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Clean Energy Transition and Intertemporal Socio-Economic Development: A Case Study of Households in Indonesia

Satrio Arga Effendi
Universitas Indonesia, Indonesia
Email: arga.effendi@gmail.com
*Correspondence: arga.effendi@gmail.com

ABSTRACT: The use of polluting energy sources for daily household needs can lead to complex issues, ranging from health deterioration and reduced quality of life to adverse socioeconomic consequences. While previous studies have predominantly focused on the health and welfare impacts of dirty energy use, this research highlights the effects of clean energy transition on household socioeconomic development, employing an innovative approach through the Household Development Index (HHDI). This longitudinal study utilizes data from the Indonesian Family Life Survey (IFLS) conducted in 2007 and 2014, revealing the dynamics of household energy consumption changes over a seven-year period. The study employs the Propensity Score Matching (PSM) method to calculate the average treatment effect on the treated of household clean energy transition. The analysis results show that households transitioning to cleaner energy sources experienced a 3.72% higher increase in development index compared to if they had continued using unclean energy. Robustness tests were conducted using the Coarsened Exact Matching (CEM) technique and a combination of CEM-PSM. These robustness tests also yielded similar and consistent results. Impact estimations performed on different sub-samples indicate that the impact of energy transition in rural areas is greater than in urban areas. This research makes an important contribution by presenting new empirical evidence on the comprehensive impact of clean energy transition on household socio-economic development.
Keywords: Clean Energy Transition, Socio-Economic Development, HHDI, CEM PSM

INTRODUCTION

Climate change and energy poverty have become two major interconnected global challenges in the energy sector. These two issues are of major concern in efforts to improve global welfare and maintain environmental sustainability (Chakravarty & Tavoni, 2013) (Luomi, 2020) (Nations, 2024). One of the main contributors to these two issues is the household sector, which significantly contributes to 72% of greenhouse gas emissions (Hertwich & Peters, 2009).

The impacts of climate change are wide-ranging, including increased frequency of extreme weather, threats to food security, and impacts on health and education (Druckman & Jackson, 2016; Luomi, 2020)(Husain, Akram, Al-Kubaisi, & Hameed, 2023). Climate change also affects the subjective wellbeing of communities (Grün & Grunewald, 2010) and household food security (Mekonnen et al., 2021).

On the other hand, energy poverty also has a significant impact on human welfare. According to the International Energy Agency (2022), about 775 million people in the world still live without access to electricity, and many rely on traditional energy sources that are high in emissions. The use of traditional fuels contributes to Indoor Air Pollution (IAP), which has the potential to harm cardiovascular and respiratory health (WHO, 2013; Miller & Xu, 2018). The use of unclean energy also limits access to education, information, and economic opportunities (Biswas & Das, 2022) (Oktaviani & Hartono, 2022).

These two global challenges have a direct impact on household socio-economic development. Socio-economic development itself can be defined as a series of changes in the social and economic realm of a society, which includes economic growth, social welfare, income distribution, availability of basic services, and an overall improvement in living standards (Chojnicki, 2010). In the context of households, socio-economic development involves improvements in various dimensions, including education, income, assets, and access to information.

Household socio-economic development is often related to these 2 global problems in the energy sector. However, there is optimism that the clean energy transition at the household level can be a potential solution to address both global problems while encouraging household socio-economic development. The energy transition, which involves switching from traditional energy sources to cleaner and more efficient energy sources, offers the potential to reduce greenhouse gas emissions while improving the quality of life of households (Damette, Delacote, & Del Lo, 2018) (Muvhiiwa, Hildebrandt, Chimwani, Ngubevana, & Matambo, 2017).

Previous research has shown that access to clean energy can bring various socio-economic benefits to households. For example, access to electricity has been shown to increase the allocation of time to study and work (Arraiz & Calero, 2015), opening up new job opportunities (Barron & Torero, 2019), increasing household income (Khandker, Barnes, & Samad, 2013) (Chakravarty & Tavoni, 2013), and improving school participation rates and educational performance (Khandker et al, 2013; Hassan & Lucchino, 2016). In terms of health, the transition to clean energy can reduce exposure to indoor air pollution and reduce the incidence of respiratory diseases (Barron & Torero, 2019).

Although the benefits of the clean energy transition on individual aspects of household socio-economic development have been extensively researched, a comprehensive understanding of the impact of the energy transition on overall household socio-economic development is still limited. One of the studies that tried to fill this gap was conducted by Mamidi et al. (2021), which found that households that switched to clean energy experienced an average increase of 12.2% in household construction.

Understanding the relationship between clean energy transition and household socio-economic development is critical because it can provide valuable insights for policymakers in designing effective strategies to improve household well-being while addressing the challenges of climate change and energy poverty.

Therefore, this study aims to analyze the causal impact of the clean energy transition on household socio-economic development as measured by the growth of the Household Development Index (HHDI) score intertemporarily. By adopting a multidimensional approach that covers three important aspects of household development (education, household income and assets, and access to mass media), this study seeks to provide a more holistic picture of household development in the context of the energy transition.

The ultimate goal to be achieved in this study is to analyze the causal impact of the clean energy transition on household socio-economic development as measured by the growth of the Household Development Index (HHDI) score in an intertemporal manner (between times). This research will explore how the transition from dirty energy to clean energy can affect various aspects of household life, including health, education, productivity, and general well-being. Thus, this study aims to provide a deeper understanding of the relationship between clean energy transition and household socio-economic development.

By filling the research gap from previous research, it is hoped that this study can add insight and provide new empirical evidence on the impact of the household energy transition from dirty energy use to cleaner energy on the development of household socio-economic development. By adopting a multidimensional approach that includes three important aspects of household development (education, household income and assets, and access to mass media). This research offers a more comprehensive perspective by trying to provide a more holistic picture of household development in the context of the energy transition.

RESEARCH METHODOLOGY

Using two waves of IFLS surveys in 2007 and 2014, the study will map the transition of household-level households from dirty energy to clean energy. The marginal effect of the clean fuel transition in the HHDI Intertemporal will be estimated using one of the linear regression tools, namely Ordinary Least Square (OLS) through equation 3.11.

$$\text{Intertemporal HHDI} = \beta 0 + \beta 1ETi + \sum n\ \beta nXn, i + \varepsilon i \qquad (3.11)$$

With ETi being the household energy transition i, Xn,i being the control variable, and εi being the error term. These control variables include household-level demographic features: Residential (Urban/Rural), Household Size, Household Consumption Expenditure, Below or Above the Poverty Line, Household Head Education, and Household Development Index (HHDI) quantiles and their four sub-indexes. The use of this covariate variable follows and adjusts the research conducted by (Mamidi, Marisetty, & Thomas, 2021)

Although OLS is a commonly used estimation method, this approach has some limitations in the context of this study. First, OLS is susceptible to selection bias due to non-random sample selection. In these cases, households that switch to clean fuels may have certain characteristics that differ from those that do not switch, so a direct comparison between these two groups can result in biased estimates (Rosenbaum & Rubin, 1983).

PSM overcomes the problem of selection bias by creating a control group that is comparable to the treatment group based on observable characteristics. This method calculates the probability (propensity score) of each unit of observation to receive a treatment based on the observable variables, then matches the units of the treatment and control groups that have similar propensity scores (Caliendo & Kopeinig, 2008). Thus, PSM creates a more valid comparison between households switching to clean fuels and those that do not, reducing the potential for bias due to non-random sample selection.

Second, OLS is also susceptible to endogenicity problems. Endogenicity occurs when an independent variable correlates with an error term in a regression model, which can be caused by omitted variables, measurement errors, or simultaneity (Wooldridge, 2010). In the context of this study, endogenicity may arise due to the existence of a two-way relationship between clean fuel use and household welfare levels (Churchill, Inekwe, Ivanovski, & Smyth, 2020). For example, more prosperous households may be more likely to switch to clean fuels, while the use of clean fuels can also improve household well-being.

PSM can help address endogenicity issues in a similar way to handling selection bias. By matching households based on observable characteristics, PSM reduces the influence of variables that may be a source of endogenicity. Although PSM cannot fully address endogenicity caused by unobservable variables, this method can significantly reduce estimation bias compared to OLS (Rosenbaum & Rubin, 1983).

Furthermore, PSM allows for an estimate of the Average Treatment Effect on the Treated (ATT), which is the causal effect of the treatment in the group receiving the treatment. In the context of this study, ATT reflects the impact of the switch to clean fuels on HHDI Intertemporal for households that are actually switching. This approach provides a more accurate and interpretable estimate compared to the OLS coefficient that may be biased (Imbens & Wooldridge, 2009).

RESULT AND DISCUSSION

Linear Regression Using *Ordinary Least Square* (OLS)

Table 1 shows the results of the basic estimation of the effect of energy transition on the HHDI Intertemporal after including several control variables. The selection of the control variable in the OLS estimation is also adjusted to the research of (Mamidi et al., 2021)which uses the HHDI quantum variable and its sub-index to represent household characteristics. Where the quantile of the four sub-indices can be considered as proxies that represent household characteristics in the dimensions of education, assets/finance, and mass media access. By including it as a covariate, it is hoped that it can control the difference in these characteristics among households.

The energy transition variable shows a positive and significant coefficient. This is in line with previous findings that show that households using non-clean energy tend to have lower average Intertemporal HHDI, while households switching to clean energy have higher Intertemporal HHDI. Basic OLS results estimate an increase of approximately 4.76% in Intertemporal HHDI compared to households that continue to use unclean fuels. The variables of household size (hhsize), poverty status (grs_mskn), and region did not show a significant influence on the intertemporal of HHDI, with a coefficient value of 0 each. 000637, -0.00107, and 0.00724. Although not significant, this variable can still be maintained because literature studies show the influence of this variable on household energy transition decisions.

The quantitative variables of various HHDI sub-indices showed a significant influence. The HHDI quantile had a significant negative influence of -0.196, indicating that an increase of one unit in the HHDI quanti tended to decrease the HHDI intertemporal by 0.196 points. This result represents that the higher the HHDI score of a household, the slower the growth of HHDI, and not as strong as the growth of HHDI in households with low scores.

Table 1 Basic Estimation Results Using OLS

	(1)
VARIABLES	HHDI_int
ET	0.0476***
	(0.00563)
hhsize	0.000637
	(0.000919)
grs_mskn	-0.00107
	(0.00591)
region	0.00724
	(0.00533)
TOTEXP	0.00580***

	(0.00151)
hh_educ	-0.00269***
	(0.000900)
HHDI_kuantil	-0.196***
	(0.00526)
HHADI_kuantil	0.0131***
	(0.00287)
HHAEI_kuantil	0.0473***
	(0.00274)
HHMI_kuantil	0.0352***
	(0.00470)
Constant	0.375***
	(0.0117)
Observations	6,903
R-squared	0.328

Standard errors in parentheses
p<0.01, p<0.05, p<0.1

The HHAEI and HHADI quantiles had a significant positive influence, suggesting that an increase of one unit in the HHAEI and HHADI quantiles tended to increase the HHDI intertemporal range. The model has an R-squared of 0.328, which means that 32.8% of the variation in HHDI can be explained by the variables in this model.

Overall, these results show that the energy transition has a significant influence on the *Intertemporal Household Development Index* (HHDI_int) of 4.76%. However, due to the possibility of endogenousness and selection bias, OLS estimation can be biased. Therefore, a matching-based causal inference approach is needed to produce a stronger estimate of the impact of the clean energy transition on the HHDI Intertemporal Approach.

***Propensity Score Matching* (PSM)**

In the early stages of the analysis, the first step is to estimate the *propensity score*, which is the conditional probability that an individual will receive treatment based on a given set of covariates. In this study, a probit model is used to estimate the conditional probability of the clean energy transition. The dependent variable is the clean energy transition (ET), while the independent variable includes household characteristics such as household size, area of residence, poverty status, total household expenditure, adult education, and several HHDI sub-indexes.

The propensity score matching used in this study uses *the command psmatch2* with the Stata 18 application. The results of the probit estimation are shown in Table 2. Household size has a significant negative coefficient, suggesting that households with larger sizes tend to have a lower probability of making a clean energy transition. Meanwhile, households in urban areas have a higher tendency to make a clean energy transition compared to rural areas. Households above the poverty line also have a higher probability of making a clean energy transition. The variable of total household expenditure has a significant positive coefficient, indicating that households with greater expenditure tend to have a higher probability of making a clean energy transition. The HHDI quantum variable also has a positive effect on the probability of clean energy transition. Meanwhile, the HHMI quantum variable is not significant in influencing the probability of clean energy transition in this model. The results of this probit regression will be used to estimate *the propensity score* which will then be used in the *propensity score matching analysis*.

Table 2 ***Probit Regression to Determine Propensity Score***

	(1)
VARIABLES	ET
hhsize	-0.0151**
	(0.00612)
region	0.655***
	(0.0349)
grs_mskn	-0.282***
	(0.0385)
TOTEXP	0.0428***
	(0.0110)
hh_educ	0.0164***
	(0.00588)
HHDI_kuantil	0.249***
	(0.0338)
HHADI_kuantil	0.0545***
	(0.0191)
HHAEI_kuantil	-0.0570***
	(0.0184)
HHMI_kuantil	0.0119
	(0.0309)
Constant	-0.475***
	(0.0766)
Observations	6,903
Log likelihood	-3904.219
LR chi2 (9)	1161.91
Prob > chi2	0.0000
Pseudo R2	0.1295

Standard errors in parentheses
p<0.01, p<0.05, p<0.1

Balance Between Groups Before and After *Matching*

Prior to the matching (*propensity score matching*), there were still significant differences between the *treatment* group (which made the clean energy transition) and the control group in almost all the variables analyzed (see Table 3). This difference is indicated by a statistically significant *mean difference* value (marked by *p<0.001). The differences between the groups here are different from those previously detected by the CEM. Where CEM looks at differences between groups based on the similarity of the characteristics of predetermined variables, while PSM looks at differences between groups based on the probability of a household getting *treatment* (making an energy transition).

Table 3 ***T-test Mean Differences*** **Before and After** ***Matching*** **PSM**

	(1)	(2)
	Before Matching	After Matching
Household Development Index (HHDI)	0,0556564*	0,0016
	(-25,0218)	(0,14)
Household Adult Education Index (HHAEI)	0,0351215*	-0,0036

	(-11,8228)	(-1,4)
Household Assets, Debts, and Income Index (HHADI Index)	0,0033025*	0,00007
	(-12,2346)	(0,3)
Household Massmedia Index (HHMI)	0,1689254*	0,00559
	(-26,1397)	(1,04)
Poverty Status (grs_mskn)	-0,2222089*	0,00876
	(18,1458)	(0,86)
Total Expenditure (totexp)	0,6549918*	-0,0094
	(-14,6034)	(-0,22)
Household Size (hhsize)	-0,0263801	-0,0282
	(0,3673)	(-0,48)
Urban/Rural (regional)	0,2974675*	0,00876
	(-24,9858)	(0,83)
Adult Aggregate Education (adult_educ)	-0,6276344*	0,0795
	(-11.2079)	(1,38)
Number of Observations	6903	6903
t statistics in parentheses		
Mean Difference = Mean of Control - Mean of Treatment		
**p<0.001 **p<0.05 ***p<0.1*		

Table 3 displays the results of the *t-test mean differences* for various variables between the group of households that undergo the clean energy transition (*treatment*) and the group of households that do not transition (control), before and after the *propensity score matching* (PSM) is carried out. Before matching, it was seen that almost all variables had a statistically significant mean difference between the two groups, which was characterized by a p-value of less than 0.001 (*p<0.001). This significant difference indicates that there is an imbalance between the two groups before matching.

After *propensity score matching*, all mean differences between the two groups became statistically insignificant, as indicated by a p-value greater than 0.1. The success of PSM in minimizing the mean difference between groups can be visualized as shown in Figure 4.4. The graph is a visualization of the *mean difference* between the *treatment* and control groups for each variable before and after the *propensity score matching*. The horizontal axis shows the mean difference value, with a value of zero as the reference point where there is no difference between the two groups.

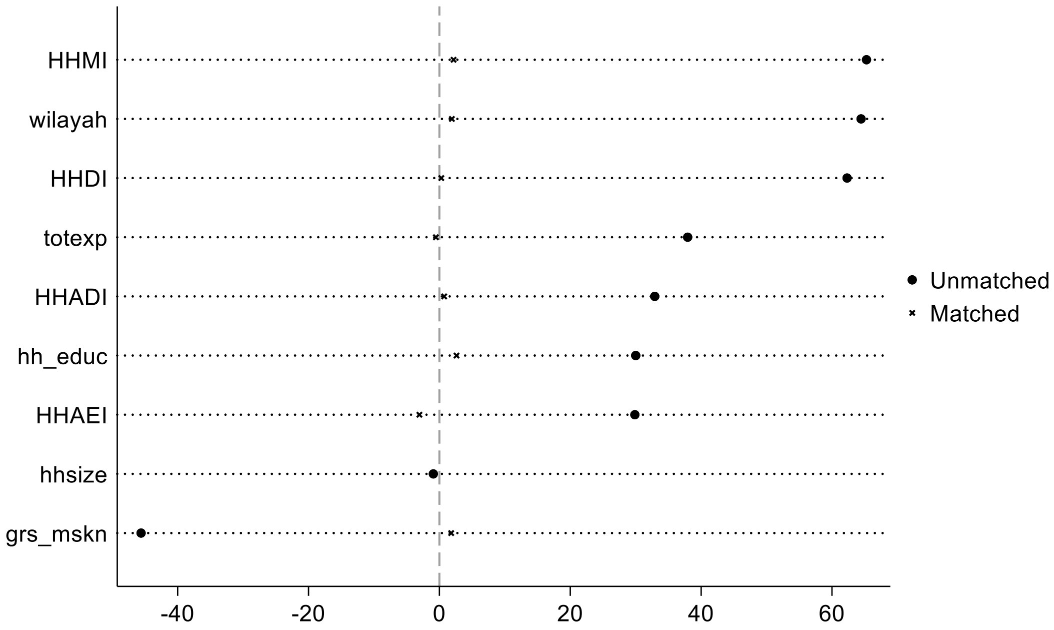

Figure 1 Visualization *T-test Mean Differences* Before and After *Matching* PSM

If you look at the chart, the points before *the matching* are still far from zero. Meanwhile, after *matching* using *the propensity score*, all variables are getting closer to zero, which means that the average difference between the groups is getting smaller and less significant.

The validity of the matching results can then be seen from *the %bias* in the *pstest results. pstest* is one of the *commands* in Stata that is used to test the validity of the *propensity score matching results*. Table 4 displays the results of *the pstest* to evaluate the %bias after the *propensity score matching process*. In general, the results of *the pstest* show that the *matching* process has succeeded in balancing the characteristics between the two groups well. For all variables, the percentage of bias after *matching* is below 5%, which is considered an acceptable level of bias.

Table 4 Result Validity *Matching* With *Pstest*

	Mean			t-test		V(T)/
Variable	Treated	Control	%bias	t	p>t	V(C)
hhsize	5.8383	5.8665	-1.0	-0.48	0.635	1.11*
region	.52647	.51771	1.9	0.83	0.408	.
grs_mskn	.3755	.36674	1.8	0.86	0.392	.
TOTEXP	2.0776	2.087	-0.5	-0.22	0.827	0.76*
hh_educ	8.8515	8.772	2.6	1.38	0.168	1.17*
HHDI_kuantil	2.5341	2.5399	-0.6	-0.27	0.791	0.94*
HHADI_kuantil	2.5027	2.544	-4.0	-1.84	0.066	0.99
HHAEI_kuantil	1.6768	1.6719	0.4	0.19	0.851	1.01
HHMI_kuantil	2.0139	2.0147	-0.1	-0.04	0.970	1.00

* if variance ratio outside [0.94; 1.07]

Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.001	7.31	0.605	1.4	1.0	5.7	1.10	57

*if B>25%, R outside [0.5; 2]

The assumption of covariate equilibrium has been satisfactorily fulfilled. Differences in characteristics between the treatment and control groups were minimized, with a B Rubin value also of 5.7 and well below the 25% limit. The value of R Rubins' variance is also very good, where the value is no more than 2, even very close to the value of 1. This value showed that the covariance between the treatment and control groups after *matching* was almost the same, which means that the covariate was balanced and *the matching* successfully reduced the difference between the two groups.

The results of these statistical tests indicate that the *propensity score matching* process successfully balances the characteristics between *the treatment* and control groups very well, so that there is almost no significant difference between the two groups for most of the observed variables. Thus, estimating the impact of the clean energy transition can be done more accurately because it has reduced the bias caused by the imbalance of characteristics between the two groups.

Common Support* Before and After *Matching

In addition to checking the balance between groups, the quality *of matching* was then seen overlapping *propensity scores* (*pscore*) between groups. *The overlap assumption test* was performed to ensure that there was sufficient *overlap* between the covariate characteristics of the treatment group and the control group. Figure 2 on the left shows a distribution diagram of *the pscore* before *matching.* Overall, the distribution pattern of *pscore* between groups was much different. The majority of the treatment group had *high pscore* scores, while the control group's *pscore* scores were mostly concentrated in low scores. Figure 2 on the right shows the psocre distribution diagram after *matching*. By comparing the two images, it can be concluded that PSM significantly improved the score deviation between the two groups.

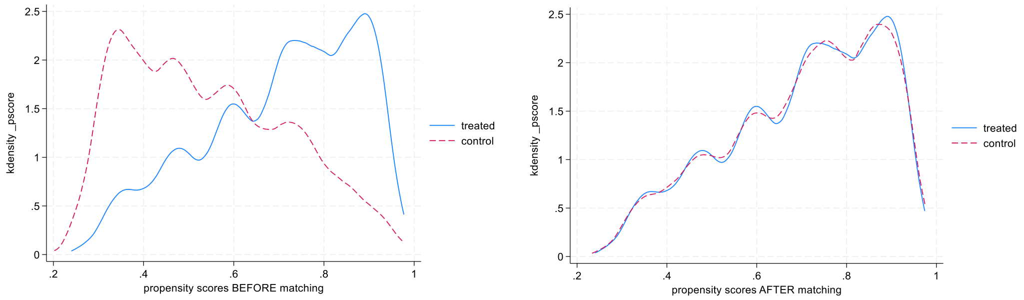

Figure 2 *Propensity Score Graph* (*psgraph*) before (left) and after matching (right)

Furthermore, the common support assumption has also been met, where *the psgraph* graph shows very satisfactory results (see Figure 3). Based on *the psgraph*, only 2 samples were found that were *off support* because they had extreme *propensity scores*, so they did not have a suitable pair after *matching*. This number is very small compared to the total observation of 5,950 households that were matched. This further proves that the good *quality of matching* has been carried out by PSM.

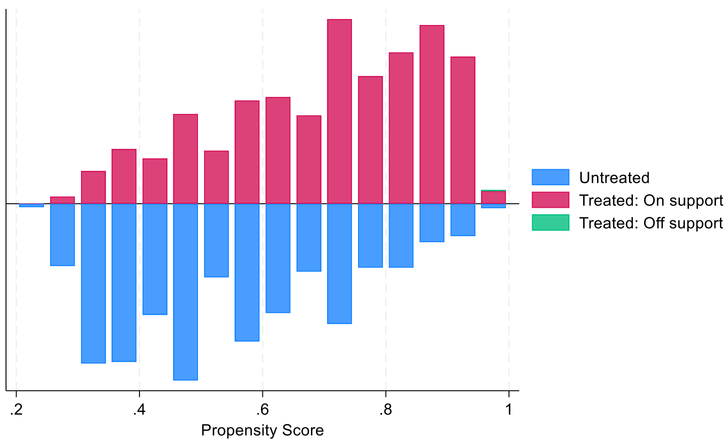

Figure 3 ***Propensity Score Graph*** **(*pagraph*)**

Estimated Impact of Clean Energy Transition on HHDI Intertemporal

This study uses PSM to estimate the impact of the clean energy transition on HHDI Intertemporal Health. After *the matching* is successful, PSM through *the psmatch2 command* will automatically estimate the impact of *the treatment* by comparing the *variable outcomes* between the treatment and control groups. ATT is estimated as the mean difference between *the variable outcomes* in the *treatment* and control groups after *matching*.

Table 5 Estimated Results *Average Treatment Effect on the Treated* (ATT)

Variable	*Sample*	*Treated*	*Controls*	*Difference*	*S.E.*	*T-Stat*
HHDI_int	*Unmatched*	.103310604	.140427238	-.037116634	.006280902	-5.91
	ATT	.103370837	.066212003	.037158834	.008832037	4.21

Note: S.E. does not take into account that the propensity score is estimated.

Table 5 shows the results of the estimated average treatment effect on the *treated group* (*Average Treatment Effect on the Treated*) for variable HHDI_int. The mean difference in HHDI_int (ATT) between the control group and *the treated* group is 0.037158834. The ATT value is statistically significant (*t-stat* of 4.21). It can be concluded that although both groups have experienced an increase in HHDI, households that carry out the clean energy transition have a 3.72% higher HHDI growth compared to continuing to use unclean energy.

Although it may seem small, this effect is quite substantial given the complexity and multi-dimensionality of household development. (Willis, Bridges, & Fortune, 2017) in a study on energy interventions in developing countries found that similar effects can have significant long-term implications for household well-being. In addition, the absence of a household sample in Eastern Indonesia allows the results of this ATT to be *underestimated*. Based on BPS data (2022), 65.88% of households in West Papua Province still use kerosene as the main fuel for cooking. North Maluku as much as 51.58%, and Maluku as many as 66.56% of households still use kerosene for cooking. This allows for an even greater estimate of the impact of the energy transition if households from Eastern Indonesia are included in the study's observations.

In the context of the broader literature, these findings are in line with previous studies that show the positive impact of clean energy access on household development. For example, research conducted by (Mamidi et al., 2021)found that the clean energy transition can increase the growth of household socio-economic development by 12%. Research by (Andadari, Mulder, & Rietveld, 2014) in Indonesia also found that the conversion program from kerosene to *Liquified Petroleum Gas* (LPG) improved household welfare, with a 30% reduction in spending on cooking fuel after switching to LPG.

(Rao, 2013) found that rural electrification in India has a positive impact on household income and education. Where access to electricity increases household income by 17-38%. The research also found an increase in literacy by 0.5 percentage points and an increase in the school year by 0.3 years. Similarly, (Khandker et al., 2013) showed the positive effect of electrification on household welfare in Vietnam, where household electrification increased per capita income by 28% and expenditure by 23%. Lenz et al. (2017) found that access to electricity in Rwanda increased the household asset index by 0.09-0.10 standard deviation, which equates to an increase of about 4-5%. Meanwhile, Grimm et al. (2017) in a study in Tanzania found that access to picoscale solar power systems increased household spending by 4.3-5.5%.

Heterogeneity Test

After analyzing the overall impact of the clean energy transition on intertemporal HHDI, it is important to investigate whether the effect is consistent across populations or varies among different subgroups. *The heterogeneity test* aims to reveal potential differences in *treatment effects* among various household characteristics. The heterogeneity of treatment effects was carried out based on 2 geographical categories, namely villages/cities and Javanese/non-Javanese. The results of the heterogeneity test can be seen in table 6.

Table 6 *Heterogeneity test*

		HHDI_Intertemporal
Island	*Javanese*	0,0414***
		(0,115)
	Obs	3.263
	R2	0,1161
	Non-Javanese	0,0410***
		(0,146)
	Obs	3.623
	R2	0,1549
Region	*Village*	0,0464***
		(0,009)
	Obs	3.993
	R2	0,0781
	City	0,0353***
		(0,131)
	Obs	2.910
	R2	0,0547

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

For the comparison of Java and non-Java, the results showed that the impact of the clean energy transition on HHDI Intertemporal was relatively similar in both regions, with a coefficient of 0.0414 for Java and 0.0410 for non-Java, both significant at the level of 1%. While the impacts are similar, it is important to note that the initial conditions and characteristics of each region may differ. These findings show that the clean energy transition program has the potential to provide equal benefits throughout Indonesia, both in Java and outside Java. This is in line with the study of (Resosudarmo & Vidyattama, 2006) which emphasizes the importance of equitable policies to reduce development inequality between regions in Indonesia.

The analysis based on urban and rural areas reveals more obvious differences. The impact of the clean energy transition on HHDI Intertemporal was greater in rural areas (coefficient 0.0464) compared to urban areas (coefficient 0.0353), both significant at the level of 1%. These findings show the greater potential of clean energy transition programs to improve socio-economic development in rural areas. These results are consistent with previous studies such as Khandker et al. (2013) and Chakravorty et al. (2016) which showed a significant impact of rural electrification on increasing household income and quality of life.

The difference in impact between urban and rural areas can be explained by several factors. First, rural areas generally have more limited access to clean energy before the implementation of the program, so the marginal impact of the energy transition is greater. According to BPS data (2020), the level of electrification in rural areas is still lower than in urban areas, with some remote rural areas still relying on traditional energy sources such as firewood.

Second, different economic structures and energy consumption patterns between urban and rural areas can affect how the energy transition impacts household development. In rural areas, economic activity is often more dependent on the agricultural sector and small-scale household industries. Access to clean energy can directly increase the productivity of these sectors, for example through the use of electric water pumps for irrigation or electrical equipment for agricultural product processing (Aklin et al., 2017). On the other hand, urban households may already have access to better energy infrastructure, so the marginal impact of the clean energy transition will be smaller.

The policy implications of these findings are substantial. First, while the impact of the clean energy transition is significant in all regions, a special focus on rural areas can yield greater benefits in the context of national development. This is in line with the recommendation of (Yang, Xia, Huang, & Qian, 2024) regarding the importance of a differentiated approach in the implementation of energy transition programs.

Second, the government needs to consider program designs that are tailored to the specific characteristics of each region to maximize positive impacts. For example, in rural areas, energy transition programs can be integrated with clean energy-based small business development initiatives. A study by Riva et al. (2018) in Tanzania shows that access to electricity in rural areas can encourage the emergence of new ventures such as milling, refrigeration of agricultural products, and mobile phone charging services, which in turn increases household income.

Third, given the relatively equal impact between Java and non-Java, the allocation of resources for clean energy transition programs should be distributed proportionally, taking into account the needs and potentials of each region. This can help reduce development inequality between regions as highlighted by Hill et al. (2008). However, it is worth noting that while the impact is similar, the implementation challenges may differ. Outside Java, factors such as more challenging geographical conditions and less developed infrastructure may require greater investment per household to achieve an equal level of energy access (ESDM, 2019).

Although the clean energy transition has a significant positive impact on the socio-economic development of households throughout Indonesia, there are important variations in the magnitude of these impacts. These findings emphasize the importance of a differentiated and contextual approach in the implementation of clean energy transition programs, with special attention to greater potential in rural areas. By understanding and responding to these variations, policymakers can design and implement more effective energy transition programs, which not only contribute to environmental sustainability goals but also significantly promote inclusive socio-economic development across Indonesia.

Robustness Test

After conducting the impact of the clean energy transition on intertemporal HHDI and exploring the effects of heterogeneity in different regions, it is important to test *the robustness* of the ATT results. *The robustness test* aims to verify whether the main findings of the study remain consistent and reliable in the face of various changes in the analysis method.

Coarsened Exact Matching

Before *matching, an* imbalance test before matching *was carried out*. *Multivariate imbalance* measures the imbalance between the treatment group and the control group by considering all the covariate variables together. One way to measure it is to use multivariate L1 distance. These values range between 0 and 1, where values close to 0 indicate high equilibrium (meaning that the distribution of covariate variables between the two groups is very similar), while values close to 1 indicate high imbalance.

In table 7, it can be seen that the multivariate value of L1 distance is 0.57964549, indicating that there is a significant imbalance between the *treatment* group and the control group when considering all the covariate variables together. This number is not close to 0, which means that the distribution of covariate variables between the two groups is not yet balanced.

Table 7 *Multivariate* and *Univariate Imbalance* Before CEM

Multivariate imbalance	.57964549						
Univariate imbalance	L1	Mean	Min	25%	50%	75%	Max
hhsize_kuantil	.04379	-.0564	0	0	0	0	0
region	.29747	.29747	0	0	1	1	0
grs_mskn	.22221	-.22221	0	0	-1	0	0
totexp_kuantil	.24553	.63985	0	1	1	1	0
hh_educ	.07115	.91371	0	0	0	0	2
HHDI_kuantil	.26396	.64073	0	1	1	0	0
HHADI_kuantil	.18376	.4476	0	1	1	0	0
HHAEI_kuantil	.09505	.27757	0	0	0	0	0
HHMI_kuantil	.26118	.52235	0	0	2	2	0

In addition, imbalances were also seen at the univariate level for several specific variables. For example, the hhsize variable has an *L1 distance* of 0.04379, indicating a considerable difference between the treatment and control groups in terms of the distribution of these variables. Other variables also showed different levels of imbalance with *a fairly high* L1 distance value.

After *matching* using CEM, the results showed a very significant improvement in the balance between *the treatment* and control groups (see Table 8). *The multivariate L1 distance* after *matching* dropped drastically to 3.082e-15 (or by 0.000000000000000003082), indicating that the multivariate imbalance was almost completely eliminated. This shows that the covariate distribution between the *treatment* and control groups becomes very similar after *matching*.

At the univariate level, imbalances are also significantly reduced. The variable 'region', for example, has an *almost zero L1 distance* (1.1e-15), indicating that the *univariate* imbalance for this variable has been eliminated almost completely. Other variables also showed a decrease *in L1 distance* to a very small level and close to zero. Overall, these results show that the *matching* process is able to reduce heterogeneity between treated and control households not only in the mean but also in the shared distribution of data (Nilsson et al., 2019).

Table 8 Multivariate and Univariate Imbalance After CEM

Multivariate imbalance	3.082e-15						
Univariate imbalance	L1	Mean	Min	25%	50%	75%	Max
hhsize_kuantil	1.9e-15	-1.3e-15	0	0	0	0	0
region	1.1e-15	-2.2e-15	0	0	0	0	0
grs_mskn	1.0e-15	-6.1e-16	0	0	0	0	0
totexp_kuantil	2.0e-15	-1.8e-15	0	0	0	0	0
hh_educ	9.9e-16	-6.4e-14	0	0	0	0	0
HHDI_kuantil	2.3e-15	-1.2e-14	0	0	0	0	0
HHADI_kuantil	2.2e-15	-9.8e-15	0	0	0	0	0
HHAEI_kuantil	5.5e-16	-2.2e-16	0	0	0	0	0
HHMI_kuantil	1.1e-15	-5.3e-15	0	0	0	0	0

Although there is no generally accepted standard level for L1, Firestone (2015) recommends 0.2 as an acceptable level. Therefore, with an L1 size of 3.082e-15 or 0.000000000000003082, it can be concluded that the treatment household group can be compared with the control household group, and both are valid and appropriate *counterfactual* groups for ATT estimation.

Table 9 shows the distribution of observations before and after the matching process using the *Coarsened Exact Matching* (CEM) method. The total initial sample consisted of 6,903 observations, with 2,442 households not making the energy transition (control group) and 4,461 households doing the energy transition (treatment group).

Table 9 Distribution of observations after the process *matching* with CEM

	0: No transition	1: Energy transition	Total
All	2.442	4.461	6.903
Matched	1.976	2.916	4.892
Unmatched	466	1.545	2.011

After the matching process, the number of successful observations was matched to 4,892, with 1,976 households in the control group and 2,916 households in the treatment group. The number of observations that did not match or did not participate in the matching process was 2,011, consisting of 466 households in the control group and 1,545 households in the treatment group. Unmatched observations will be removed from observation before proceeding to the next stage, which is ATT estimation.

The results of the estimation of *Average Treatment Effect on the Treated* (ATT) using the *Coarsened Exact Matching* (CEM) method can be seen in Table 4.10. In the table, it can be seen that the clean energy transition (ET) has a significant positive impact on the growth of household socioeconomic development as measured by HHDI Intertemporal (HHDI_int). The coefficient for the ET variable is 0.0396 with a standard error of 0.00770. This indicates that households that make an energy transition from firewood or kerosene to LPG or electricity have an Intertemporal HHDI increase of 3.96% greater than households that do not make an energy transition. This increase was significant at the p<0.01 level, which indicates that this result is statistically very strong.

Table 10 ATT estimation results using CEM

	(1)
VARIABLES	HHDI_int
ET	0.0396***
	(0.00770)
Constant	0.0678***
	(0.00637)
Observations	4,892
R-squared	0.007

Robust standard errors in parentheses
p<0.01, p<0.05, p<0.1

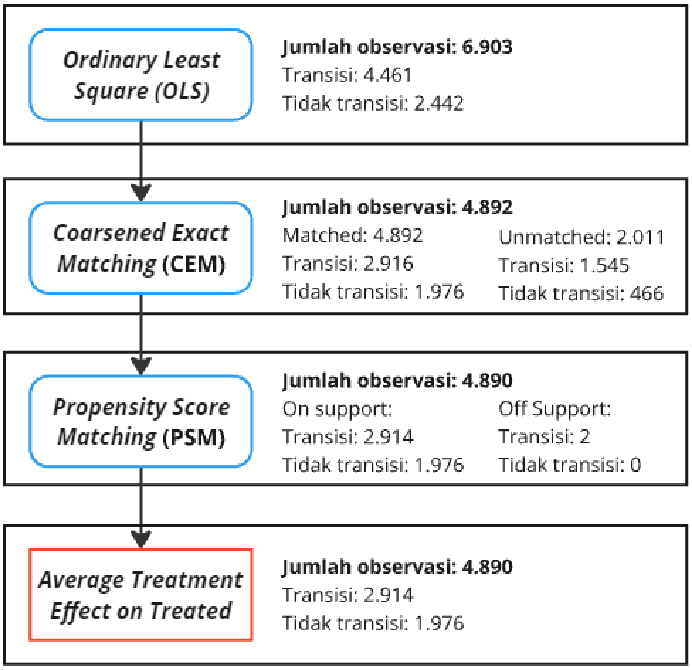

Figure 4 Changes in the distribution of observations at each stage

Figure 4 shows the change in the distribution of observations at each stage carried out. At the *matching* using CEM, there are 2,011 households that do not have a partner (*unmatched*). The number of observations that *unmatched* This is natural, given the use of covariate variables *matching* which is quite a lot (9 variables), so that the algorithm *exact matching* will be stricter in pairing households in the control group and *treatment*. The use of these nine variables is carried out by equalizing the covariate variables used in the PSM method, so that the comparison of ATT estimation results can be done properly.

CEM-PSM combination

The next method used for *robustness test* analysis is the CEM-PSM combination approach. After previously matching using CEM and unmatched data being deleted, the next step is *to rematch the remaining data using PSM.*

Table 11 ATT estimation results using CEM-PSM

	(1)
VARIABLES	HHDI_int
ET	0.0395***
	(0.00694)
Constant	0.0678***
	(0.00542)
Observations	4,888
R-squared	0.008

Robust standard errors in parentheses
p<0.01, p<0.05, p<0.1

The results of the estimates in Table 11 show that the clean energy transition (ET) has a significant positive impact on the growth of household socioeconomic development as measured by the HHDI Intertemporal (HHDI_int). The coefficient for the ET variable is 0.0395 with *a standard error* of 0.00694, which indicates that households that undergo energy transition experience an increase in Intertemporal HHDI by 3.95% greater than households that do not undergo energy transition. This increase was significant at the p<0.01 level, indicating that this result is statistically very robust.

Comparison of ATT estimation results

Table 12 shows a comparison of the results of the Average Treatment Effect on the Treated (ATT) estimation using four different methods: *Ordinary Least Squares* (OLS), *Propensity Score Matching* (PSM), *Coarsened Exact Matching* (CEM), and CEM-PSM combination. In the table, it can be seen that all methods show positive and significant effects of the energy transition (ET) on the household development index (HHDI_int). OLS gave the highest estimate (0.0476), while PSM gave the lowest estimate (0.0372). CEM and CEM-PSM gave very similar results (0.0396 and 0.0395). The ET coefficients ranged from 0.0372 to 0.0476, all of which were significant at the 1% level (p<0.01). This indicates the strong *robustness* of the study's main findings.

Table 11 Comparison of ATT estimation results

	OLS	PSM	CEM	CEM-PSM
VARIABLES	HHDI_int	HHDI_int	HHDI_int	HHDI_int
ET	0.0476***	0.0372***	0.0396***	0.0395***
	(0.00563)	(0.00632)	(0.00770)	(0.00694)
Constant	0.375***	0.0662***	0.0678***	0.0678***
	(0.0117)	(0.00526)	(0.00637)	(0.00542)
Observations	6,903	6,898	4,892	4,888
R-squared	0.328	0.007	0.007	0.008

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

OLS tends to provide biased estimates because it does not take into account the potential for selection bias. As explained by Angrist and Pischke (2008), OLS can produce biased estimates if there are unobserved variables that affect both the decision to perform treatment and the *outcome*. The significant difference in the results of OLS estimation which is much higher than the results of other methods indicates an overestimation in OLS estimation. Therefore, the robustness *test* measurement in this study uses 2 other methods, namely ATT estimation using CEM and a combination of CEM-PSM.

The ATT estimates produced by the CEM and CEM-PSM methods have values similar to the main ATT estimates, which range from 3.7 to 3.9 percent. The consistency of results across different *matching* methods strengthens the validity of the findings of this study. That the energy transition has an impact on increasing the growth of household socio-economic development by 3.7-3.9 percent.

Discussion

The results of the average treatment impact estimate (ATT) show that households that carry out the clean energy transition have a 3.7-3.9% higher HHDI growth than if they continue to use unclean energy. The results are *robust* based on testing several *matching methods*. The findings of this study are quite interesting, where the positive impact of the clean energy transition on HHDI shows that the benefits extend beyond the energy sector and penetrate into various aspects of household development. This is in line with the concept of the "energy-development nexus" discussed by Nerini et al. (2018), which emphasizes the close link between access to clean energy and the achievement of various Sustainable Development Goals (SDGs).

The results of this study are inseparable from the policies that have been carried out by the Government of Indonesia before. The kerosene to LPG conversion program, which began in 2007, is the main policy of the Indonesian government in encouraging the clean energy transition at the household level. The program has successfully converted more than 50 million households from kerosene to LPG use (Thoday et al., 2018). The success of this program shows that the right policies can drive significant changes in household energy use. In addition, the rural electricity and national electrification program has also contributed to increasing access to electricity in Indonesia. The national electrification ratio has reached 99.20% at the end of 2019 (ESDM, 2020).

However, it is important to note that while the results of this study show a positive impact, policy implementation needs to consider potential challenges. For example, there are still gaps in the quality and reliability of electricity supply in some areas. Where in certain areas, especially outside the island of Java, with the frequency of power outages still often occurring and the duration is quite long (PLN, 2020). This can certainly have an impact on the inhibition of household socio-economic growth outside the island of Java. In addition, a study by Thoday et al. (2018) in Indonesia found that despite the increasing adoption of LPG, many households still use firewood as a secondary fuel due to cultural and economic factors. As seen in Figure 4.5, there are still 11.76% of households that use firewood for cooking, and 2.78% use kerosene.

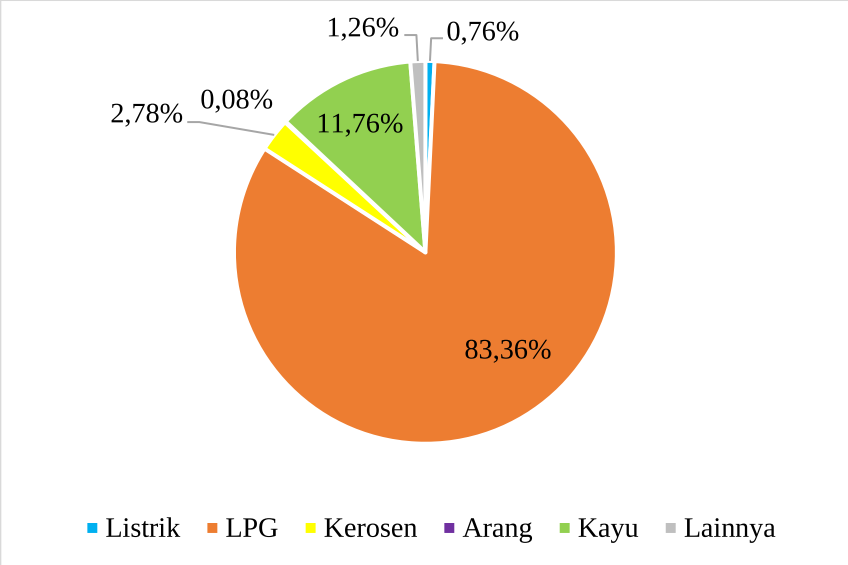

Figure 5 Main fuel use for household cooking in Indonesia in 2021

Source: BPS, has been reprocessed

Because the clean energy transition is so important to support the improvement of household socio-economic development, the use of clean energy for cooking and access to electricity for lighting needs to continue to be developed. There are several things that the government can do in this regard, for example continuing the LPG conversion program. The government can expand the scope of the LPG conversion program to areas that still use firewood as the main fuel. This program needs to be accompanied by education about the safe and efficient use of LPG. Andadari et al. (2014) found that the adoption of LPG in Indonesia is not only related to availability, but also to the perception of safety and ease of use.

The government also needs to continue to encourage household electrification, considering that until the end of December 2023 there were 185,662 households that did not have access to electricity. In addition, the government also needs to improve the quality of electricity. The focus is not only on expanding access to electricity, but also on improving the quality and reliability of electricity supply, especially in rural and remote areas. The maturity of electricity infrastructure has a significant effect on household social and economic growth (Alam et al., 2016).

Another program that the government can carry out to encourage clean energy transition efforts in households is by continuing to educate the public. Increase public awareness about the benefits of using LPG and electricity for household health and productivity. This education must consider local cultural factors and customs.

The government also needs to integrate the clean energy transition program with the existing poverty alleviation program, considering that the poverty line variable has a significant negative coefficient (-0.282***) in the probit model, which shows that households above the poverty line tend to make the energy transition. This shows that there is a correlation between household income and the decision to make a clean energy transition. In addition, the government also needs to develop policies to encourage a clean energy transition that takes into account the specific characteristics of the region. Given the difference in the results of the ATT estimation where the village sub-sample shows a greater impact than the city sub-sample. For example, focus on electrification in remote areas or conversion from firewood to LPG in rural areas.

In general, the findings of this study provide empirical evidence on the positive impact of the clean energy transition (from firewood/kerosene to LPG/electricity) on household welfare as measured through HHDI. This strengthens the urgency for the government to continue and expand the energy conversion and electrification program. Comprehensive policies, involving aspects from subsidies to infrastructure development, are needed to ensure a just and inclusive transition. With proper implementation, the clean energy transition will not only improve the quality of life of households but also contribute to the sustainable development goals more broadly.

CONCLUSION

Limited access to clean energy is often linked to various factors such as poverty, education, and health problems. However, most existing research tends to focus on the relationship between gross energy use and subjective health or well-being. This research will close the gap by considering other socioeconomic aspects such as household income, education level, mass media access, and multidimensional public trust.

This study aims to calculate the impact of the clean energy transition on the growth of household socio-economic development in Indonesia. Using data from two periods of household surveys in Indonesia, this study calculates the estimated causal effect using the propensity score matching (PSM) method. This study concluded that the transition to clean energy can increase the development of household socio-economic development by 3.72%. These results can be said to be robust based on the similarity of ATT estimation results carried out using different matching methods and approaches, namely Coarsened Exact Matching (PSM) and CEM-PSM combinations. With estimated results ranging from 3.72% to 3.96%.

This study also conducted a heterogeneity test by comparing village-city and Javanese-non-Javanese sub-samples. The results show that the impact of the clean energy transition on HHDI Intertemporal is relatively similar between Java and non-Java, which is 4.1%. Meanwhile, the analysis by urban and rural areas reveals clearer differences. Where the impact of the transition in rural areas is much greater (4.6%) than in urban areas (3.5%). These findings show the greater potential of clean energy transition programs to improve socio-economic development in rural areas.

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