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The Impact of Electricity Consumption to Human Development Index in Asian Countries: Analysis Panel Vector Error Correction Model

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ABSTRACT

This study answers the question of the effect of the level of electricity consumption (LEC) on the level of human welfare both in the short and long term. Recently, many studies that investigated the impact of LEC to economic growth has been conducted. Most of them argued that electricity consumption have positive impact to economic growth. However, the study that analyzes LEC's impact on the Human Development Index (HDI) and Happiness Index (HI) still needs to be completed. The research data uses secondary data sourced from the World Bank from 2012-2019. The number of countries as sample of this study were 38 countries in Asia. We choose and analyze the countries that have complete data for all variables until 2019. The analysis tool used is the Panel Vector Error Correction Model (PVECM). We analyzed data using PVECM because we wanted to understand the impact of LEC on HDI and HI both in the short and long run. The results revealed the relation between LEC and human welfare indicators. Finally, we found in the long run, there are no variables that have a significant effect on electricity consumption. Meanwhile, based on the short-term equation, it was found that in model 1 with the LEC dependent variable, it was found that only the previous period's LEC variable was significant. In Model 2, with the HDI dependent variable, it is known that the previous period's HDI variable has a significant effect. These results are also similar to the HI and LAK variables. The HI and LAK variables are only influenced by HI and LAK variables in the previous time lag. The implication of this study is increasing of electricity consumption would not direct impact on human development index and happiness index.

Keywords: Electricity Consumption, Human Development Index, Happiness Index, Work Force, Panel Vector Error Correction Model
JEL Classifications: O13, Q54, Q56

1. INTRODUCTION

Electrical energy consumption has a close relationship with a country's economic growth (Sarkodie and Adams, 2020). Electricity has an important role in economic activity, both in the production and consumption of goods and services. The role of electricity is increasing along with advances in technology, population growth, urbanization, and increased industrialization. The source of such progress is electricity consumption.

Some evidence shows that the level of electricity consumption is the key to improving people's welfare (Odhiambo, 2009; Martínez, 2015; Purnomo, 2023). Several studies have stated that there is a correlation between the level of electricity consumption on economic growth and the Human Development Index (HDI). The level of electricity consumption is in line with the increase in industrialization and urbanization.

The economic growth hypothesis reveals that electricity consumption has a direct influence on economic growth as a complement to labor and capital in the production process (Apergis and Payne, 2011). Aslan (2014) in his research revealed that there is a link between electricity consumption and the workforce in Turkey.

The availability of electricity is also considered to have helped to improve living standards in various countries (Apergis and Payne, 2011). Afia's research (2019) proves that energy consumption affects the level of people's happiness in 47 countries. Higher electricity consumption will accelerate a country's economic growth (Deutch, 2017).

In the last two decades, the demand for electrical energy has increased. The developments in industrialization, increasing urbanization, and living standards have positively impact electricity consumption. Most emerging countries have experienced it, especially in several countries, South Korea, China, and Malaysia. In decade, these countries show high achievement in economic growth. The higher the level of energy consumption indicates that there are production activities that involve many investors and workers (Makholm, 2022). Furthermore, Pata (2018) explained that the development of industrial countries is always supported by the availability of electricity and tends to have a higher level of welfare compared to agrarian countries.

Figure 1 shows a comparison of electricity consumption per capita for four emerging Asian countries. South Korea is the highest country for GDP per capita, followed by Malaysia, China, and Indonesia. Based on the figure, GDP per capita positively correlates with electricity consumption.

The causal relationship between electricity consumption and economic growth is still being debated in various literature and research. This is because the direction of the causal relationship between electricity consumption and economic growth has significant policy implications. If there is no causal relationship between the two variables, it indicates that the economy is less dependent on electrical energy. Energy conservation policies will not have an impact on economic growth, on the contrary when there is a causal relationship between electricity consumption and economic growth, it indicates economic dependence on autonomous energy for electrical energy will have an impact on economic growth (Aslan, 2014).

Many studies have tried to find the relationship between economic growth and electricity consumption. However, few studies are still rare that explain the linkage of electricity consumption to human welfare indicators, such as human development and happiness. Electrical energy consumption is very important, especially in supporting the industrialization process which will have an impact on economic growth and people's welfare (Odhiambo, 2009). Knowing the causal relationship between electrical energy consumption and economic growth variables can show appropriate policy implications in the energy sector, especially electrical energy.

Based on existing research gaps, this study seeks to find the empirical evidence about the correlation between the level of electricity consumption on human welfare in the short and long term. Second, there are still differences in results between empirical evidence related to the effect of the level of electricity consumption on labor force. The research is intended as empirical evidence by looking at the causal relationship between electricity consumption on economic growth and the level of welfare.

2. RESEARCH METHODS

2.1. Data

This study uses panel data from 37 countries in the Asian region during the period 2012 to 2019 obtained from World Bank data. Research data includes *Electricity Consumption per Capita*, Total Work Force, Human Development Index (HDI), and Happiness Index (HI).

The following Table 1 is a list of 37 countries in Asia that are the object of this study:

2.2. Panel Unit Root Test and Panel Cointegration

The first stage in this empirical study is represented by stationary analysis using the, Levin et al., (LLC) method (Levin et al., 2002); *ADF-Fisher Chi-square* and *ADF-Choi Z-stat* methods (Choi, 2001) to check the order of integration. Unit root tests must be performed on variables to see whether the variable data has unit roots which can result in *spurious regression problems* or pseudo/false regression (Shao et al., 2021).

$$y_{it} = \rho_i y_{it-1} + \delta_i X_{it} + \varepsilon_{it} \quad (1)$$

Where i = 1,2,3,…. describes the country that is the object of research, t = 1,2,3,… is the time period of the study, and X_{it} is an exogenous variable, while ρ_i is an autoregression coefficient, and ε_{it} is a stationary process. If $\rho_i < 1$, then there is a weak stationary trend, whereas if $\rho_i = 1$ then there is a unit root in the data.

After analyzing the stationarity of the data, the second step is to carry out a cointegration test to determine whether there is a long-term relationship between the variables being analyzed (Roco et al., 2015) (Engle and Granger, 1987). In this study, Pedroni's (1999, 2000) method for measuring panel cointegration allows for accommodating heterogeneity across individual members in the panel data.

2.3. Vector Error Correction Model (VECM)

The first step to identify the direction of causality was the *Granger Causality Test* (1987) on the variables of electricity consumption, work force, HDI, and HI. The second step estimates the long-run model specified in Eq. to obtain an estimated residual. Next, estimating the Granger causality model with dynamic error correction based on Holtz-Eakin et al. (1988).

The following is the VECM empirical model:

$$\begin{aligned}\Delta EC_{it} = {} & \alpha + \textstyle\sum_{j=1}^{n} \beta 1 \Delta EC_{i,\,t-1} + \sum_{j=1}^{n} \beta 2 \Delta AK_{i,\,t-1} \\ & + \textstyle\sum_{j=1}^{n} \beta 3 \Delta HDI_{i,\,t-1} + \sum_{j=1}^{n} \beta 4 \Delta HI_{i,\,t-1} \gamma e_{it} + \mu_{it}\end{aligned} \quad (2)$$

$$\begin{aligned}\Delta AK_{it} = {} & \alpha + \textstyle\sum_{j=1}^{n} \beta 1 \Delta AK_{i,\,t-1} + \sum_{j=1}^{n} \beta 2 \Delta EC_{i,\,t-1} \\ & + \textstyle\sum_{j=1}^{n} \beta 3 \Delta HDI_{i,\,t-1} + \sum_{j=1}^{n} \beta 4 \Delta HI_{i,\,t-1} \gamma e_{it} + \mu_{it}\end{aligned} \quad (3)$$

Table 1: List of research object countries

Afghanistan	Hong Kong	Kazakhstan	Pakistan	Turkmenistan
Armenian	India	Korea	Philippines	United Arab Emirates
Azerbaijan	Indonesia	Kuwait	Qatar	Uzbekistan
Bahrain	Iran	Kyrgyz Rep.	Saudi Arabia	Vietnamese
Bangladesh	Iraq	Lao	Singapore	Yemen
Cambodia	Israel	Malaysia	Sri Lanka	
China	Japan	Mongolia	Tajikistan	
Georgian	Jordan	Nepal	Thailand	

Source: Worldbank

$$\Delta HDI_{it} = \alpha + \sum_{j=1}^{n} \beta 1 \Delta HDI_{i,\,t-1} + \sum_{j=1}^{n} \beta 2 EC_{i,\,t-1} + \sum_{j=1}^{n} \beta 3 \Delta AK_{i,\,t-1} + \sum_{j=1}^{n} \beta 4 \Delta HI_{i,\,t-1} \gamma e_{it} + \mu_{it} \tag{4}$$

$$\Delta HI_{it} = \alpha + \sum_{j=1}^{n} \beta 1 \Delta HI_{i,\,t-1} + \sum_{j=1}^{n} \beta 2 EC_{i,\,t-1} + \sum_{j=1}^{n} \beta 3 \Delta AK_{i,\,t-1} + \sum_{j=1}^{n} \beta 4 \Delta HDI_{i,\,t-1} \gamma e_{it} + \mu_{it} \tag{5}$$

Where ΔEC is the first difference from the natural *electricity consumption logarithm* for country i, and year t; ΔAK the first difference from the natural logarithm of the labor force for country i, and year t; ΔHDI first difference from HDI for country i, and year t; ΔHI the first difference from the Happiness Index for country i, and year t.

3. EMPIRICAL ANALYSIS AND DISCUSSION

3.1. Panel Unit Root Test

The results of the panel unit root test in this study showed that all four variables were stationary at the *first difference level*. Based on Table 2, it is found that the four variables are stationary at the *first difference level* because the probability value is <5% alpha. Then one of the conditions in the PVECM method, namely stationary at level 1, has been fulfilled and the model in this study is free from *spurious regression problems* or pseudo/false regression.

3.2. Optimal Lag Test

Based on the optimal lag test in Table 3, lag 4 was selected as the optimal lag based on the LR, FPE, and AIC criteria. So the model used in this study is PVECM with lag 3 or PVECM (3).

3.3. Cointegration Panel

Based on the cointegration test results in Table 4, it shows that the variables in this study have a cointegration to the ADF t-statistic of −5.56 with a probability of 0.00 less than an alpha of 5%. Cointegration is a condition that occurs when two random variables, each of which is a random walk or not stationary, but the linear combination between the two variables is a stationary time series.

3.4. Panel Vector Error Correction Model (VECM)

Table 5 presents the estimation results of the Panel Vector Error Correction Model (VECM). The first two columns to the left of the table report the results of long-run estimates. If the results in the second column are expressed in the long-run equation, the sign of the estimated coefficient of each coefficient will reverse from negative to positive, or vice versa. Meanwhile, the right side of the table reports short-run estimation results consisting of four models.

Table 2: Panel unit root test – first difference

Method	DLEC	DLAK	DHDI	DHI
ADF – Fisher Chi-square	164,904*	114.027*	104,841*	95.5162*
ADF – Choi Z-stat	−4.70209*	−0.93481*	−1.92367*	−1.04700

Source: secondary data, processed, Description: *significant at 5% alpha

Table 3: Optimal lag test

lag	LogL	LR	FPE	AIC	SC	HQ
0	963,639	NA	5.73	−16.83	−16.74	−16.79
1	1030465	126.7907	2.35	−17.73	−17.25*	−17.53*
2	1052.161	39.96620	2.13	−17.82	−16.96	−17.47
3	1080607	50.40432	1.72	−18,046	−16.79	−17.54
4	1106722	44.44039*	1.44*	−18.22*	−16.59*	−17.56*

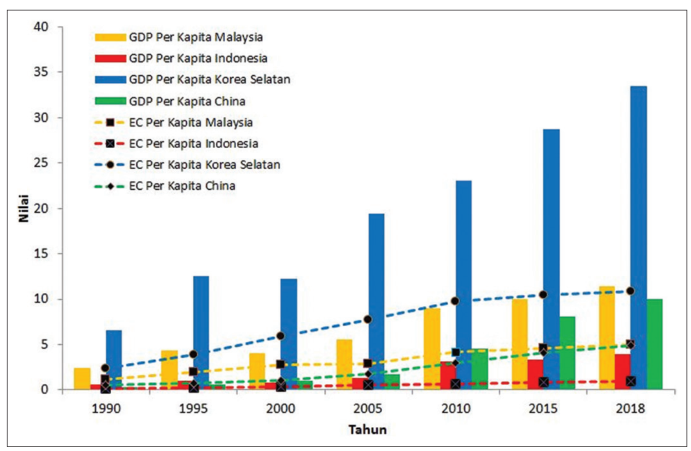
Source: Secondary data, processed

Table 4: Cointegration panels

ADF	t-statistic	Prob
	−5.56	0.0000

Source: Secondary data, processed

Figure 1: Comparison of per capita electricity consumption levels among Asian countries (www.iea.org)



The long-run equation from the results of Table 5 can be stated as follows.

$$LEC_{t-1} = -0.21 + 48.14HDI_{t-1} - 0.23HI_{t-1} - 0.35LAK \tag{6}$$

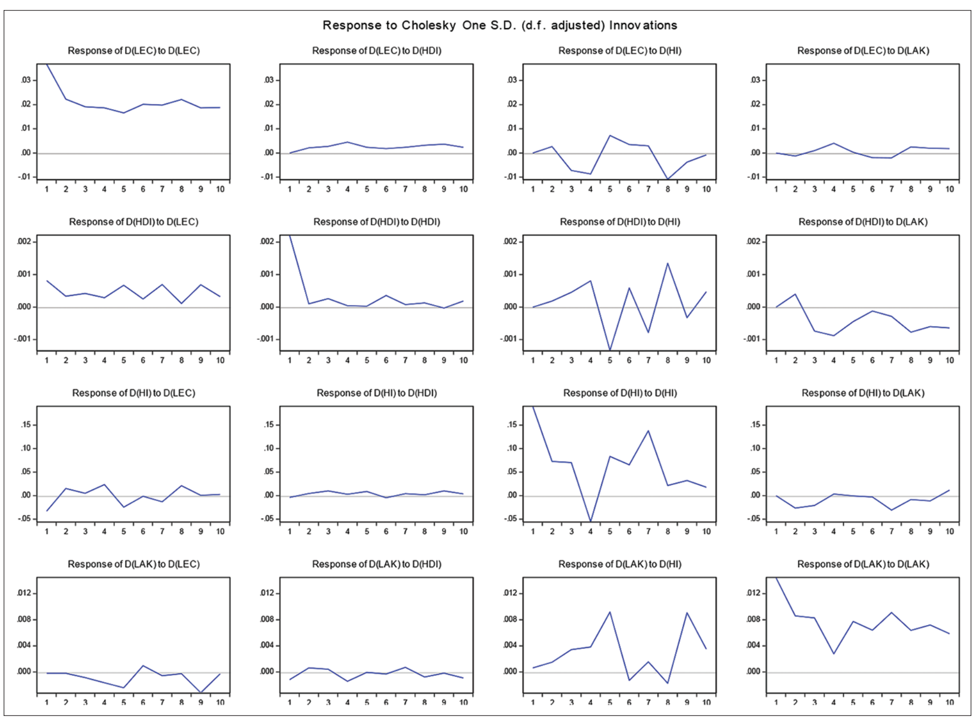
In the long run, electricity consumption has a long-run relationship with HDI and the workforce (LAK) significantly. This result

Table 5: Panel vector error correction model (VECM)

Long-term		Short-term				4D Model
		Model 1D (LEC)	2D (HDI) models	3D Models (HI)		(LAK)
DLEC	1.000000	D (LEC(−1), 2)	−0.357916*	−0.007732	0.080149	−0.00588
(−1)			[−2.20418]	[−0.74210]	[0.94088]	[−0.09158]
DHDI (−1)	−48.14	D (LEC(−2),2)	−0.276893*	−0.002472	0.418684	0.020259
	[−8.76]		[−2.13428]	[−0.29701]	[0.61617]	[−0.39439]
DHI (−1)	0.23	D (LEC (−3),2)	−0.161584	−0.001227	0.297366	−0.026852*
	[0.86]		[−1.62219]	[−0.19195]	[0.57000]	[−0.68085]
DLAK	03.35	D (LEC(−4),2)	−0.161584*	−0.001569	−0.081093	−0.036496*
	[−2.75]		[−2.13428]	[−0.34600]	[−0.21913]	[−1.30455]
C	0.21	D (HDI(−1),2)	−1.097621	−0.143799*	−2.041657	0.384461
			[−0.76093]	[−2.07155]	[−0.36031]	[1.39068]
		D (HDI(−2),2)	−0.470200	−0.078408	2.034920	0.503447
			[−0.51426]	[−1.33656]	[0.42494]	[−1.49903]
		D (HDI(−3),2)	0.675435	−0.091246*	0.736244	−0.526839
			[0.76093]	[−1.60213]	[0.15837]	[−1.49903]
		D (HDI(−4),2)	0.239333	−0.086610	1.419054	0.184216
			[0.28516]	[−1.60835]	[0.32282]	[0.55435]
		D (HI(−1),2)	0.024321*	−0.002927	−0.591261*	0.007055*
			[0.67586]	[0.67586]	[−3.13714]	[0.49518]
		D (HI(−2),2)	0.028646*	−0.001054	−0.366868*	0.007055
			[−0.77618]	[−0.44515]	[−1.89796]	[1.16841]
		D (HI(−3),2)	−0.041111*	0.002341*	−0.840266*	0.017751*
			[−0.81284]	[0.72126]	[−3.17208]	[0.88642]
		D (HI(−4),2)	0.046998	−0.005488	−0.162699	0.045457*
			[0.64573]	[−1.17513]	[−0.42681]	[1.57740]
		D (LAK (−1),2)	−0.230304	0.082821	−2.080908	−0.045457*
			[−0.67900]	[0.64960]	[−1.17139]	[−3.12331]
		D (LAK (−2),2)	−0.057761	0.016090	−1.720469	−0.206485
			[−0.14963]	[0.64960]	[−0.85094]	[−1.35092]
		D (LAK (−3),2)	0.092893	−0.015083	0.211684	−0.429624*
			[0.22271]	[−0.56360]	[0.09690]	[−2.60146]
		D (LAK (−4),2)	−0.268739	−0.000249	−1.286592	0.092374
			[−0.69621]	[−0.77133]	[−0.63640]	[0.60441]

Source: secondary data, processed, *Significant at 5% level

Figure 2: Impulse responses



Source: secondary data, processed

Table 6: Variance decomposition

Period	SE	D (LEC)	D (HDI)	D (HI)	D (LAK)
Variance decomposition of D (LEC)					
1	0.036615	100,0000	0.000000	0.000000	0.000000
2	0.043012	99.27658	0.243486	0.391250	0.088686
3	0.047691	96.76598	0.529323	2.592634	0.112065
4	0.052300	93.22606	1.174913	4.911623	0.687404
5	0.055401	92.06839	1.228632	6.088328	0.614645
6	0.059116	92.47885	1.171160	5.700971	0.649024
7	0.062487	92.79329	1.192348	5.330173	0.684193
8	0.067275	90.81817	1.250878	7.200526	0.730428
9	0.070048	90.88723	1.425573	6.932205	0.754994
10	0.072590	91.33938	1.429394	6.466703	0.764522
Variance decomposition of D (HDI)					
1	0.002349	12.06955	87.93045	0.000000	0.000000
2	0.002416	13.36439	83.33102	0.596301	2.708287
3	0.002614	14.02754	72.17486	3.530429	10.26717
4	0.002888	12.47481	59.13331	10.69200	17.69988
5	0.003282	13.86370	45.79910	24.79921	15.53798
6	0.003364	13.75323	44.70865	26.62183	14.91629
7	0.003536	16.33063	40.51272	28.99563	14.16101
8	0.003867	13.73729	33.98278	36.44528	15.83465
9	0.003987	15.88755	31.98212	34.97728	17.15305
10	0.004083	15.77601	30.71304	34.67828	18.83267
Variance decomposition of D (HI)					
1	0.191768	2.864600	0.032261	97.10314	0.000000
2	0.207355	3.010357	0.080324	95.31653	1.592791
3	0.220297	2.719983	0.287330	94.69044	2.302244
4	0.228297	3.620645	0.286107	93.92693	2.166319
5	0.244509	4.148436	0.385116	93.57757	1.888874
6	0.253210	3.870244	0.388415	93.96796	1.773380
7	0.290346	3.140052	0.317234	94.09697	2.445743
8	0.292060	3.636040	0.317502	93.55021	2.496245
9	0.294205	3.584080	0.435284	93.38551	2.595129
10	0.295049	3.572954	0.451146	93.23793	2.737975
Variance decomposition of D (LAK)					
1	0.014497	0.016577	0.640726	0.181454	99.16124
2	0.016935	0.025542	0.600847	0.921388	98.45222
3	0.019190	0.214314	0.514003	3.932857	95.33883
4	0.019886	0.885255	0.987131	7.397290	90.73032
5	0.023367	1.715922	0.715402	20.83902	76.72966
6	0.024289	1.743883	0.680220	19.56953	78.00636
7	0.026004	1.569458	0.668529	17.43846	80.32355
8	0.026847	1.481689	0.708690	16.77465	81.03497
9	0.029417	2.393333	0.593707	23.50609	73.50687
10	0.030217	2.276381	0.652190	23.63958	73.43185
Cholesky Ordering: D (LEC) D (HDI) D (HI) D (LAK)					

Source: Secondary data, processed

conforming the finding of Ouedraogo (2013). HDI has a positive association, while the workforce has a negative association with electricity consumption. Meanwhile, based on the short-run equation, it was found that in model 1 with the LEC as a dependent variable, HI, HDI, and LAK have no effect on LEC. This is not in line with research by Afia (2019) where there is a causal relationship between electricity consumption and happiness. The level of electricity consumption is only affected by the level of electricity consumption in the previous year and two years.

In Model 2, HDI as the dependent variable is known that the LEC variable, HI variable, and LAK variable are not proven to have a significant influence. The HDI variable is only influenced by the last year's period HDI variable. The level of electricity consumption affects the level of income but does not affect the level of quality of human life (Wang et al., 2018), (Cowan et al., 2014). Niu et al. (2016) stated that high electricity consumption drives HDI when a country's income level is already high. Conversely, when income tends to be low, the effect tends to be negative because it is accompanied by environmental externalities. These results are also different from the research by Zheng and Wang (2022), in their research that primary energy affects HDI.

In model 3, the HDI, LEC, and LAK variables do not affect the level of happiness. The HDI variable with three dimensions seems unable to explain the happiness variable (Basu et al., 2018). The variable that has a significant effect is only the HI variable in the past period.

Whereas in model 4, the LEC variable, HDI variable, and HI variable do not affect the LAK variable. The level of electricity consumption in the short term and long term does not affect the level of the workforce. Likewise, the higher the quality of human life does not affect the work force (Fajriyyah and Budiantara, 2015).

The current and future impacts of each variable caused by the shock on other variables can be illustrated through the graphs of impulse responses (Figure 2), as follows:

The first column of Figure 2 shows the impact of LEC on shock itself, HDI on LEC shock, HI on LEC shock, and LAK on LEC shock. Electricity consumption responds to self-shock in positive value. However, the shock effect tends to decrease and stabilize. Meanwhile, the HDI was affected by a shock in electricity consumption with an initial impact that increased but the subsequent impact was unstable and with a positive value. In contrast to HI, the initial impact of electricity consumption shock increases even though the subsequent impact tends to be unstable in negative and positive values. However, it appears that in the end the impact stabilizes around zero. Finally, the labor force responds negatively to electricity consumption shocks with an unstable impact but with a negative net impact.

From Table 6, it is stated that electricity consumption, HDI, HI, and labor force are most dominantly affected by the shock itself, respectively. The HDI shock most dominantly affects HDI, and the HI shock is the second largest shock that affects HDI. Likewise, HI shock most dominantly affects HI, and electricity consumption shock is the second largest shock that affects HI. The conclusion is that a positive shock to electricity consumption has more of an impact on the happiness index than the HDI. This indicates that increasing access to electricity increases happiness as a representation of people's welfare. Electricity has important and fundamental benefits in all aspects of life that can increase happiness.

4. CONCLUSION

This study uses the VECM method to explore the relationship between the four variables, namely LEC; HDI; HI; and LAK in the long term and short term in the period 2012 to 2019. There are 3 main findings. First, there is a cointegration relationship between variables. Second, there is no empirical evidence to suggest that there is a long-term relationship between the variables level of electricity consumption, quality of human life, level of happiness, and the work force. Third, in the short term it is known that the electricity consumption variable is only influenced by the electricity consumption variable of the previous period. The HDI variable is also influenced by the previous period's HDI variable, as well as the HI and LAK variables.

The implication of this research is that an increase in electricity consumption does not directly improve the quality of human life. An increase in electricity consumption will drive an increase in income. After that, an increase in income will improve the quality

Whereas in model 4, the LEC variable, HDI variable, and HI variable do not affect the LAK variable. The level of electricity consumption in the short term and long term does not affect the level of the workforce. Likewise, the higher the quality of human life does not affect the work force (Fajriyyah and Budiantara, 2015).

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The implication of this research is that an increase in electricity consumption does not directly improve the quality of human life. An increase in electricity consumption will drive an increase in income. After that, an increase in income will improve the quality
of human life. The variable quality of human life also does not

affect the level of electricity consumption. The higher the degree of health or education does not increase electricity consumption. The happiness level variable is not determined by the high level of human life quality and high electricity consumption.

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