.

This reflects the increasing demand for convenience and services, especially in elderly households. In contrast, direct emissions from energy use such as cooking fuel and transportation are relatively stable, with no clear pattern of increase or decrease. This is likely due to the constant basic energy needs and limitations in technological change or energy access across age groups. Classification of groupings per sector *(Appendix 1)*

Consumption patterns in older households show a shift from quantity to quality, with an increase in consumption of high-carbon goods such as electronics, medical devices, and furniture, which still allow emissions even though the volume of consumption is low. In addition, the category of housing and other goods shows a significant upward trend in emissions in older ages, indicating that even though the number of household members decreases, basic energy consumption (such as electricity) continues, increasing per capita emissions, a phenomenon known as the household size paradox.

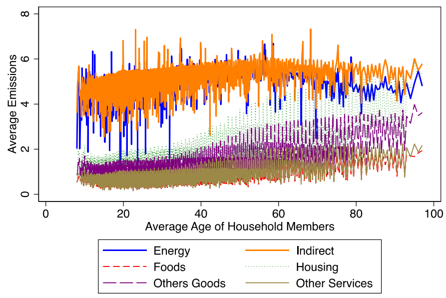

Figure 1. Distribution of Average Emissions and Average Age of Household Member
Source: Susenas Data Processed, 2025

Meanwhile, emissions from food and other services remain low and stable, except for a slight increase in health services in the elderly group. The large fluctuations in young ages, especially under 30 years, reflect the high heterogeneity in the structure of young households. Overall, these findings suggest that age affects the structure of household carbon consumption and emissions in a complex manner, and support the need for a non-linear regression approach in the analysis, in line with the visual pattern in Figure 1.1.

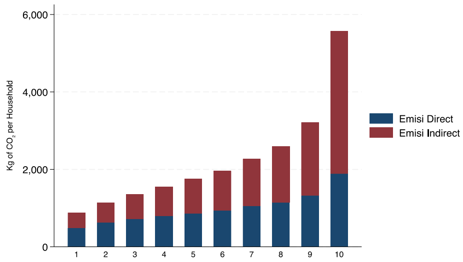

Figure 2. The average household carbon emissions per income decile
Source: Susenas Data Processed, 2025

It can be seen that both direct and indirect emissions increase with increasing income levels in Figure 2, with the sharpest spike occurring in the 10th decile (the richest group). This pattern confirms that high-income households have a much greater intensity of energy and goods/services consumption than lower-income groups, consistent with the findings of Gough et al. (2011) and Irfany & Klasen (2016) which highlight the disparity in carbon emissions across economic groups in developing countries.

The regression results in Table 1.3 show that the average age of household members has a significant effect on carbon emissions per capita. The initial model (Column 1) shows that every one-year increase in average age is correlated with an increase in emissions of 0.85% (coefficient 0.0085; $p < 0.01$), although with a low R^2 (0.0242). The model (Column 2) adds a quadratic component and shows a non-linear inverted U-shaped pattern, with a positive age coefficient (0.0472) and a significant negative age^2 (-0.0005), supporting the Life Cycle Hypothesis (Modigliani & Brumberg, 1954) and the findings of Hu et al. (2025).

The advanced models (Columns 3-5) include household socio-demographic and physical control variables. Household size has a negative impact on emissions (-0.0198), indicating economies of scale (Hu et al., 2025), while education has a positive impact (0.0393), reflecting the tendency of highly educated households to lead more consumptive and carbon-intensive lifestyles (Büchs & Schnepf, 2013; Li et al., 2024). The use of modern fuels (LPG/electricity) also shows a significant increase in emissions (0.4835), in line with Sun & Lu (2023) findings on the rebound effect of the clean energy transition. The final model shows that renter status and urban location significantly increase emissions, likely related to limited access to efficient technologies and intensive consumption patterns in urban areas. This model has the highest R^2 (0.7385), indicating that the combination of demographic, economic, and environmental variables explains about 74% of the variation in emissions. Although the coefficient of age is small (0.0022 in Model 5), its effect is statistically significant and reflects marginal but consistent changes in consumption.

The emission turning point occurs at the age of 36, a phase when households are at their peak consumption due to the need for children's education, high mobility, and home ownership of more complete goods. After this age, consumption and emissions tend to decline. To gain a more substantive understanding of the magnitude of the influence of household age structure on carbon emissions, this study adopts a standard deviation-based interpretation approach as applied in previous studies by Kis-Katos and Sparrow (2015) and Baker and Nasrudin (2021). This approach allows the transformation of the regression coefficients in the log-linear model into a more understandable economic meaning, namely in the form of a percentage change. Based on the results of the main model estimation, the average coefficient of household member age on the carbon emission log is 0.0022. Considering that the standard deviation (SD) of the age variable in this study sample is 15.39 years, the effect of age changes is one standard deviation 0.0338. Furthermore, to translate changes in the emission log into percentage changes, the exponential transformation formula ($e^{0.0338}$) is used. Thus, these results indicate that an increase in the average age of household members by one standard deviation (about 15.39 years) correlates with an increase in carbon emissions of 3.44%. Given that the average total emissions are 708.7196 Kg CO_2, a 3.44% increase means an increase of about 24.4 Kg CO^2 per capita for every one standard deviation increase.

The magnitude of the increase of 3.44% can be categorized as a statistically significant and economically substantial change, especially in the context of climate change issues and carbon emission control efforts. Although numerically small, on a large population scale, the cumulative impact of demographic shifts such as population aging can contribute significantly to the increase in total national carbon emissions. This finding strengthens the argument that household age structure remains an important factor influencing household carbon footprint, even after considering various other control variables such as household size, education level, income, home ownership, type of cooking fuel, and location of residence. This standard deviation-based approach provides a more intuitive and communicative way of conveying results to policymakers and stakeholders, so that the results of the study are not only relevant in a statistical context but also in evidence-based decision making. This pattern is in line with the findings of Hu et al. (2025) who showed a similar non-linear relationship in China, with a turning point at an average age of 61 years. The difference in turning point figures can be explained by the different structural contexts and consumption cultures between Indonesia and China. In Indonesia, households tend to form a nuclear family structure more quickly and start large consumption at a younger age, while in China, high consumption occurs in middle to old household members due to urbanization factors and slower wealth accumulation. However, the direction of the relationship remains similar, namely increasing emissions with age up to a certain point, then gradually decreasing.

This finding is also in line with Liddle & Lung (2010), who through the STIRPAT approach found that productive-age households (around 40-60 years old) contribute the highest emissions because they are in the peak income phase, high mobility, and greater asset ownership. In addition, Xue et al. (2020) emphasized that household carbon emissions are greatly influenced by changes in consumption preferences based on the family life cycle. The age of young household members is more energy efficient due to high mobility outside the home and limited ownership of goods, while middle-age household members start to make large expenditures, such as vehicles, electronic equipment, and household comfort. On the other hand, the age of elderly household members experiences a decrease in consumption along with decreasing mobility needs, decreasing number of household members, and shifting to a more frugal lifestyle.

Table 3. OLS Regression Results: Effect of the Average Age of Household Members on Carbon Emissions

	(1) Baseline	(2) Squared	(3) + RT Characteristics	(4) +Economy	(5) + Environment
Age	0.0085 ***	0.0472 ***	0.0013 ***	0.0014 ***	0.0022 ***
	(0.0001)	(0.0005)	(0.0003)	(0.0003)	(0.0003)
Age *(Squared)*		-0.0005 ***	-0.0000274 ***	-0.0000188 ***	-0.0000307 ***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Size House Ladder			-0.0198 ***	-0.0179 ***	-0.0215 ***
			(0.0008)	(0.0007)	(0.0007)
Education			0.0393 ***	0.0324 ***	0.0281 ***
			(0.0003)	(0.0003)	(0.0003)
Income			0.9564 ***	0.9191 ***	0.9041 ***
			(0.0017)	(0.0015)	(0.0015)
Cooking Grill				0.4835 ***	0.4551 ***
				(0.0023)	(0.0022)
Home Ownership					0.0134 ***
					(0.0020)
Location					0.1390 ***
					(0.0015)
Constant	5.8917 ***	5.1911 ***	-9.8083 ***	-9.5379 ***	-9.3065 ***
	(0.0037)	(0.0089)	(0.0280)	(0.0252)	(0.0251)
Observation	341802	341802	341802	341802	341802
F	7293.8865	8057.8603	123106.0783	127369.4069	98416.7690
R^2	0.0242	0.0453	0.6761	0.7329	0.7385

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.0$
Source: Susenas Data Processed, 2025

The regression results show that household size has a negative effect on carbon emissions per capita (-0.0215), supporting the concept of economies of scale. In contrast, education shows a positive effect (0.0281), reflecting that educated households tend to live a more modern and carbon-intensive lifestyle. Income is the most dominant factor (0.9041), indicating that a 1-unit increase in log income (about 2.7 times) is correlated with a 90% increase in emissions, as also emphasized by Buchs & Schnepf (2013) and Ivanova & Wood (2020). The use of modern fuels (0.4551) also increases emissions, indicating that the energy transition in Indonesia is not yet efficient. The variables of home ownership and urban location also have a positive effect, where urban households have around 13.9% higher emissions due to greater access to carbon-intensive goods, services, and energy. The addition of a non-linear age structure strengthens the analysis model, where the inverted U-shape pattern remains significant and consistent throughout the model, with a turning point around 36 years. This indicates that middle-aged households are the highest contributors to emissions, along with increasing needs of active households (children's education, mobility, and ownership of goods). This finding fills a gap in the Indonesian literature such as the study by Alyasa et al. (2023) which has not explicitly considered the role of age structure. Overall, the final model explains 74% of the variation in carbon emissions (R^2= 0.7385), indicating that the combination of demographic, socio-economic, and environmental factors is able to capture the complexity of household consumption behavior. Although the effect of age is relatively small numerically, its influence is statistically significant and systematic and cumulative. This finding supports the importance of a life cycle and household structure-based approach in designing more targeted carbon mitigation policies.

Table 1.4 shows that the average household age has a significant positive effect on carbon emissions per capita (0.0037), while its square is significantly negative (-0.0000333), confirming the inverted U-shape pattern consistent with the Life Cycle Hypothesis (Modigliani & Brumberg, 1954). Emissions increase in productive age and decrease in old age.

Analysis based on age composition shows that households dominated by the elderly have lower emissions than the adult group (-0.0584), while households dominated by adults and children show the highest emissions (0.0527). Multigenerational households (children-elderly) exhibit the lowest emissions (-0.1784), indicating a conservative consumption pattern and cross-generational substitution, consistent with the findings of Sun and Lu (2023).

The control effects remain consistent, household size decreases emissions (-0.0210), while education, income, modern fuels, and urban location have positive effects on emissions. Adult-elderly households also showed a decrease in emissions (-0.0196), supporting the argument that the presence of elderly people plays a role in reducing consumption intensity in adult households. In contrast, the combination of adults and children increases emissions, reflecting the dual energy needs of adult productivity and children's growth and development needs.

Households with a child and elderly structure have the lowest emissions (-0.1784) which is very important from a policy perspective. This type of household has the potential to be a primary target for energy efficiency interventions and clean energy subsidies because they have a low consumption. Thus, this result is in line with the energy justice distribution approach that emphasizes the importance of designing policies based on structural vulnerability, not just consumption quantity.

Overall, this analysis shows that household age structure is not only a demographic predictor, but also a strong determinant of household lifestyles, energy needs, and carbon footprints. Therefore, energy transition programs and emission reduction policies need to consider household age composition as a key factor in evidence-based policy planning and targeting.

With an R^2 of 0.7391, the model explains 74% of the variation in per capita emissions, highlighting the strong influence of age structure and household socio-demographics.

Figure 3 shows that households dominated by "adults" and "adults & elderly" have the highest average per capita emissions, while those dominated by children and elderly have the lowest emissions. However, when controlled for other variables in the regression model Table 4.8, the pattern shifts. The effects of age structures such as "adults & children" appear to have a positive contribution to emissions, indicating that after controlling for income, household size, and other variables, these structures contribute more emissions than they appear in the raw data. In contrast, "children & adults" households remain consistent as the group with the lowest emissions contribution in both the descriptive and regression data, reflecting conservative consumption patterns across generations.

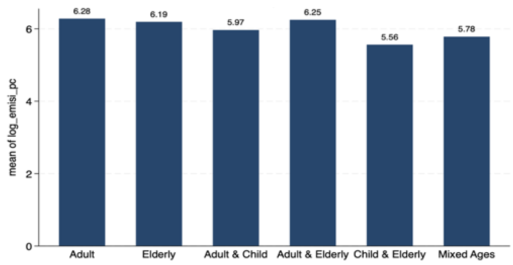

Figure 3. Bar Chart Based on Group Age
Source: Susenas Data Processed, 2025

Differences in carbon emissions across household age structures stem from variations in life stages, lifestyles, and consumption patterns that are typical for each age group. Households dominated by adults tend to show high consumption because they are at the peak of their productivity and mobility.

In contrast, households dominated by the elderly or a combination of children and elderly tend to have more frugal energy consumption, conservative lifestyles, and expenditures that are more focused on basic needs. Income factors, access to modern technology, and resource sharing habits also help explain significant differences in emissions between these groups. This finding is consistent with the life cycle theory (Modigliani & Brumberg, 1954).

Table 4. Regression Results with Additional Age Category Variables

Variables	(1)
Age	0.0037 ***
	(0.0003)
Age *(Squared)*	-0.0000333 ***
	(0.0000)
Mature	0.0000
(Reff . Adult)	(.)
Elderly	-0.0584 ***
	(0.0054)
Adults & Children	0.0527 ***
	(0.0024)
Adults & Seniors	-0.0196 ***
	(0.0045)
Children & Seniors	-0.1784 ***
	(0.0207)
Age Mixture	0.0291 ***
	(0.0051)
Size House Ladder	-0.0210 ***
	(0.0007)
Education	0.0288 ***
	(0.0003)
Income	0.9037 ***
	(0.0015)
Home Ownership	0.0133 ***
	(0.0020)
Cooking Fuel	0.4538 ***
	(0.0022)
Location	0.1381 ***
	(0.0015)
Constant	-9.3637 ***
	(0.0256)
Observation	341802
F	60743.8598
R^2	0.7391

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Susenas Data Processed, 2025

The results of the main regression analysis show that the domestic age structure plays a significant role in influencing the level of carbon emissions per capita, especially through the pattern of non-linear relations in the form of inverted U-Shape. That is, households with medium average age (productive) produce the highest carbon emissions, while young households and the elderly tend to produce lower emissions. These findings not only support the Life Cycle Hypothesis (Modigliani & Brumberg, 1954), but also provide continuous empirical evidence of the Hu et al. (2025), showing that household energy consumption follows the life cycle, increases with the need for productivity and economic stability, then decreases in line with the reduced activity and consumption needs in old age.

The important discussion of this finding lies in the identification of the "peak phase of energy consumption". The turning point of this non-linear relationship provides a picture of the average age of households that are most at risk of high emissions. In the context of Indonesia, this phase often correlates with the time when the household already has children who go to school, have settled, and have high purchasing power. This condition results in an increase in electricity consumption, transportation, and purchase of carbon intensive household goods. Therefore, domestic age is not only biological indicators, but also structural indicators that describe the level of accumulation of consumption and lifestyle preferences.

Furthermore, analysis based on the composition of the age group in the household adds an equally important dimension. Households dominated by the elderly have lower emissions, not merely due to decreased purchasing power, but also due to adjusting lifestyle towards more energy-efficient consumption (Basso et al., 2023). This shows that the elderly play the role of a potential actor in reducing emissions, both directly through consumption patterns and indirectly through conservative values carried in the household.

Conversely, households consisting of productive adults and children show the highest level of emissions, reflecting the conditions of multiple consumption where the productivity needs and mobility of adults combined with the child's growth and development needs. This category is a key group that requires special attention in the formulation of household energy intervention policies.

One of the most interesting findings emerged from multigeneration groups with a combination of children and the elderly, which actually had the lowest emissions. This indicates that cross - generation interactions in the household can create more efficient consumption patterns, through the effects of consumption substitution and sharing resources. This phenomenon is consistent with the findings of Sun and Lu (2023), which states that the family's social structure also moderates carbon intensity.

CONCLUSION

This study examines the relationship between household age structures and carbon emissions in Indonesia using large -scale micro data from Susenas (341,802 households). The results of the analysis show that the average age and composition of age groups significantly affect carbon emissions, with inverted U-Shape patterns that consistently increase emissions at productive age and decrease at the age of the elderly in line with the life cycle hypothesis theory (Modigliani & Brumberg, 1954; Hu et al., 2025). Households with productive age dominance tend to have the highest emissions, while the combination of children is actually the lowest. Other variables such as education, income, type of fuel, and location also have a significant affecting emissions. Although limited to cross-section data and has not yet observed dynamic consumption behavior, this study contributed new empirical to the study of household carbon in Indonesia.

In terms of policy, these results emphasize the importance of including demographic dimensions into the national emission reduction strategy. Interventions should be focused on productive age households through energy saving technology incentives, green consumption education, and carbon -based price policies for high income groups. In urban areas, policies need to be directed at low public transportation emissions and reduction of carbon intensive consumption, while in rural areas it is important to ensure fair access to net energy. Considering the transportation sector contributes significant emissions to adult households, strategies such as electric vehicle incentives and strengthening the low carbon mobility system are also key. Public awareness campaigns based on household structure need to be encouraged so that energy transitions can take place more fairly, inclusive, and effective.

REFERENCES

Alyasa, F. M., Rachman, A., & Yuliana, A. (2023). Who emits more emission? The association between CO_2 emissions and socio-economic characteristics of Indonesian household. Jurnal Ekonomi & Studi Pembangunan, 24(1), 55–66.

Badan Pusat Statistik. (2021). Statistik penduduk lanjut usia 2021. Jakarta, Indonesia: BPS. https://www.bps.go.id/publication/2021/12/31/20f2e1f38bfb33db602b473d/statistik-penduduk-lanjut-usia-2021.html

Baker, J. & Nasrudin, R. (2021. Is Indonesian police violence excessive? the dynamics of police shootings, 2005–2014. J Contemp Asia. https:// doi. org/ 10. 1080/ 00472 336. 2022. 21387 73

Basso, H. S., Dimakou, O., & Pidkuyko, M. (2023). How consumption carbon emission intensity varies across Spanish households. SERIEs, 15(1), 95–125.

Buchs, M., & Schnepf, S. V. (2013). Expenditure as proxy for UK household emissions? Comparing three estimation methods. Ecological Economics, 90, 114–123.

Buchs, M., & Schnepf, S. V. (2013). Who emits most? Associations between socio-economic factors and UK households' home energy, transport, indirect and total CO_2 emissions. Ecological Economics, 90, 114–123.

Burgess, M., & Whitehead, M. (2020). Just transitions, poverty, and energy consumption: Personal carbon accounts and households in poverty. Energies, 13(22), 5953

European Environment Agency. (2016). Total GHG emissions in the EU-28: National emissions reported to the UNFCCC and to the EU greenhouse gas monitoring mechanism.

Fritzsche, D. J. (1981). An analysis of energy-consumption patterns by stage of family-life cycle. Journal of Marketing Research, 18(2), 227–232. https://doi.org/10.1177/002224378101800209

Glass, T.A. and Balfour, J.L. (2003) Neighborhoods, aging, and functional limitations. In: Kawachi, I. and Berkman, L.F., Eds., Neighborhoods and Health, Oxford University Press, New York, 303-334.

Glick, P. C. (1955). The family life cycle. American Sociological Review, 20(2), 164–174.

Gough, I., Abdallah, S., Johnson, V., Ryan-Collins, J., & Smith, C. (2011). The distribution of total greenhouse gas emissions by households in the UK, and some implications for social policy. CASE Paper, 152.

Hu, Y., Chen, Y., Li, Y., & Yang, W. (2025). Age structure impacts on household carbon emissions: Based on a social interaction perspective. Environmental Science and Pollution Research. https://doi.org/10.1016/j.ecolecon.2025.108534

Hubacek, K., Baiocchi, G., Feng, K., & Patwardhan, A. (2017). Poverty eradication in a carbon constrained world. Nature Communications, 8(1), 912 Global carbon inequality

Intergovernmental Panel on Climate Change (IPCC). (2006). 2006 IPCC guidelines for national greenhouse gas inventories. https://www.ipcc-nggip.iges.or.jp/public/2006gl/

Intergovernmental Panel on Climate Change (IPCC). (2019). 2019 refinement to the 2006 IPCC guidelines for national greenhouse gas inventories. https://www.ipcc-nggip.iges.or.jp/public/2019rf/

Intergovernmental Panel on Climate Change, Climate Change 2021: The Physical Science Basis – Sixth Assessment Report (AR6).

Irfany, M. I., & Klasen, S. (2016). Inequality in emissions: Evidence from Indonesian households. Environmental Economics and Policy Studies, 18(3), 459–483. https://doi.org/10.1007/s10018-015-0119-0

Ivanova, D., & Wood, R. (2020). The unequal distribution of household carbon footprints in Europe and its link to sustainability. Global Sustainability, 3, e18. https://doi.org/10.1017/sus.2020.12

Kementerian Energi dan Sumber Daya Mineral Republik Indonesia. (2022). Statistik ketenagalistrikan Indonesia 2022. https://www.esdm.go.id/

Kementerian Lingkungan Hidup dan Kehutanan Republik Indonesia. (2017). Peraturan Menteri Lingkungan Hidup dan Kehutanan Republik Indonesia nomor P.73/Menlhk/Setjen/Kum.1/12/2017 tentang pedoman penyelenggaraan dan pelaporan inventarisasi gas rumah kaca nasional.

Kementerian Lingkungan Hidup dan Kehutanan Republik Indonesia. (2021). National greenhouse gas inventory report: Indonesia's third biennial update report to the UNFCCC. Jakarta, Indonesia: KLHK.

Kis-Katos, K., & Sparrow, R. (2015). Poverty, labour markets and trade liberalization in Indonesia. Journal of Development Economics, 117, 94–106

Li, K., Li, H., Wang, Y., Yang, Z., & Liang, S. (2024). Household carbon footprints of age groups in China and socioeconomic influencing factors. Science of the Total Environment, 923 (2024) 171402

Li, Y., Zhao, R., Liu, T., Zhao, J., (2015). Does urbanization lead to more direct and indirect household carbon dioxide emissions? Evidence from China during 1996-2012. J. Clean. Prod. 102, 103–114.

Liddle, B., & Lung, S. (2010). Age-structure, urbanization, and climate change in developed countries: Revisiting STIRPAT for disaggregated population and consumption-related environmental impacts. Population and Environment, 31(5), 317–343.

Modigliani, F., & Brumberg, R. H. (1954). Utility analysis and the consumption function: An interpretation of cross-section data. In Post-Keynesian economics (pp. 388–436). Rutgers University Press.

Murphy, P. E., & Staples, W. A. (1979). A modernized family life cycle. Journal of Consumer Research, 6(1), 12–22. https://doi.org/10.1086/208742

Oswald, Y., Owen, A., & Steinberger, J. K. (2020). Large inequality in international and intranational energy footprints between income groups and across consumption categories. Nature Energy, 5(3), 231–239. https://doi.org/10.1038/s41560-020-0579-8

Otto, I. M., Kim, K. M., & Lenton, T. M. (2020). Socio-metabolic class theory. Ecological Economics, 174, 106668.

PLN Research Institute. (2022). Program konversi kompor LPG ke kompor induksi: Evaluasi dan prospek. Jakarta, Indonesia: PLN.

Sun, Q., & Lu, G. (2023). 9 (2023). The effect of the elderly and child care on household carbon emissions. Heliyon, e17706

Sun, Y., Ren, S., & Yan, Z. (2023). How consumption carbon emission intensity varies across income groups: Evidence from China. Journal of Cleaner Production, 394, 136381. https://doi.org/10.1016/j.jclepro.2023.136381

Velenturf, A. P. M., & Purnell, P. (2021). Principles for a sustainable circular economy. Sustainable Production and Consumption, 27, 1437–1457. https://doi.org/10.1016/j.spc.2021.02.018

Wells, W. D., & Gubar, G. (1966). Life cycle concept in marketing research. Journal of Marketing Research, 3(4), 355–363. https://doi.org/10.2307/3149826

Wiedenhofer, D., Lenzen, M., & Steinberger, J. K. (2017). Energy requirements of consumption: Urban form, climate and lifestyle effects. Journal of Industrial Ecology, 21(3), 593–606.

Wiedmann, T., Allen, C. (2021). City footprints and SDGs provide untapped potential for assessing city sustainability. Nature Communications, 12(1), 3751. https://doi.org/10.1038/s41467-021-23968-2

Wiedmann, T., Lenzen, M., Turner, K., & Barrett, J. (2011). A review of recent multi-region input–output models used for consumption-based emission accounting. Ecological Economics, 69(2), 211–222. https://doi.org/10.1016/j.ecolecon.2009.08.026

Xue, Y. (2020). Empirical research on household carbon emissions characteristics and key impact factors in mining areas. Journal of Cleaner Production, 256, 120470. https://doi.org/10.1016/j.jclepro.2020.120470

Zhang, X., Luo, L., & Skitmore, M. (2015). Household carbon emission research: An analytical review of measurement, influencing factors and mitigation prospects. Journal of Cleaner Production, 103, 532–543. https://doi.org/10.1016/j.jclepro.2015.04.024

Zhang, Y.M., Wang, F., Zhang, B. (2023). The impacts of household structure transitions on household carbon emissions in China. Ecol. Econ. 20

Appendix 1. Categories of Emissions by Consumption Sector

Category	Emission Sector	Description
Direct	Energy	Fuels, generators, and transportation.
Indirect	Food	Food and household clothing.
	Housing	Emissions related to construction, maintenance, rent, electricity, and household operations, including energy consumed within the home.
	Other Goods	Emissions excluding food, including clothing, electronics, furniture, etc.
	Other Services	Financial, public, health/social care, communication services, and non-food primary sectors.