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Rebound effect with energy efficiency determinants: a two-stage analysis of residential electricity consumption in Indonesia

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Abstract

This study aims to estimate the economy-wide rebound effect using the determinants of household energy demand in Indonesia. Identifying the size of the rebound effect is essential for the government's energy efficiency and carbon emission reduction programs. The estimation of the rebound effect uses a two-stage analysis with panel data of every province in Indonesia from 2002 to 2018. We employ the Input Demand Function of the Stochastic Frontier Analysis to measure the energy efficiency of residential aggregate in Indonesia. In the second stage, we adopt the dynamic panel data model to estimate the economy-wide rebound effect. The estimated dynamic panel data model reveals that the magnitudes of the short-run and long-run rebound effects were 87.2% and -45.5%, respectively. In other words, a 1% increase in household energy efficiency results in a reduction in energy consumption of 0.13% in the short term and 1.45% in the long term. Our research also discovers that a backfire rebound effect exists in provinces with high energy efficiency. Therefore, we prove to backfire claims that improving energy efficiency will increase energy use. Henceforth, energy efficiency programs in the household sector still need to be implemented, followed by increasing technological innovation and improving housing policy.

Keywords: Electricity demand, energy efficiency, rebound effect, stochastic frontier analysis

JEL: Q41, Q43, E7, C23

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1. Introduction

Indonesia is currently suffering high carbon emissions affected by soaring energy consumption. For illustration, data from IEA (2019) shows that electricity consumption reached 793% from 1990 to 2018. This increasing energy consumption also boosts carbon emission, which ascended to 313% since 1990, going from 131Mt of CO_2 to 543Mt of CO_2 in 2018. Then, one of the sectors with the highest growth in electricity consumption is the residential sector as shown in Fig 1.

With the expanding use of electricity and the warning of carbon emissions, the Indonesian government has given attention to energy conservation and efficiency efforts since the issuance of Indonesian Government Regulation Number 70 of 2009. Afterwards, The Ministry of Energy and Mineral Resource of Republic of Indonesia (KESDM) has arranged General Plan of National Electrical Energy. In this planning, the government established two primary plans; one for the supply side and another for the demand side. In the demand aspect, the government focused on encouraging programs for efficiency of electrical energy.

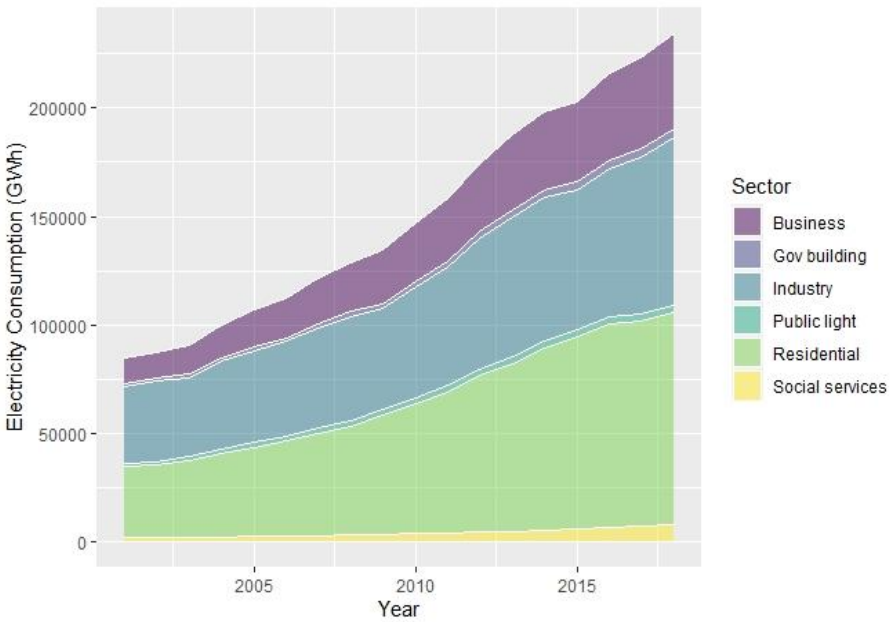

Fig 1. Electricity consumption by consumer sector in Indonesia, 2000-2018. Sources: PLN (2009, 2018)

However, as shown by historical data, the total electricity consumption in Indonesia continues to expand every year, as illustrated in Figure 1. Since the government established an energy efficiency and energy conservation program in 2009, total electricity consumption has doubled. Particularly for the residential sector, in which consumption has increased by 78.2%. The condition presents energy savings from improvement in energy efficiency are usually lower than expected, as many previous studies predicted (Freire-González, 2017).

Some of the factors that cause the phenomena are consumers' failure to invest their incomes for energy efficiency (Hausman, 1979) and consumers' failure to reduce their consumption because energy efficiency gains will reduce the actual price per unit of energy services, thus encourage energy consumption (Bentzen, 2004). The second factor is known as the rebound effect (Berkhout et al., 2000; Saunders, 1992). Rebound effect becomes more appealing to be discussed because although it is one of the factors causing efficiency gap, it received barely attention from policymaker (Gillingham & Palmer, 2014). Therefore, measuring the economy-wide rebound effect is essential for policymakers to control energy demand and carbon emission.

According to van den Bergh (2011), the idea of rebound effect is initially taken from Jevon's paradox (Jevons, 1866), who found that energy efficiency from a steam machine in the United Kingdom did not cause a decline in coal consumption. In contrast, the opposite happened, and the coal's usage increased. Brookes (1979) conducted a similar study, and Khazzoom (1980) elaborated the feedback mechanism, specifically in machine and household tools, which are more efficient in energy use.

The rebound effect has long been a hot discussion topic (Greening et al., 2000; Sorrell et al., 2009), and many of the discussion is about the magnitude of rebound effect (Frondel & Vance, 2013; Zhang et al., 2015). However, from the number of research previously conducted on rebound effect, the natural rebound effect approach using energy efficiency elasticity is rarely employed. The reason is the data for energy efficiency is hard to obtain and has accuracy problem (Orea et al., 2015; Sorrell et al., 2009).

Some estimated economy-wide rebound effects using energy efficiency elasticity were previously conducted by Saunders (2013), Orea et al. (2015), and Adetutu et al. (2016). Saunders (2013) still uses energy intensity in his analysis, which has been argued by Filippini and Hunt (2011). In that case, it is different from Orea et al. (2015), who is calculated the rebound effect using frontier analysis based on a model developed by Filippini and Hunt (2011, 2012). The study, which was conducted in United States with 48 states data of the time period from 1995 to 2011, discovered that the average amount of rebound effect was 56-80%. Meanwhile, a closer study with ours was conducted by Adetutu et al. (2016) in which economy-wide rebound effect was calculated by measuring energy efficiency elasticity employing Stochastic Frontier Analysis (SFA). Using a panel data from 55 countries from the period of 1980 to 2010, Adetutu et al. (2016) discovered that in a short-run, 100% of energy efficiency improvement would be followed by 90% rebound effect in energy consumption, and 136% decreasing number in long-run energy consumption.

The difference between our study and previous research is in the preference of the estimation model, not only in estimating energy efficiency but also in measuring the rebound effect. Our study employs the Input Demand Function proposed by Filippini and Hunt (2011, 2012) from Stochastic Frontier Analysis. The input demand function or the energy demand frontier model provides the minimum value used by households in specific outputs. Therefore, the difference between the observed input and the demand for minimal input costs reflects both technical efficiency and allocative efficiency. It is crucial in analyzing residential aggregates, where the frontier model presents the minimum energy consumption required by households to produce a certain level of energy services (Filippini & Hunt, 2012). Furthermore, in the second stage, the short-run and long-run rebound effect are estimated by utilizing dynamic panel data with the Corrected-Least Square Dummy Variable or better known as the LSDVC proposed by Kiviet (1995), because LSDVC is better at estimating dynamic panel data with small samples (Bruno, 2005).

Therefore, based on the problems previously described, the main objective of this study is to determine the size of the economy-wide rebound effect applying the aggregate household energy demand in Indonesia. Besides, our research has several contributions. First, the estimation results support evaluating the energy efficiency program that the Indonesian government is carrying out. Second, this study presents an overview of energy efficiency and the rebound effect in every province in Indonesia. It can be employed to make derivative policies for several local governments. Third, methodically, this study offers an alternative in estimating the rebound effect based on aggregate household energy demand. Although using a small sample, it produces robust estimates.

The paper is organized as follows; section 2 reviews the literature, section 3 describes the methodology and data. Section 4 presents the empirical results, and section 5 offers conclusion and policy implications.

2. Literature Review

Research on the energy rebound effect has been conducted numerous times by employing an economic or engineering approach. Therefore, in our literature review, we only focus on studying the economy-wide rebound effect, the research method used to estimate the economy-wide rebound effect and the rebound effect associated with the elasticity of energy efficiency.

Based on the appearance mechanism, the rebound effect is classified as the direct rebound effect, the indirect rebound effect and the economy-wide rebound effect (Greening et al., 2000; Sorrell et al., 2009). The term economy-wide rebound effect is obtained from the accumulation of direct and indirect rebound effects based on improvements in energy efficiency. The accumulated rebound effect is also carried out in an aggregate method so that the economy-wide rebound effect is also often associated with the macro rebound effect. Hence, in our paper, we use these two terms in turns.

Furthermore, it should be noted that our method of estimating the rebound effect can capture the overall direct and indirect effect because we employ aggregate household energy demand in all provinces in Indonesia. Therefore, our estimation includes the economy-wide rebound effect.

Previously conducted studies of macro rebound effect frequently used Computable General Equilibrium (CGE), some of which are done by Hanley et al. (2009), who measured economy-wide rebound effect in the use of electrical and non-electrical energy in Scotland. The result showed that there was a tendency of increasing rebound effect in Scotland. The increasing rebound effect led to the 'backfire' phenomenon. Another study employing CGE was conducted by Turner (2009), who estimated the rebound effect in the UK using data from 2000. The study result showed the rebound effect ratio for electrical consumption is 54,7% in the long term and 23,1% in the short term. Broberg et al. (2015) studied the economy-wide rebound effect toward increasing energy efficiency in Swedish industries using the CGE approach. The study showed 5% upgrade in energy efficiency caused an economy-wide rebound effect of 40% up to 70%. However, the problem is that most estimates using CGE do not provide clear evidence and the mechanism for the emergence of a measure of the economy-wide rebound effect.

Several studies estimate the size of the rebound effect based on the elasticity of energy efficiency obtained from stochastic frontier analysis (e.g., Orea et al. (2015), Adetutu et al. (2016), Llorca and Jamasb (2017), and Amjadi et al. (2018)). In estimating the rebound effect, Orea et al. (2015) employ the energy demand frontier model proposed by Filippini and Hunt (2011, 2012). The study result showed a close connection between increasing efficiency with the model established by Filippini and Hunt (2011, 2012). Orea et al. (2015) attempted to establish a model using US frontier residential aggregate energy demand for 48 states in the period between 1995 and 2011. The average score of rebound effect obtained was about 56% to 80%.

Llorca and Jamasb (2017) studied energy efficiency and rebound effect in road transportation to 5 European countries from 1992 to 2012. They employ the energy demand stochastic frontier approach. They found that the average rebound effect is relatively low, only 4%, with a fuel efficiency of 89%. The study also discovered a more significant rebound effect score in countries with higher fuel efficiency and logistic transportation quality.

Amjadi et al. (2018) employed a similar approach with the previous studies conducted by Orea et al. (2015) and Llorca and Jamasb (2017). Amjadi et al. (2018) measured the rebound effect in Swedish heavy industry using panel data in four intensive energy sectors in Sweden, i.e. the iron and steel industry, pulp and paper industry, and chemical and mining. It is discovered that the rebound effect, which occurs either in fuel or electricity, is lower than the energy-saving potential. The determining factor to focus on is the intensity of CO_2 and fuel or electricity share.

We consider that all three studies use the same model, based on the energy demand frontier model or the input demand function proposed by Filippini and Hunt (2011, 2012). Then, in estimating the rebound effect, they reduce the restrictive assumption in the economy-wide rebound effect model, then intensify the effect of increasing efficiency on energy consumption in the aggregate. As a result, the estimated energy efficiency obtained might be higher. Therefore, the results of the rebound effect measurement are not depicted actually.

A slightly different approach is employed by Adetutu et al. (2016). They used two-staged analyses, particularly Shephard Input Distance Function (SIDF), to determine the energy efficiency and Generalized Method of Moments (GMM) to determine the economy-wide rebound effect in the short run and the long run. The data used in this study were obtained from 55 countries from 1980 to 2010. The study explained that in the short term, 100% improvement of energy efficiency was followed by a 90% rebound effect in energy consumption, while in the long term, the rebound effect is higher, which is a 136% decrease in energy consumption.

However, compared to SIDF, our study uses the Input Demand Function (IDF) or energy demand frontier proposed by Filippini and Hunt (2011, 2012) in measuring energy efficiency. It is because IDF accepts information on the price of energy use and the quantity of output, thus providing the outcome of minimizing the cost of energy use services and the price of energy itself. In contrast, SIDF only includes information on energy efficiency that comes from technical efficiency. In addition, estimates from IDF provide the minimum value used by households in specific outputs, thus providing information on overall economic efficiency, both technical efficiency and allocative efficiency. According to Filippini and Hunt (2012), It is crucial in analyzing residential aggregates, where the frontier model presents the minimum energy consumption required by households to produce a certain level of energy services.

Then, the energy efficiency estimation results obtained from the IDF are used to measure the size of the rebound effect using a dynamic panel data model. This method distinguishes the study we conducted with Orea et al. (2015), Llorca and Jamasb (2017) and Amjadi et al. (2018). The dynamic panel data model that we use is the Corrected-Least Square Dummy Variable or LSDVC proposed by Kiviet (1995). The sample data we use is small, so LSDVC is a better choice to accommodate the situation than other dynamic models (Bruno, 2005).

Furthermore, with the approach we use, there are some advantages that we get. First, our approach can capture the overall energy efficiency in aggregate, both allocative efficiency and technical efficiency, to provide a more comprehensive understanding of the condition of energy demand. Second, in measuring the amount of rebound effect, we do not relax the restrictive assumptions in the model. The rebound effect we get is the actual energy efficiency elasticity value from the dynamic panel data model. Third, the model we use allows it to be adapted especially for developing countries because the energy demand factor that we use is more specific to capturing conditions in developing countries.

3. Methodology and Data

Based on the purposes to discover the size of the macro rebound effect in household electricity consumption, the approach employed in this study is economy-wide rebound effect. Saunders (2000) provides a clear elaboration of the economy-wide rebound effect:

$$\eta^{EC} = \frac{\delta EC}{\delta Ef} \tag{1}$$

Energy conservation from the increased efficiency can be defined as elasticity of energy use with respect to the change in energy efficiency. *E* refers to energy, which in this case is household electricity consumption while *Ef* is energy efficiency. η^{EC} can be defined as the elasticity efficiency of energy demand (Adetutu et al., 2016). Therefore, economy-wide rebound effect can be determined based on the ratio of η^{EC}.

$$R = 1 + \eta^{EC} \tag{2}$$

From the ratio of R and η^{EC} above, five types of rebound effect can be inferred based of some possible outcomes (Adetutu et al., 2016; Saunders, 2000), namely backfire ($R > 1\ or\ \eta^{EC} > 0$), full rebound ($R = 1\ or\ \eta^{EC} = 0$), partial rebound ($0 < R < 1\ or\ -1 < \eta^{EC} < 0$), zero rebound ($R = 0\ or\ \eta^{EC} = -1$), and lastly is super conservation ($R < 0\ or\ \eta^{EC} < -1$).

3.1. Energy demand frontier

As mentioned earlier, to obtain a rebound effect size, this study applies a two-stage analysis, which is the energy demand frontier (Filippini & Hunt, 2011, 2012), to obtain an energy efficiency score. Afterwards, the dynamic-panel data model estimated using LSDVC is applied to determine elasticity efficiency to count the size of macro rebound effect in both short term and long term.

The function of household energy demand for panel data in this study is as follows:

$$EC_{it} = F(P_{it}, IC_{it}, Pop_{it}, DD_{it}, Rain_{it}, Floor_{it}, Size_{it}, Water_{it}, Toilet_{it}, Ef_{it}) \quad (3)$$

Where EC_{it} is the residential electricity consumption in province i and year t, P_{it} is the price of residential electricity, IC_{it} is the gross domestic regional product, Pop_{it} is the population. Then, DD_{it} is the degree days summation of the cooling degree days and heating degree days. Still, since the typical temperature in Indonesia is warm (tropical area) then the calculation of HDD in many regions become zero. Therefore, we add rainfall ($Rain_{it}$) to cover that flaws. The $Floor_{it}$ is the average housing width by referring to the percentage of housing suitable with the WHO standard (10m^2 for each family member). The average standard for appropriate housing is a minimum of 50m^2 in Indonesia. The $Size_{it}$ is the population size per household electricity user, $Water_{it}$ is the percentage of water pump in providing clean water in the household. The $Toilet_{it}$ is the percentage of households that own private toilet facilities, Ef_{it} is the level of 'underlying energy efficiency' in Indonesian household.

Along with the use of IDF, our study applies the True Random Effect Model (TREM) by Greene (2005a, 2005b) to obtain transient energy efficiency and Kumbhakar and Heshmati (1995) Random Effect Model (KHREM) to get a persistent energy efficiency score. The Hausman test results also confirm the application of the Random Effect Model. According to Kumbhakar et al. (2015), the advantages of KHREM is that it can produce persistent efficiency without imposing a parametric form of time dependence. Therefore, in this study, KHREM gives information about the constant (time-invariant) part of efficiency, and TREM is used to provide information about the transient (time-varying) part of efficiency.

Identifying the ratio of persistent efficiency is essential because it describes the impact of input variable existing in the model where each region has different variation though it does not happen from time to time Kumbhakar et al. (2015). For instance, the housing policy released by the local government.

Based on the approach used in this study where energy efficiency level assumed from all province can be measured using the one-sided term, the function of panel log from Equation 3 above will adopt stochastic frontier function by Aigner et al. (1977), as stated by the function below:

$$lnEC_{it} = \alpha + \alpha_p lnP_{it} + \alpha_{IC} lnIC_{it} + \alpha_{Pop} lnPop_{it} + \alpha_{DD} lnDD_{it} + \alpha_{Rain} lnRain_{it} + \alpha_{Floor} lnFloor_{it} + \alpha_{Size} lnSize_{it} + \alpha_{Water} lnWater_{it} + \alpha_{Toilet} lnToilet_{it} + \varepsilon_{it} \quad (4)$$

Furthermore, the error term from function (4) has a different composition from TREM and KHREM, as elaborated below:

$$\varepsilon_{it} = v_{it} + u_{it} \quad (5)$$

It is used for True Random Effect, in which the first part, v_{it}, is symmetric disturbance utilized to absorb noise effect. The second part, u_{it}, is the level of energy efficiency (Ef_{it}). This function is a one-sided random disturbance term that can change at any time and assumed to follow the half-normal distribution.

$$\varepsilon_{it} = -u_i + \omega_{it},$$
$$\omega_{it} = v_{it} - \left(\tau_{it} - E(\tau_{it})\right) \quad (6)$$

It is used for Random Effect by Kumbhakar and Heshmati (1995) model (Kumbhakar & Lovell, 2000; Kumbhakar et al., 2015). Where the error component u_i dan ω_{it}, is zero mean and constant variance random variables. The model above uses one-way error component standard which can be estimated using GLS.

Furthermore, after estimation function 4 is generated, then the regional efficiency make it possible to estimate using conditional mean of the efficiency term, $E[u_{it}|v_{it} + u_{it}]$ proposed by Jondrow et al. (1982), and from the equation, we also get the term for persistent efficiency, which is $E[u_i|\omega_{it} - u_i]$. Therefore, the level of energy efficiency can be elaborated as follow:

$$Ef_{it} = \frac{E_{it}^f}{E_{it}} = \exp(-\hat{u}_{it}) \tag{7}$$

Where the E_{it} is electrical energy consumption in province *i* and year *t* and E_{it}^f is frontier energy demand.

3.2. Rebound effect

After obtaining the accumulation of efficiency score using energy demand frontier, then calculation of short-run and long-run rebound effect for each province will be done using equation (2); $R = 1 + \eta^{EC}$, where η^{EC} is the elasticity of energy consumption in households with respect to energy efficiency $\frac{\delta EC}{\delta Ef}$.

Besides, estimating the short-run and long-run rebound effect, we apply the dynamic-panel data model with LSDVC estimator proposed by Kiviet (1995). We did not employ the GMM estimator because LSDVC is better in estimating a small sample especially for $T \leq 20$ and $N \leq 50$, or in other words, with a small sample, LSDVC is better than GMM (Bruno, 2005; Filippini, 2011). LSDVC used is a bias correction initialized by Arellano and Bond estimation.

$$lnEC_{it} = \beta lnEC_{it-1} + \beta_p lnP_{it} + \beta_{IC} lnIC_{it} + \beta_{Pop} lnPop_{it} + \\ \beta_{Ef} Ef_{it} + \mu_i + \varepsilon_{it} \tag{8}$$

EC_{it} is the total electrical energy consumption in households in province *i* and year *t,* EC_{it-1} is lagged term of EC_{it} which in this model becomes explanatory variable, P_{it} is the household electricity price, IC_{it} is the GDRP of each province, Pop_{it} is the number of populations in each province, Ef_{it} is energy efficiency levels in each province obtained from stochastic frontier analysis. The composite disturbance term $\mu_i + \varepsilon_{it}$ consists of one unobserved individual specific effect μ_i and noise error term ε_{it}.

3.3. Data

In this study, we employ balance panel data from 33 provinces in Indonesia (i=1,…,33), excluding North Kalimantan because it is the youngest province meaning that the data are limited, and from 2002 to 2018 (t=2002,…,2018).

Description	Var	Mean	Std. dev.	Min	Max
Electricity Consumption (10^6 kWh)	*EC*	1910	3280	47.7	17,900
Price rate (Rp/kWh)	*P*	583.72	159.8	153.09	1362.29
Gross Domestic Regional Product (2010, Rp Billions)	*IC*	215,765	309,792	8640	1,736,291
Population (Thousands Person)	*Pop*	7202.53	10300	619	48700
Degree days (HDD+CDD)	*DD*	91.52	10.75	39.2	117.9
Rainfalls (mm)	*Rain*	2362.01	838	460.9	5652
Percentage of residential floor area which more than $50m^2$ (%)	*Floor*	0.54	0.14	0.13	0.86
Ratio of population to residential electricity customer (Person)	*Size*	8.16	4.31	2.14	25.76
Percentage of Water pump user (%)	*Water*	0.1	0.21	0.01	4.77
Percentage of private toilet facilities in resident (%)	*Toilet*	0.63	0.13	0.28	0.91

Table 1. Descriptive statistics

From the data shown in table 1, data on household electricity consumption and prices are obtained from the annual report on Indonesian electricity statistics published by The National Electricity Company (PLN). Moreover, the data of the Gross Domestic Regional Product, population, temperature and rainfall are obtained from the Central Bureau of Statistics (BPS) and also Bureau of Statistics Unit from 33 Provinces. Additionally, for data of floor area, water source and sanitation are based on National Socio-Economic Survey, Central Bureau of Statistics.

4. Results and Discussions

As previously mentioned, this study adopts a two-stage analysis where in the first stage, we measure the level of energy efficiency using the SFA approach. And in the second stage the magnitude of the economy-wide rebound effect will be measured using dynamic panel data analysis based on the efficiency elasticity obtained from the previous SFA estimations.

	KHREM		TREM	
	Coefficient	Standard error	Coefficient	Standard error
Constant (α)	-2.965***	0.856	-10.23***	1.520
α_P	-0.040*	0.024	-0.090***	0.024
α_{IC}	0.438***	0.031	0.538***	0.038
α_{Pop}	0.624***	0.038	0.905***	0.090
α_{DD}	0.322***	0.084	0.311***	0.079
α_{Rain}	0.035*	0.021	0.027	0.018
α_{Floor}	-0.251***	0.048	-0.290***	0.048
α_{Size}	-0.794***	0.028	-0.656***	0.031
α_{Water}	0.051***	0.011	0.047***	0.010
α_{Toilet}	0.380***	0.068	0.367***	0.068
Regional effects	No		Yes	
σ_u	-4.526***	0.291	-4.031***	0.185
σ_v	-4.821***	0.140	-5.407***	0.215
log-likelihood	446.656		381.934	

***significant at 0.01 level, **significant at 0.05 level, *significant at 0.10 level

Table 2. Estimation results of energy efficiency

The estimation results reveal that the variables used in this study provide an expected sign and remain statistically significant at the 1% level (except for rainfall) and generate almost similar estimation for the two models. The coefficients shown on both sigma for *u* and *v* are significant in the model. It means that the contribution given by u_{it} and v_{it} for the error term ε_{it} in the one-sided error component is relatively substantial.

As it is a log-log variable, the estimation result shows that household electricity demand is price-inelastic but relatively small, with a price elasticity varying from -0.04 to -0.09. In addition, household electricity demand has an income elasticity between 0.45 and 0.54. Population elasticity in this study is relatively high, between 0.62 and 0.90, making the population factor greatly affected the electricity demand. Besides, based on the estimation results, the value of rainfall relatively has no significant effect.

The interesting part of our study is the use of housing and sanitation factors in measuring household electrical efficiency. The first is the variable of housing area (floor area). Variables, such as floor area, have been used in the previous study conducted by Otsuka (2017). Still, this study has different definitions due to the diversity of housing models in Indonesia. It is known from this study that the floor area variable has a negative sign (-0.25 to -0.29) and significant at 1%, which means that if the percentage of livable houses increases by 10%, the electricity demand will decrease by 2.5% -2.9%. It is undoubtedly fascinating to discuss because habitable places significantly affect electricity consumption in this study. By encouraging the construction of livable houses for the community, the housing sector policy will reduce the electricity demand. It may be because habitable housing uses electricity more efficiently than inhabitable housing.

Furthermore, the variable size indicates that it has a negative effect, specifically -0.65 to -0.79, and is significant at 1%. If the population ratio to household electricity customers increases by 10%, the electricity demand will decrease by 6.5% -7.9%. It means that the electrification program carried out by the government will further reduce the ratio. However, it will increase the electricity demand because everyone will endure the power in their houses.

The water variable refers to applying a water pump in the housing with a clean water supply. As alluded to earlier, water pumps in Indonesian houses have increased, especially for housing that has not received water connection from water providers, especially accommodation located in remote areas. Difficult access to water from the government makes people use the water pumps. The study discovered that the use of a water pump has a positive effect on electricity consumption. The estimation results show a value of 0.05, which is relatively small compared to other variables.

The last variable is toilets, which is the availability of private toilet facilities in the housing. Proper sanitation is one of the development priorities. The study results showed that this variable is positive (0.36 to 0.38) and significant in the model, indicating that increased use of private toilet facilities will boost electricity demand. It does not mean we should reduce the use of private toilet facilities, but energy-friendly toilet equipment should be a further concern.

Appendix 1 displays a statistical description of the two models, both KHREM and TREM. As expected, the mean of persistent efficiency is smaller than the mean of transient efficiency. The condition is similar to the results of studies conducted by Filippini and Hunt (2016), which measure efficiency in the US, and Filippini and Zhang (2016), that measure efficiency in every province in China. This condition explains that the efficiency resulting from short-term efforts, such as household concerns to improve their living conditions, including using energy-efficient appliances, will produce a higher efficiency level than the efficiency impact resulting from the energy policy released by the government. Because as explained earlier, this persistent efficiency is assumed not to change over time and has differences in each region. Furthermore, the total efficiency obtained from the multiplication of persistent and transient efficiency.

The results of the average energy efficiency estimated for every province are shown in Appendix 3, which shows Bali is the most efficient province based on the model proposed in this study. Apart from Bali, the regions with the high-efficiency score were Yogyakarta, Gorontalo, Bangka Belitung, and North Maluku. On the other hand, Riau has the worst score of efficiency, followed by East Nusa Tenggara, East Kalimantan, Papua and Banten. Meanwhile, Jakarta, as the capital city and at the same time the centre of business and government of Indonesia, is ranked sixth as the province with the high level of efficiency.

Based on the average distribution of efficiency scores in every province, viewed by geographical spread, the regions in western Indonesia tend to have higher efficiency scores than eastern Indonesia. However, some areas in the west have lower efficiency scores, such as Riau and Banten. It is partly because the domestic income of the western part of Indonesia tends to be higher than that of eastern Indonesia. With increased income, households will spend their income to satisfy the requirements of energy-efficient devices. For example, buying LED lights, energy-efficient refrigerators, energy-saving air conditioners and so on. On the other hand, in Indonesia, the price of household appliances that have been certified as energy efficient tends to be more expensive. It makes it difficult for households with lower-middle incomes to access these energy-efficient devices.

The next step is to measure the size of the rebound effect using a dynamic panel data model (Eq. 8). Table 3 presents the estimation results of LSDVC estimator and a bias correction initialized Arellano and Bond estimation. Overall, the estimates produce expected signs where electricity price and efficiency negatively affect electrical energy consumption.

	Coefficient	Std. Error
Lagged EC	0.9124***	0.0254
β_p	-0.0225*	0.0165
β_{IC}	0.0417	0.0429
β_{Pop}	0.0891	0.0697
β_{Ef}	-0.1284*	0.0765

***significant at 0.01 level, **significant at 0.05 level, *significant at 0.10 level

Table 3. Dynamic model with LSDVC estimator

From the LSDVC estimation results, the energy efficiency elasticity is obtained at -0.128 for the short run and -1.454 for the long run. It means that in the short term, a decline in energy consumption is smaller than the proportional level of increased efficiency, where a 1% increase in energy efficiency in Indonesia results in a 0.13% reduction in energy consumption. However, in the long term, it shows an improving condition. The decrease in energy consumption is more significant than the proportional level of increased efficiency, particularly a 1.45% reduction in energy consumption resulting from a 1% increase in energy efficiency in Indonesia.

Based on the efficiency elasticity score, we can calculate the economy-wide rebound effect size (from Eq. 2) in Indonesia. Our estimation shows 87.2% for the short-run rebound effect and -45.5% for the long-run rebound effect. The result indicates that the rebound effect that occurs in Indonesia in the short term is a partial rebound effect, and it becomes better in the long term, specifically super conservation. Besides, the LR rebound effect size is smaller than the SR rebound effect, indicating a process of innovation and efforts to improve technology in the long term to increase energy-saving efforts. Hence, the results of this study also prove that there is no backfire rebound effect in Indonesia, before-mentioned as the results of a study by Adetutu et al. (2016).

In addition, the estimation results of the economy-wide rebound effect from the model proposed in this study confirm that the size of the rebound effect is quite large in the short term. It indicates that energy saving from increasing energy efficiency has not been achieved optimally. This condition is empirically related to the low cost of energy services due to increased efficiency. In general, this condition is a typical macro rebound effect that arises due to economic growth, driven by consumption growth.

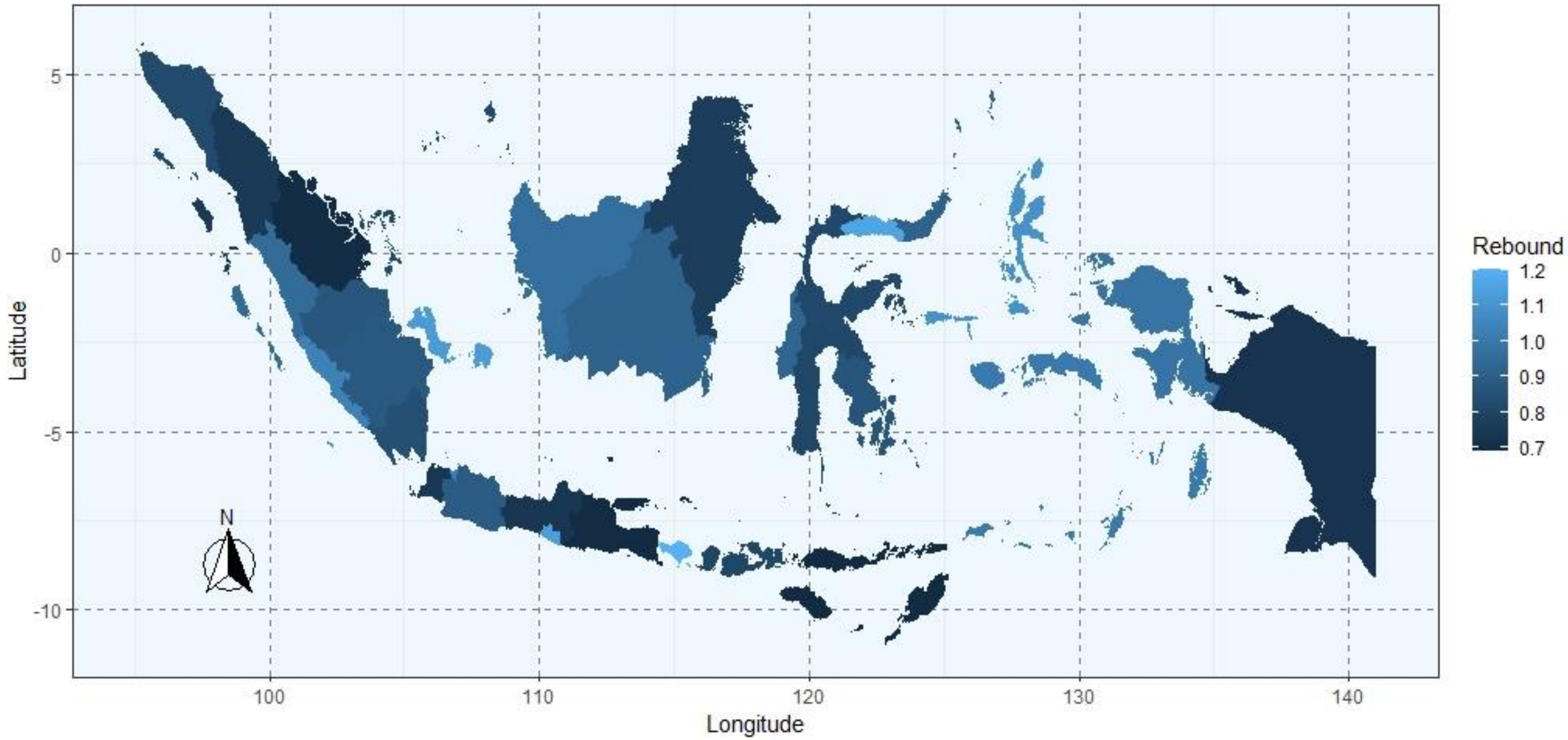

Fig 2. Estimation of average rebound effect across provinces

The distribution of the rebound effect size across provinces can be seen in Figure 2. From the figure, we can see that the rebound effect is almost evenly distributed in every region in Indonesia. The province with the brightest color indicates the high magnitude of the rebound effect in that province. It can be recognized that Bali has the brightest color, indicating that Bali is the province with the highest rebound effect size. On the other hand, from the figure, we can see that the province with the darkest color is Riau, which indicates that Riau is the province with the smallest rebound effect size. The average size of the economy-wide rebound effect in each province can be seen in appendix 3.

However, if we classify the province based on efficiency scores and rebound effect size, most provinces with high-efficiency scores tend to have high rebound effect sizes. We can see in appendix 2, which shows that all provinces that have a high level of energy efficiency (except West Java) also have a high rebound effect size. Moreover, seven of the eight provinces have a rebound effect size of more than 100%, which indicates a backfire rebound effect. The seven provinces are Bali, Yogyakarta, Gorontalo, Bangka Belitung, North Maluku, Jakarta and Bengkulu. It means that increasing energy efficiency in the seven provinces will increase their energy consumption.

Furthermore, our study proves that energy efficiency has the potential to drive the rebound effect in the case of Indonesia. Therefore, the energy efficiency policy should be carried out more carefully. The use of efficient technology in households, offices and industries does help control energy consumption while reducing carbon emissions in Indonesia (Shahbaz et al., 2013), but it will also lead to a higher rebound effect at the same time.

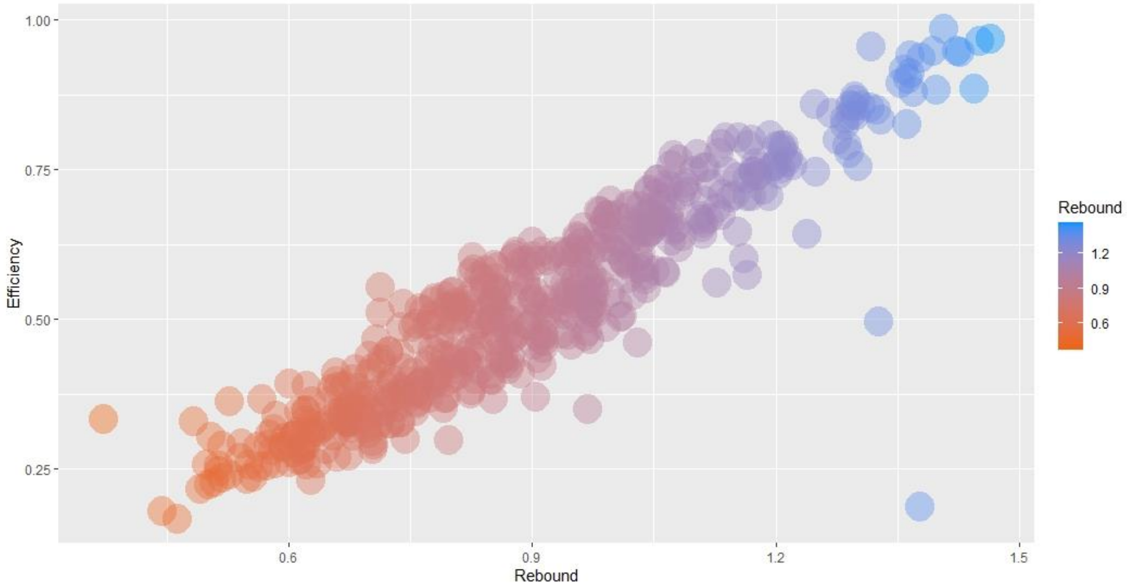

Fig 3. Efficiency and rebound effect

The findings can be viewed in Figure 3, where efficiency scores positively related to the rebound effect. It has implicated the distribution of the average rebound effect, where the estimated rebound effect for each province shows that several provinces with high levels of efficiency also have high levels of rebound effects (see Appendix 2). That finding also proves the backfire claims, which state that improving energy efficiency will increase energy use. As Jenkins et al. (2011) stated, the more efficient use of energy on a macro scale will increase overall income and productivity, thus encouraging energy substitution for other production factors. This condition will eventually encourage faster economic growth and energy consumption (Gillingham et al., 2016). In aggregate household energy consumption, the improving energy efficiency that drives the rebound effect is caused by several factors.

First, changes in energy costs resulting from energy efficiency make the household sector reallocate its income to then be used as input in encouraging its economy, thereby increasing its energy consumption. This condition is similar to the direct rebound effect, but for macro conditions, these changes occur in aggregate, so that the input used is not only energy itself but also other production factors.

Second, the government's energy efficiency and conservation policies, especially local governments, lead to different innovations that consequently create different growth accelerations in each region. At the same time, these differences encourage each region to increase economic growth, leading to an increase in energy consumption.

5. Conclusions and policy implications

The main objective of this study is to determine the size of the economy-wide rebound effect applying the aggregate household energy demand in Indonesia. The measurement of the rebound effect uses a two-stage analysis with panel data from 33 Provinces in Indonesia from 2002 to 2018. The first stage calculates energy efficiency by employing the input demand function from the stochastic frontier analysis. We then estimate the elasticity of energy efficiency in the second stage to determine the size of the economy-wide rebound effect applying an autoregressive dynamic panel data model with an LSDVC estimator.

The estimation results find that elasticity of energy efficiency in Indonesia is -0.128 in the short term and -1.454 in the long term. If energy efficiency increases by 100% in the short term, it will reduce energy consumption by only 12.8%. However, in the long term, the decrease in energy consumption is higher than the proportional level of energy efficiency, where every 100% increase in energy efficiency will be followed by a 145.4% decrease in energy consumption.

The energy efficiency elasticity derived from the dynamic panel data estimation results becomes the base for calculating the economy-wide rebound effect. As a result, the size of the rebound effects in Indonesia in the short-run and long-run are 87.2% and -45.5%, respectively. In the long term, the size of the rebound effect is smaller than in the short term, indicating an innovation process in improving technology and improving household energy efficiency policies in Indonesia.

However, our study proves that improving energy efficiency will increase energy consumption, or in other words, energy efficiency has the potential to stimulate a rebound effect. This condition is commonly called backfire. It can be seen in the size of the rebound effect in every province in Indonesia, which confers that province with high energy efficiency scores tend to have high rebound effect sizes. As an illustration, seven of the eight most efficient provinces in Indonesia have a rebound effect size of more than 100%, meaning that any efforts to increase energy efficiency in these provinces will simultaneously increase their energy consumption.

Based on the findings, several policies can be formed for the government. First, at the macro level, the government's energy efficiency and conservation policies have a positive impact on efforts to reduce national energy consumption in the long term. However, these efforts have not been optimal in reducing short-term energy consumption. In order to improve these conditions, the government needs to issue policies to accelerate the implementation of energy efficiency and conservation programs through increasing technological innovations for inexpensive, energy-friendly and environmentally friendly household appliances.

Second, the government's energy efficiency policy should still be carried out but with attention to the existence of the backfire rebound effect, as proven in this study. It is undoubtedly related to household energy efficiency policies. This research proves that the housing quality factor is an essential part of influencing energy consumption. Therefore, along with the technological innovation process carried out at a macro level, housing policies, significantly improving the quality of housing and sanitation, must be carried out in each region, especially in low efficient provinces.

The limitation of the study lies in the lack of accommodation of essential factors in influencing efficiency level, for example, the energy subsidy for household level in each province. It is partly due to the limited data at the regional level. Therefore, further research is expected to accommodate energy subsidy factors in determining household electrical energy efficiency.

Appendix

Appendix 1. Summary of energy efficiency estimates

	KHREM	TREM
	Persistent	Transient
Mean	0.708	0.758
Std. dev.	0.125	0.205
Min	0.535	0.280
Max	0.99	0.99

Appendix 2. Province's classification

Classification	Efficiency score	Provinces
Low efficient province	$Ef < 0.522$	Riau, East Nusa Tenggara, East Kalimantan, Papua, Banten, East Java, North Sumatra, Aceh, Central Sulawesi, West Nusa Tenggara, Central Java, South Sulawesi, Riau Archipelago, Southeast Sulawesi, Lampung, Jambi
Moderately efficient province	$0.522 < Ef < 0.597$	Central Kalimantan, North Sulawesi, South Sumatra, South Kalimantan, West Sulawesi, West Papua, West Sumatra, Maluku*, West Kalimantan
Highly efficient province	$Ef > 0.597$	Bengkulu*, West Java, Jakarta*, North Maluku*, Bangka Belitung*, Gorontalo*, Yogyakarta*, Bali*

Note:
- *Backfire rebound effect
- The classification based on lower than the median for low efficient province, between the median and 75% quartile for the moderately efficient, and higher than the 75% quartile for highly efficient province (Filippini & Zhang, 2016).

Appendix 3. Estimated energy efficiency scores, rank and average rebound effect

Province	Efficiency Score	Efficiency Rank	Rebound Effect (%)
Aceh	0.458	26	82.5
North Sumatera	0.449	27	75.7
West Sumatera	0.585	11	95
Riau	0.390	33	70
Riau Archipelago	0.489	21	82.2
Jambi	0.521	18	86.8
South Sumatera	0.533	15	88.2
Bangka Belitung	0.667	4	112.5
Bengkulu	0.600	8	103.7
Lampung	0.505	19	84
Jakarta	0.625	6	102.4
West Java	0.607	7	89.4
Banten	0.431	29	74.5
Central Java	0.479	23	74.1
Yogyakarta	0.718	2	113.7
East Java	0.446	28	69.4
West Kalimantan	0.597	9	96.7
Central Kalimantan	0.522	17	91.6
South Kalimantan	0.534	14	92.1
East Kalimantan	0.422	31	77
Bali	0.769	1	120.3
West Nusa Tenggara	0.472	24	80.8
East Nusa Tenggara	0.409	32	69.1
North Sulawesi	0.527	16	91.8
Gorontalo	0.715	3	116
Central Sulawesi	0.470	25	81.6
South Sulawesi	0.483	22	80.8
West Sulawesi	0.553	13	93.3
Southeast Sulawesi	0.500	20	86.6
Maluku	0.588	10	100.8
North Maluku	0.655	5	109.4
Papua	0.427	30	73.2
West Papua	0.555	12	98.5

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