Economics Development Analysis Journal Vol. 13 (4) (2024)

Economics Development Analysis Journal

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

Energy Poverty and Labor Supply in Eastern Indonesia

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Article Information

History of Article
Received July 2024
Accepted September 2024
Pusblished November 2024

Keywords:
Energy Poverty, Labor Supply, Indonesia

Abstract

Gender inequality in economic participation is a crucial aspect of sustainable development strategies aimed at improving living standards. The high level of inequality is primarily driven by stagnation in female labor supply. One of the factors influencing labor supply is energy povertyIn Indonesia, studies addressing the relationship between energy poverty and economic participation remain scarce. Therefore, this research aims to fill the existing research gap by analyzing the relationship between energy poverty and labor supply, particularly in Eastern Indonesia. To address endogeneity issues caused by selection bias, this study employs the Two-Step Heckman method. Using data from the 2021 Susenas, the findings reveal that energy poverty significantly reduces working hours in Eastern Indonesia. This impact is more pronounced among male workers compared to female workers and is more dominant in urban areas than in rural areas. These findings underscore the importance of policy interventions aimed at reducing energy poverty as a means of improving labor productivity, particularly in Eastern Indonesia. This study also contributes to understanding the dynamics of labor markets in regions facing energy and economic development challenges.

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ISSN 2252-6560

INTRODUCTION

The role of energy is crucial in connecting various aspects of socio-economic development (Li et al., 2024). This is reflected in the Sustainable Development Goals (SDG Goal 7), which emphasize the strong relationship between energy access and economic growth. Adequate energy access can improve educational and health outcomes, increase income and labor productivity, create job opportunities, drive economic growth, and enable better use of information and communication technologies (ADB, 2019).

However, disparities in energy access persist globally, with 675 million people still lacking electricity and 2.3 billion people relying on unclean cooking fuels, the majority of whom reside in Sub-Saharan Africa and Asia (IEA et al., 2023). In Indonesia, the energy access gap between western and eastern regions remains significant. Although disparities in electricity access are relatively minor, but the percentage of households still using unclean cooking fuels is significantly higher in eastern Indonesia, reaching over 90 percent in several provinces (BPS, 2024).

Energy poverty is a complex phenomenon that has yet to be universally defined. The International Energy Agency (2020) defines energy poverty as the inability of households to access reliable and affordable clean cooking facilities and electricity to meet basic energy needs.

Energy poverty has severe implications for health, the economy, and the environment (González-Eguino, 2015). Phoumin & Kimura (2019) found that energy poverty increases the risk of health problems, raises medical expenses, contributes to school dropout rates, and reduces opportunities for earning a decent income. Furthermore, in regions with limited energy resources, many households and businesses cannot utilize modern appliances and technology, leading to lower labor productivity, stagnant economic activity, and diminished employment opportunities (Shi et al., 2022).

In labor supply theory, factors such as time savings and health play a crucial role in encouraging labor force participation. Energy poverty can affect labor participation and productivity through both factors, as it increases the risk of health issues and inefficiencies in time use.

Several studies have shown that energy poverty results in greater time consumption for household production tasks, such as fuel collection and inefficiencies in household appliances (Li et al., 2024). Moreover, the use of cleaner cooking fuels, electricity, and energy-based/electronic household appliances can reduce time allocated for household chores, with potential savings ranging from 20 minutes to an hour per day (Afridi et al., 2022; World Bank, 2008; Greenwood et al., 2005). These time savings, in turn, enhance income-generating opportunities.

Energy poverty also poses health risks, particularly through the use of unclean cooking fuels that generate high levels of toxic pollutants. Such air pollution increases the prevalence of respiratory problems and various non-communicable diseases, including stroke, ischemic heart disease, chronic obstructive pulmonary disease (COPD), and lung cancer, ultimately reducing labor force participation and productivity (WHO, 2024; Verma & Imelda, 2022).

Although several studies have demonstrated that energy poverty reduces labor participation and productivity—such as lowering wage levels (Bakehe, 2022; Wu et al., 2021) —the impact of energy poverty on labor force participation remains a subject of debate. This is because other studies suggest that while improved electricity access reduces time spent on household chores, it does not significantly affect the total hours allocated to paid work in Ghana (Coulombe & Wodon, 2008). Similarly, Lewis & Severnini (2017) argue that household electricity use does not directly increase current labor participation but instead enhances labor participation in the next generation.

In Indonesia, numerous studies on labor supply have been conducted; however, research linking labor supply to energy remains limited. Existing studies primarily focus on the role of socio-demographic factors and social norms (Cameron et al., 2019; Schaner & Das, 2016; Ogawa, 2007). One study that examines the relationship between labor supply and energy is by Verma & Imelda (2022), which focuses on the impact of the kerosene-to-LPG conversion program. Therefore, this study aims to bridge the existing research gap by analyzing the relationship between energy poverty and labor supply, particularly in eastern Indonesia, where energy poverty remains high.

RESEARCH METHODS

The data used in this study are sourced from the 2021 National Socioeconomic Survey (Susenas) conducted by BPS, with the unit of analysis being the working-age population (15 years and older) residing in eastern Indonesia. This working-age threshold is based on the definition established by BPS (2023a) and the International Labor Organization (ILO, 2016). The provinces included in the eastern Indonesia region are Bali, West Nusa Tenggara, East Nusa Tenggara, North Sulawesi, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, West Sulawesi, Maluku, North Maluku, Papua, and West Papua.

The approach to energy poverty used in this study follows the definition provided by the International Energy Agency (2020), which describes energy poverty as the inability of households to access clean cooking facilities and electricity to meet basic energy needs. This concept has also been adopted in previous studies, such as Bakehe (2022). Therefore, individuals are classified as energy-poor if they do not use modern energy sources for either lighting or cooking.

The dependent variable in this study is labor supply, proxied by total working hours. Additionally, several control variables are included to address potential omitted variable bias by isolating the relationship between energy poverty and labor supply. The control variables considered in this study include the number of young children, the presence of toddlers, per capita expenditure, the presence of other non-working adults, homeownership, residential area, age, gender, education, marital status, and household head status. The selection of these control variables is based on previous studies. The definitions of the operational variables used in this study are summarized in Table 1.

Table 1. Operational Variables

Variable	Code	Operational Definition
Independent Variables		
Labor Force Participation	labor_participation	Employment status (1 = Employed; 0 = Unemployed)
Working Hours	working_hours	Total working hours per week (hours)
Key Independent Variable		
Energy Poverty	energy_poverty	Energy poverty status (1 = Experiencing energy poverty; 0 = Not experiencing energy poverty)
Control Variables		
Number of Young Children	num_children	Number of children aged 5–17 years in the household (persons)
Presence of Infants	infant_presence	Presence of infants aged 0–4 years (1 = Present; 0 = Not present)
Presence of Non-Working Adults	nonworking_adults	Presence of other non-working adults in the household (1 = Present; 0 = Not present)

Variable	Code	Operational Definition
Ln Per Capita Expenditure	ln_percapita_expenditure	Natural logarithm of per capita expenditure
Home Ownership	home_ownership	Ownership status of residential buildings (1 = Own; 0 = Do not own)
Residential Area	residential_area	Classification of residential area (1 = Urban; 0 = Rural)
Age	age	Age (years)
Education	education	Completion of basic education (9 years) (1 = Completed; 0 = Not completed)
Marital Status	marital_status	Marital status (1 = Married; 0 = Other)
Household Head Status	household_head	Household head status (1 = Household Head; 0 = Not Household Head)

Source: Data Processed, 2024

This study employs two models: the Ordinary Least Squares (OLS) model as the baseline model and the Two-Step Heckman model as the primary model. The Two-Step Heckman method is applied to address potential endogeneity issues in the baseline model, such as selectivity bias. The possibility of selectivity bias arises due to non-random sample selection. This occurs because information on working hours is only available for employed individuals, whereas labor supply encompasses both employed and unemployed individuals.

Therefore, to correct the selectivity bias resulting from non-random sample selection, a bias correction is necessary to ensure the accuracy of the estimation results (Heckman, 1979). The first step in the Heckman method involves estimating the probability of employment or unemployment among the working-age population, as specified in Equation 1 below:

$$\text{labor\_participation}_i = \alpha_o + \alpha_1 \text{energy\_poverty}_\text{i} + \alpha_2 \text{X}_i + v_r + \varepsilon_i \text{ ...(1)}$$

where $\text{labor\_participation}_i$ presents labor participation, $\text{energy\_poverty}_\text{i}$ denotes energy poverty status, and X_i includes all control variables used in the study. Meanwhile, v_r represents the province fixed effect, and ε_i is the error term.

At this stage, the selectivity correction factor (inverse Mills ratio, λ) is generated, which will be included as one of the control variables in the second stage. In the Heckman modeling approach, the assumption of exclusion restriction is required, meaning that at least one independent variable is included only in the first stage. This is done to prevent collinearity or to reduce the correlation between the selectivity correction factor and other control variables in the model. The exclusion restriction variables used in this study are per capita expenditure, the presence of other non-working adults, and homeownership.

The second stage of the Heckman method estimates the effect of energy poverty status on labor supply, proxied by total working hours, as specified in Equation 2. If the selectivity correction factor (inverse Mills ratio) is found to be statistically significant, it indicates the presence of selectivity bias in the model.

$$\text{working\_hours}_i = \beta_o + \beta_1 \text{energy\_poverty}_\text{i} + \beta_2 \text{X}_i + \lambda_i + v_r + \varepsilon_i \text{ .... (2)}$$

Where working_hours_i represents total working hours, $\text{energy\_poverty}_\text{i}$ denotes energy poverty status, and X_i includes all control variables except for the exclusion restriction variables. Meanwhile, λ_i represents the inverse Mills ratio, v_r is the province fixed effect, and ε_i is the error term.

Differences in demographic characteristics, such as gender, as well as variations in infrastructure conditions and energy adoption levels between urban and rural areas, may lead to differing impacts of energy poverty on labor supply. Therefore, to enhance the depth of analysis, this study also conducts a heterogeneity analysis based on gender and residential area.

RESULTS AND DISCUSSION

Table 2 presents a summary of the statistical values of various variables used in this study. The table indicates that the majority of the working-age population in eastern Indonesia has entered the labor market, with an average weekly working hour of 40.52 hours. This suggests that, on average, workers in the region are still within the normal working hour limits, although some individuals work up to 97 hours per week. Meanwhile, individuals with zero working hours represent those who have a job or business but are temporarily not working.

Table 2. Summary Statistics of Research Variables

Variable	Observations	Mean	Std. Dev.	Min	Max
Labor Force Participation (1 = employed)	296,212	0.63	0.48	0	1
Total Working Hours (hours)	186,658	40.52	17.75	0	97
Energy Poverty Status (1 = energy poor)	296,212	0.55	0.50	0	1
Number of Young Children (persons)	296,212	1.24	1.22	0	14
Presence of Infants (1 = present)	296,212	0.32	0.47	0	1
Per Capita Expenditure (million)	296,212	7.02	9.07	0.11	45.50
Presence of Non-Working Adults (1 = present)	296,212	0.42	0.49	0	1
Home Ownership (1 = own)	296,212	0.58	0.49	0	1
Residential Area (1 = urban)	296,212	0.29	0.46	0	1
Age (years)	296,212	38.53	16.37	15	97
Gender (1 = male)	296,212	0.50	0.50	0	1
Education (1 = completed basic education)	296,212	0.56	0.50	0	1
Marital Status (1 = married)	296,212	0.64	0.48	0	1
Household Head Status (1 = household head)	296,212	0.35	0.48	0	1

Source: SUSENAS & BPS, 2022 (processed)

When viewed based on energy poverty status, 55% of the working-age population still experiences energy poverty. The provinces with the highest proportion of individuals living in energy poverty are Maluku and East Nusa Tenggara. This finding aligns with the study by Rizal et al. (2024) which states that eastern Indonesia remains vulnerable to energy poverty. This condition may be attributed to inadequate infrastructure for distributing modern energy, making energy accessibility more challenging and exacerbating energy poverty.

In terms of household characteristics, the majority of the working-age population does not have young children (68%), has an average of 1–2 children, and does not live with other non-working adults in their household (58%). Additionally, most of the working-age population resides in households that own residential buildings (88%), with an average monthly per capita expenditure of IDR 1.10 million. The lowest per capita expenditure recorded is IDR 114,515, while the highest reaches IDR 45.50 million.

Regarding place of residence, most of the working-age population lives in rural areas rather than urban areas (71%), with an average age of approximately 38–39 years. Meanwhile, based on individual characteristics, more than half of the working-age population is not the head of the household (65%), is married (64%), and has completed primary education (56%).

In examining the relationship between energy poverty and labor supply, proxied by working hours, one of the methods that can be employed is OLS. Table 3 presents the estimation results of the baseline model, with an F-test significance value of less than alpha (0.000 < 0.010), indicating that all independent variables simultaneously influence the dependent variable significantly.

Table 3 shows that energy poverty has a negative impact on the working hours of the population in Eastern Indonesia, with a 99 percent confidence level. This means that individuals experiencing energy poverty tend to have a reduction in working hours by approximately 1.775 hours per week, equivalent to around 1–2 hours. This finding is consistent with the studies of Bakehe (2022) and Wu et al. (2021), which suggest that energy poverty can reduce labor force participation and productivity. This effect may be attributed to the increased health risks and additional time allocation for household responsibilities associated with energy poverty. Based on the theory of time allocation and the theory of health capital, both factors can reduce work opportunities and the time allocated for employment.

Table 3. Baseline Model Estimation Effect of Energy Poverty on Working Hours

Variables	Working Hours		
	Entire Population	**Male**	**Female**
Energy Poverty Status (1 = energy poor)	-1.775***	-1.489***	-2.123***
(Standard errors)	(0.128)	(0.153)	(0.228)
Route Characteristics	Yes	Yes	Yes
Regional Characteristics	Yes	Yes	Yes
Individual Characteristics	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Observations	186,658	115,578	71,080
Adjusted R^2	0.079	0.071	0.048
Prob > F	0.000	0.000	0.000

Standard errors in parentheses

*p < 0.10, **p < 0.05, ***p < 0.01

Source: SUSENAS & BPS, 2022 (processed)

A deeper analysis reveals differences in the magnitude of the impact of energy poverty on labor supply between men and women. Women experiencing energy poverty tend to see a reduction in working hours of more than 2 hours per week, whereas men tend to experience a reduction of less than 2 hours per week. This indicates that women are more significantly affected by energy poverty in terms of reduced working hours. This finding may be attributed to gender norms, in which women are primarily responsible for unpaid household production, including family care and domestic chores. Prospera et al. (2023) state that women in Indonesia spend nearly three times more time on household responsibilities compared to men.

Table 4 presents a comparison of estimation results using the baseline model (OLS) and the main model (Two-Step Heckman). The results indicate that the selection correction factor (inverse Mills ratio) is statistically significant at a 95% confidence level for the full sample, the male subsample, and the female subsample. This confirms the presence of selection bias in the model, justifying the use of the Two-Step Heckman method.

The estimation results in Table 4 demonstrate that the coefficients obtained using the Heckman model are consistent (directionally similar) and have a larger magnitude compared to OLS. This suggests that endogeneity issues introduce a downward bias in the baseline model.

As shown in Table 4, energy poverty negatively affects working hours across all groups, both overall and by gender. On average, individuals experiencing energy poverty face a reduction in working hours of approximately 1.808 hours per week, equivalent to around 1–2 hours.

Energy poverty increases the risk of respiratory infections, which ultimately negatively affects labor market participation (Bakehe, 2022). In line with this, Verma & Imelda (2022) found that access to clean cooking fuels leads to improved health and increased working hours. This strengthens the argument that energy poverty may contribute to higher health risks and increased time allocation for household responsibilities, which in turn affects working hours. According to time allocation theory, an increase in time spent on household responsibilities reduces the time available for work. Similarly, based on human capital theory, a higher health risk lowers employment opportunities and productivity.

Table 4. Comparison of Estimation Energy Poverty to Working Hours

Variable	Overall		Male		Female	
	OLS	Heckman	OLS	Heckman	OLS	Heckman
Energy Poverty Status (1: energy poor)	-1.775***	-1.808***	-1.489***	-1.516***	-2.123***	-2.291***
	(0.128)	(0.129)	(0.153)	(0.153)	(0.228)	(0.233)
Number of Children	0.066*	0.094***	0.065	0.107**	0.055	0.129**
	(0.034)	(0.036)	(0.042)	(0.045)	(0.059)	(0.062)
Presence of Infants	0.254***	0.259***	0.709***	0.675***	-0.758***	-0.582**
	(0.090)	(0.090)	(0.109)	(0.110)	(0.157)	(0.164)
Residential Area	4.492***	4.580***	4.193***	4.324***	4.950***	5.188***
	(0.104)	(0.110)	(0.126)	(0.138)	(0.182)	(0.191)
Age	0.551***	0.483***	0.539***	0.452***	0.595***	0.363**
	(0.018)	(0.035)	(0.022)	(0.042)	(0.030)	(0.068)
Age Squared	-0.007***	-0.006***	-0.007***	-0.006***	-0.007***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Gender	4.145***	3.851***				
	(0.108)	(0.171)				
Education	0.272***	0.281***	0.061	0.104	0.907***	0.804***
	(0.088)	(0.088)	(0.104)	(0.106)	(0.160)	(0.162)
Marital Status	1.123***	1.074***	2.372***	2.084***	-0.245	-0.329
	(0.107)	(0.110)	(0.162)	(0.203)	(0.198)	(0.200)
Household Head Status	2.156***	1.910***	1.570***	1.434***	1.055***	0.097
	(0.113)	(0.157)	(0.164)	(0.175)	(0.250)	(0.355)
Inverse Mills Ratio		-0.877**		-1.209**		-2.595**
		(0.403)		(0.529)		(0.697)
Constant	27.747***	29.688***	30.834***	33.057***	28.383***	34.453***
	(0.396)	(0.950)	(0.473)	(1.041)	(0.640)	(1.728)
Observations	186.658	186.658	115.578	115.578	71.080	71.080
Adj. R^2	0.079	0.079	0.071	0.071	0.048	0.048
Prob> F or Chi2	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses

*p < 0.10, **p < 0.05, ***p < 0.01

Source: SUSENAS & BPS, 2022 (processed)

The impact of energy poverty on the reduction of working hours is more pronounced among female workers. This is because most women spend a significant amount of their time performing household tasks, such as cooking. In line with this, Burke & Dundas (2015) found that women's labor market participation is associated with the use of biomass-based fuels. This occurs because collecting firewood is generally a responsibility of women, and the time spent on this task limits their employment opportunities (Bakehe, 2022).

Furthermore, as shown in the estimation results in Table 4, having more children increases working hours, whereas the presence of infants reduces working hours for women. This may be due to the tendency of women to prioritize childcare at home, which significantly constrains their engagement in the labor market. This finding aligns with Cameron et al. (2019), who reported that the presence of infants negatively affects women's labor force participation.

Other characteristics, such as age, education, and place of residence, have a positive impact on working hours. This suggests that older individuals, those with higher levels of education, and those residing in urban areas are more likely to participate in the labor market. This relationship is linked to enhanced skills and greater access to employment opportunities. These findings are consistent with studies by Cameron et al. (2019), Schaner & Das (2016), and Ogawa (2007).

Gender and household head status also contribute to an increase in working hours. This indicates that being the head of the household and being male are associated with greater opportunities for labor market participation. Additionally, marital status increases working hours for men but decreases working hours for women. This finding aligns with Cameron et al., (2019), who reported that marital status negatively affects the probability of women participating in the labor market.

In this study, a heterogeneity analysis was also conducted to examine the impact of energy poverty on working hours using a subsample analysis. This subsample analysis is crucial because variations within groups or subsamples often influence estimation results, as the effect of energy poverty on women's employment status may differ across subgroups.

Table 5. Heterogeneity Analysis by Region

Variable	Rural		Urban	
	OLS	**Heckman**	**OLS**	**Heckman**
Energy Poverty Status	-1.889*** (0.144)	-2.052*** (0.145)	-2.271*** (0.276)	-2.233*** (0.277)
Inverse Mills Ratio		-3.832*** (0.404)		1.313 (1.097)
Route Characteristics	Yes	Yes	Yes	Yes
Regional Characteristics	Yes	Yes	Yes	Yes
Individual Characteristics	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Observations	136098	136098	50560	50560
Adjusted R^2	0.082	0.082	0.034	0.034
Prob > F or Chi2	0.000	0.000	0.000	0.000

Standard errors in parentheses

*p < 0.10, **p < 0.05, ***p < 0.01

Source: SUSENAS & BPS, 2022 (processed)

Table 5 shows that the correction factor (inverse Mills ratio) is significant at a 99% confidence level only in rural areas. This indicates the presence of selection bias in rural areas, making the application of the Two-Step Heckman method appropriate. However, for the urban subsample, the correction factor (inverse Mills ratio) is not significant, suggesting that the OLS method is sufficient.

The coefficient estimates for energy poverty status between rural and urban areas show no substantial variation, with values of -

2.052 (rural) and -2.271 (urban), respectively. The slightly greater impact in urban areas may be due to the higher demand for employment to meet living expenses, regardless of energy poverty conditions. This finding is consistent with Dong et al. (2023), who suggest that regions with better energy infrastructure tend to adapt more quickly and implement energy poverty alleviation policies more effectively, ultimately improving quality of life and income levels.

CONCLUSION

This study demonstrates that energy poverty significantly affects labor supply in Eastern Indonesia, where inadequate access to energy leads to a reduction in total working hours. The findings contribute to the literature by highlighting the relationship between insufficient energy access and labor market participation. Therefore, if the government aims to enhance labor productivity, policy interventions should be implemented to mitigate energy poverty, particularly in Eastern Indonesia.

The study also reveals that women experience a greater decline in working hours due to energy poverty. This finding further confirms that women are constrained by gender norms, where household responsibilities predominantly fall on them. As a result, inadequate energy access exacerbates the limitations on women's economic participation.

For future research, it is recommended to employ more comprehensive methods to address potential endogeneity issues, such as reverse causality. Additionally, utilizing longitudinal data could provide insights into the long-term effects of energy poverty on employment.

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