Sudarmaji, Eka; Achsani, Noer Azam; Arkeman, Yandra et al.

Article

Decomposition factors household energy subsidy consumption in Indonesia : Kaya identity and logarithmic mean divisia index approach

Reference: Sudarmaji, Eka/Achsani, Noer Azam et. al. (2022). Decomposition factors household energy subsidy consumption in Indonesia : Kaya identity and logarithmic mean divisia index approach. In: International Journal of Energy Economics and Policy 12 (1), S. 355 - 364.
https://econjournals.com/index.php/ijeep/article/download/12629/6620.
doi:10.32479/ijeep.12629.

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2022, 12(1), 355-364.

Decomposition Factors Household Energy Subsidy Consumption in Indonesia: Kaya Identity and Logarithmic Mean Divisia Index Approach

Eka Sudarmaji[1]*, Noer Azam Achsani[2], Yandra Arkeman[3], Idqan Fahmi[2]

[1]Doctoral Student, IPB University and University of Pancasila, Jakarta. Indonesia, [2]School of Business, IPB University, Bogor, Indonesia, [3]Department of Agro-industrial Technology, Faculty of Agricultural Technology, IPB University, Bogor, Indonesia. *Email: esudarmaji@univpancasila.ac.id

Received: 12 September 2021 **Accepted:** 28 November 2021 **DOI:** https://doi.org/10.32479/ijeep.12629

ABSTRACT

For decades, the subsidy had prompted excessive waste while offering little motivation to boost energy efficiency or reduce domestic greenhouse gas emissions in Indonesia. This paper aimed to measure household subsidy energy by examining the relationship between the Ten Variables Factors with Household Energy Subsidy. The Logarithmic Mean Divisia Index (LMDI) decomposition index were deployed to recognize the determinant effects that drive a household's subsidy energy consumption. This study also presented an ARDL model applied. The robustness of the Granger Causality, Long-run, and Short-run causality during 1990-2017 was assessed. Based on LMDI analysis, we found out that Population, Income Per Capita, Ratio National Renewal Energy over Fuel Fossil, Gross Capital Stock, Urban Household Consumption, and Ratio Household Subsidy were the positive factors that aggravated the change in household energy subsidy. The negative sign of Ratio National Energy Intensity effect, Ratio Fossil Renewal Energy effect, Ratio Capital Labour substitution, and Ratio Household over Labour Force signified the decreasing of less household energy subsidy. On the ECM, we identified a negative sign speed-of-adjustment and significant at 1%. It implied that all the ten variable factors were converging in the long run after an experience shock. The equation parameters were considered stable since the CUSUM gets inside the two critical lines. Additional RESET test of the stability to ascertain whether the estimated model was linear or correctly specified has been performed.

Keywords: ARDL, ECM, Households Subsidies Energy, LMDI, KAYA Index
JEL Classifications: P18, P28, Q47

1. INTRODUCTION

The increasing population of Indonesia also increased the number of households and urbanization. According to the Ministry of Energy and Mineral Resources Republic of Indonesia (2018), Indonesia's population reached 261,891 million, with the number of households reaching 67.173 million people. Based on the world bank data, more than 55.33% of the total population lives in the cities (World Bank Group, 2016). That makes Indonesia had become one of the fastest urbanized countries in the world. The increase in households triggered demand and the drastic use of electronic household appliances and increased energy consumption in Indonesia. As a result, the household sector had become the second-largest energy consumer. Most of the sources of energy consumption were derived from fossil sources, which led to an increase in CO_2 emissions (Krstic and Krstic, 2015).

The increase in energy use was also due to subsidies provided by the government (Nasip and Sudarmaji, 2018). These subsidies in the household sector encouraged industries to use fossil energy wastefully. Therefore, the research problems discussed in this study were: (1) Indicators of household energy consumption subsidies, explaining many developments in energy use and energy subsidies, and (2) There were so many factors that affect the relationship between energy use, activity, and economic structure. These problems were clear indicators for different industries, and background information on factors affecting the relationship between energy use and necessary activities can provide a reasonable interpretation of aggregate indicators. This study outlined Indonesia's energy consumption subsidy into ten variables factors and incorporated them into ten effects using the LMDI approach. We analyzed changes in every ten variables' effects then deployed the time series to investigate the causality between all effects related to Indonesia's energy consumption growth. It used cointegration panels and causality analysis.

Research on decoupling analysis between economic-GDP growth and CO_2 emissions to provide indicators of determining factor measurement or energy consumption had become popular since the OECD environment minister in 2001 placed it as the OECD's environmental strategy. Then popularity grew as several studies, such as Kojima and Bacon (2009) also de Freitas and Kaneko (2011), combined decoupling with an index decomposition approach. Some researchers used the decoupling decomposition analysis with LMDI and econometrics methods such as VECM (Moutinho et al., 2015; Sadikova et al., 2017; Wu, 2014; Zhao et al., 2017). With most researchers taking the study in the national sphere, the other researchers decided to enter into different business sectors fields, such as Zhao et al. (2017). As they argue, it was essential to assess the sectoral industrial situation at every stage to know the root of the problems.

This study took Toba and Seck's (2016) framework that put all decomposition factors into social, technical, environmental, and economic aspects. They integrate technical, environmental, and social aspects into the energy system to become the primary support tool for energy policy. Zhang and Su (2016) selected ten rural household energy consumption indicators, then put all of the factors into dimensions: social, economic, technical, and environmental. Their research used the same concept as Pui and Othman (2019): aggregate decomposition results in economic, technical, and social aspects. The aim was to determine the relative intensity of these three effects on changes in emissions. The objectives to be achieved in this study were to investigate the impacts of energy subsidy and how the government explores energy savings targets for 2025 and 2050 in line with Government expectations. Therefore, this study mainly analyzed the relationship between household energy subsidies in Indonesia with the other ten variables from 1990 to 2017. The Logarithmic Mean Divisia Index (LMDI) and kaya index were used to recognize the effects that drive Indonesia's energy subsidy's evolution.

2. LITERATURE REVIEW

The Laspeyres index and the Divisia index were two standard index decomposition (IDA) analyses. The Laspeyres index calculates percentage changes in some aspects of a variable over time using weights based on the value in a few previous years. The Divisia index, on the other hand, was a weighted number of logarithmic growth rates, where weight was a component factor in total value. IDA was a commonly used decomposition method due to its adaptability, ease of use, and relatively low data requirements. Ang (2015) provided a rundown of IDA's advantages and drawbacks, advocating for the general use of the logarithmic average divisia index (LMDI). Under the Laspeyres index method, the effect was calculated in the same way as presented in the section above on the 'scenario' but taken the percentage change from base year to year. This approach had disadvantages because, among other things, it did not consider interactions in decomposition. It meant that variations in decomposition variables did not always add to the exact energy consumption change. The aim was to determine the relative intensity of these three effects on changes in emissions (Cansino et al., 2019).

LMDI was used to replace the Laspeyres index and AMDI in early 1990. LMDI is used by the IEA then widely followed by most researchers in the field of energy. Prospective LMDI analysis, usable: 1) Future forecasts based on the predicted unraveling effects of retrospective analysis, 2) Parse energy saving projections or emissions reductions for next year periodically through decomposition or emission levels for the year for two different scenarios, where one scene is the usual business case (BAU), and 3) Align and compare projection results across different models and scenarios through measuring drivers or underlying effects that provide an everyday basis for comparison.

2.1. Household Energy Subsidy Consumption Model

The authors used variables that expanded to ten variables using the Extended KAYA identity to estimate Household Energy Subsidy Consumption ($HES_{Consumption}$ = E.C.). The formula was as follows:

$$\text{National Energy Consumption} = \text{GDP} \times \frac{PrimaryEnergy}{GDP} \times \frac{NationalEnergyConsumption}{PrimaryEnergy} \tag{1}$$

For Household energy consumption subsidy, the formula become:

$$\text{Household Energy Subsidy} = \text{Population} \times \frac{GDP}{Population} \times \frac{PrimaryEnergy}{GDP} \times \frac{NationalEnergyConsumption}{PrimaryEnergy} \times \frac{HouseholdEnergyConsumption}{NationalEnergyConsumption} \times \frac{HouseholdEnergySubsidi}{HouseholdEnergyConsumption} \tag{2a}$$

when we Include Renewal Energy, Capital Formation, and Labour force, the formula is as follows:

$$\text{Household Energy Subsidy} = \text{Population} \times \frac{GDP}{Population} \times \frac{PrimaryEnergy}{GDP} \times \frac{RenewalEnergyConsumption}{PrimaryEnergy} \times \frac{Fossil - FuelEnergyConsumption}{RenewalEnergyConsumption} \times \frac{CapitalFormation}{Fossil - FuelEnergyConsumption} \quad (2a)$$

The LMDI formula can be rewritten as follows:

$$\text{HES}^T = \text{Pop}^T \times \frac{GDP^T}{Pop^T} \times \frac{E^T}{GDP^T} \times \frac{RE^T}{E^T} \times \frac{FR^T}{RE^T} \times \frac{K^T}{FR^T} \times \frac{L^T}{K^T} \times \frac{HS^T}{L^T} \times \frac{HEC^T}{HS^T} \times \frac{HES^T}{HEC^T} \quad (3)$$

$$\text{HES}^T = \text{Pop}^T \times \text{IP}^T \times \text{EI}^T \times \text{RE}^T \times \text{FR}^T \times \text{IE}^T \times \text{KL}^T \times \text{HS}^T \times \text{HEC}^T \times \text{HES}^T \quad (4)$$

$$\text{HES}^T = \text{Pop}^T_{\text{effect}} \times \text{IPeffect} \times \text{EI}^T_{\text{effect}} \times \text{RE}^T_{\text{effect}} \times \text{FR}^T_{\text{effect}} \times \text{IE}^T_{\text{effect}} \times \text{KL}^T_{\text{effect}} \times \text{HS}^T_{\text{effect}} \times \text{HEC}^T_{\text{effect}} \times \text{HES}^T_{\text{effect}} \quad (5)$$

Whereas:

POP = Population effect

IP = Income Per Capita effect $\frac{GDP^T}{POP^T}$

EI= Ratio National Energy Intensity effect $\frac{E^T}{GDP^T}$

RE= Renewal Energy - Energy Substitution, Ratio National Renewal Energy effect $\frac{RE^T}{E^T}$

FR= Fossil Fuels - Renewal Energy Substitution, Ratio Fossil Renewal Energy effect $\frac{FR^T}{RE^T}$

IE= Investment Efficiency - Ratio Gross Capital Stock over Renewal Energy $\frac{K^T}{RE^T}$

KL= Capital Labour substitution - Ratio Capital labor $\frac{L^T}{K^T}$

HS= Ratio Household over Labor Force $\frac{HS^T}{L^T}$

HEC= Ratio Urban Household Consumption per Household $\frac{HEC^T}{HS^T}$

HES= Ratio Household Subsidy over Household Consumption $\frac{HES^T}{HEC^T}$

$\Delta\text{HES}^T = \left(\sum_{t=1}^{K} \Delta\text{HES}\right)$; if un-decompensated ;

$(\Delta\text{HES} = \left(\sum_{t=1}^{K} (\Delta\text{POP} + \Delta\text{IP} + \Delta\text{EI} + \Delta\text{RE} + \Delta\text{FR} + \Delta\text{IE}\right)$

f decompensated.

3. METHODOLOGY/MATERIALS

To capture the different effects of changes in household subsidy energy, the authors used addictive LMDI decomposition is used to get ten variables effects: population effect, Income Per Capita effect $\frac{GDP^T}{POP^T}$, Ratio National Energy Intensity effect $\frac{E^T}{GDP^T}$, Renewal Energy - Energy Substitution, Ratio National Renewal Energy effect $\frac{RE^T}{E^T}$, Fossil Fuels - Renewal Energy Substitution, Ratio Fossil Renewal Energy effect $\frac{FR^T}{RE^T}$, Investment Efficiency - Ratio Gross Capital Stock over Renewal Energy $\frac{K^T}{RE^T}$, Capital Labour substitution - Ratio Capital labor $\frac{L^T}{K^T}$, Ratio Household over Labor Force $\frac{HS^T}{L^T}$, Ratio Urban Household Consumption per Household $\frac{HEC^T}{HS^T}$, and Ratio Household Subsidy over Household Consumption $\frac{HES^T}{HEC^T}$.

The data of household subsidy energy was taken to decompose the ten variables, consisting of 864 observation data. The data was coming from British Petroleum World Statistics, World Development Indicators (World Bank), International Energy Association (IEA), Minister Sumber Daya Mineral (MSDM) and Biro Pusat Statistik (BPS) for the year 1990-2017. Using the decomposition approach, the authors used a regression method in data analyst techniques using the Logarithmic Mean Divisia Index (LMDI) and KAYA index. Several researchers have used LMDI to extend Kaya identity (Ma and Stern, 2008; Wang et al., 2014; Zhang, 2019). Ma and Cai (2018) and Ma et al. (2018) conducted studies in the building industry that combined Kaya identity and LMDI for decomposition to total energy-related CO_2 (Saunders, 2015). ARDL analysis was used to recognize the effects that drive the evolution of energy subsidies in Indonesia. The regression analysis was a statistical technique to model and investigate nine independent variables on one response variable (Dependent variable). The regression equation used was as follows:

$$Y = \alpha + \beta_1 POP + \beta_2 IP + \beta_3 EI + \beta_4 RE + \beta_5 FR + \beta_6 IE + \beta_7 KL + \beta_8 HS + \beta_9 SE + e$$

Description:

Y = Household Energy Subsidy Effect (HES)

α = Regression constant

β_1= Regression Coefficient for Population Effect (POP)

β_2= Regression Coefficient for Income per Capita Effect (IP)

β_3= Regression Coefficient for Ratio National Energy Intensity Effect (EI)

β_4= Regression Coefficient for Ration National Renewal Energy Effect (RE)

β_5= Regression Coefficient for Fossil Renewal Energy Effect (FR)
β_6= Regression Coefficient for Ration Capital Stock over Renewal Energy Effect (IE)
β_7= Regression Coefficient for Capital Labour Substitution Effect (KL)
β= Regression Coefficient for Household over labor Force Effect (HS)
β_9= Regression Coefficient for Household Subsidy over Household Consumption Effect (SE)
e = *error*.
The dependent variable in this study was Household Energy Subsidy Effect, and there were nine independent variables. After applying the LMDI KAYA analysis, the next step was to use ARDL and ECM. By accommodating in the model of information related to time series.

4. RESULTS AND FINDINGS

We analyze the outputs after applying the LMDI KAYA analysis. We applied ARDL time series analysis to seek more precise and reliable results in the data analyst technique. The method selection was based on the unit root test results that define the variable's stationarity for time series analysis. The empirical framework of the analysis has the following components:

1. Unit Root Tests and Cointegration Tests
2. Optimal Lags Selection
3. VEC Model Estimations
4. Causality Analysis Tests
5. Diagnostic and Stability Tests.

4.1. Decomposition Analysis

As explained in the previous paragraph, this study used the KAYA identity to decompose the household energy subsidy into several components to determine the subsidy factor's significance. The components were Population, Income Per Capita, Ratio National Renewal Energy, Gross Capital Stock, Urban Household Consumption, and Ratio Household Subsidy, Ratio National Energy Intensity effect, Ratio Fossil Renewal Energy effect, Ratio Capital Labor substitution, and Ratio Household over Labor. The sum of all ten of these factors was equal to that of household subsidy. Based on LMDI, we found out that Population, Income Per Capita, Ratio National Renewal Energy, Gross Capital Stock, Urban Household Consumption, and Ratio Household Subsidy were the positive factors that aggravated the change in household energy subsidy. The negative sign of Ratio National Energy Intensity effect, Ratio Fossil Renewal Energy effect, Ratio Capital Labor substitution, and Ratio Household over Labor Force signified the decreasing significance of less household energy subsidy, Figure 1.

Another factor that aggravated the increase in household subsidies was the population effect, characterized by urbanization. Based on Figure 2, for almost 27 years from 1990-2017, Indonesia's household subsidy effect was generated solely based on the population and GDP. Urbanization was the correct indication of the outcome of decomposition. Most factors have contributed to household subsidy due to the energy increases being consumed by households. On the contrary, since the household subsidy was targeting the low-income family. The ratio percentage of household subsidy over the total household was decreasing. Over the last decade, the outcome shows that Indonesia's GDP impact was taking off due to Indonesia's government enhancing the private sector's growth. The results showed that the GDP effect was the most influential factor in the annual household subsidy increase. This study found Indonesia's most crucial GDP effect contributing to household subsidy in the last four decades. The effect of GDP, characterized by the share of GDP production, was in line with existing literature.

The exciting facts were that both Ratio National Renewal Energy and the Ratio Fossil Renewal Energy effect have a different contribution to the household subsidy. When the government improved the renewable energy policy, it hampered all its efforts without imposing the energy conservatism policy. Hence the cornerstone of regulating rising subsidies was energy efficiency. As better energy-saving technology was adopted over time, more energy-efficient equipment can be used by economies that develop later. In this case, Indonesia could request economists to organize "Nudge units" to put the Nudge plan into action. The

Figure 1: Energy subsidy decomposition

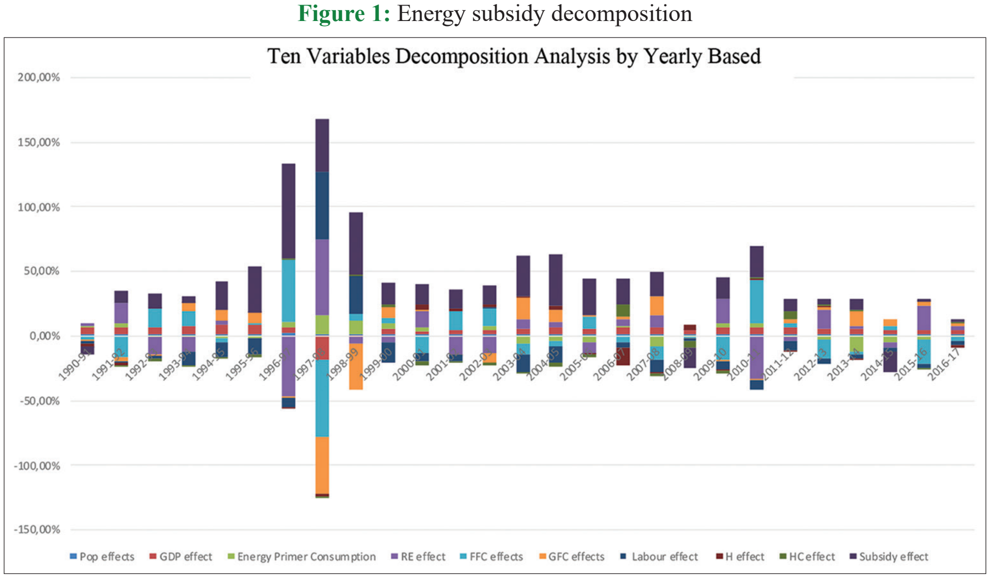
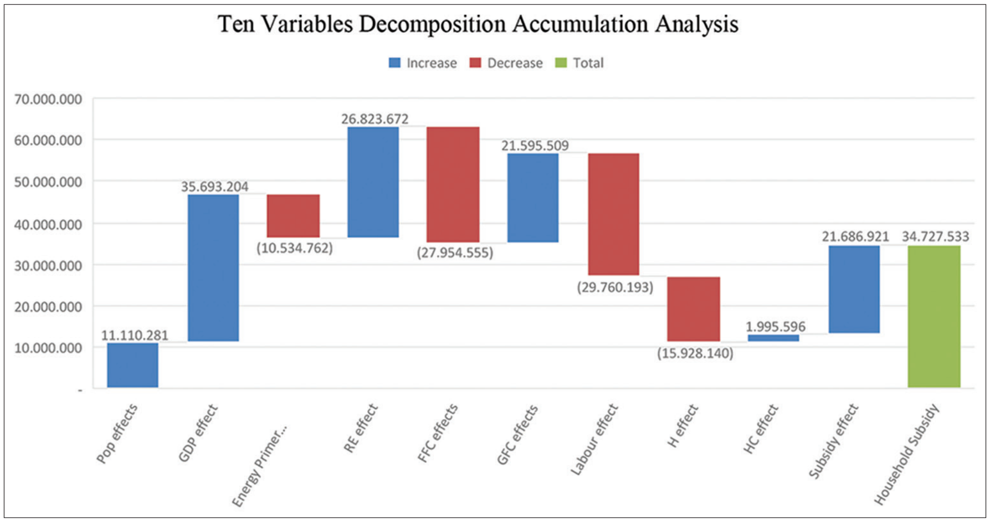


Figure 2: Energy subsidy decomposition



government can lower the cost of family energy usage by making limited options (framing) via the Nudge program. The aim is energy efficiency, conservation, and carbon emission reduction (Sudarmaji and Thalib, 2020). The labor effect factors were also very noteworthy. Energy usage increased along with GDP, and increasing energy consumption made the subsidy for households also increase. Fortunately, the rate of increase slowed over time as the economy continued to develop. It was driven by structural and technological changes in Indonesia's economy. The structure of Indonesia's economy was industry-based. Industrial societies were used more energy and realized rapid changes as Indonesia's economy transformed. In fact, in the last decade, services-oriented economies such as finance, healthcare, and software tend to grow and use less energy-intensive.

4.2. Descriptive Analysis

There were 864 total data observations on the original data taken from 1990 to 2017**.** In Table 1, the descriptive statistical test results on each value of ten variables showed a mean average with the data distribution having a maximum value, minimum value, and standard deviations for each decomposition variable.

4.3. Estimate the ARDL Model

Using the "Restricted Constant and No Trend" case, as shown in Table 2, there was a cointegration relationship between dependent and independent variables. Hence it can be said that the independent and dependent variables exhibited a long-run relationship. It meant that short-run shock would converge with time in the long run. Hence based on the bounded cointegration test, the authors pursued ARDL and ECM model. Based on the test above, we connected our short-and long-run effects to the notable predictive framework on the effects of energy intensity. Our econometric method emphasizes us to estimate short-run effects relevant to the region. The framework can also be defined as an error-correction model (ECM), where short-and long-run effects from an ARDL model were mutually measured.

When the data was strictly I(0) or purely I(1) or a mixture of both but not I(2), the ARDL model was sufficient. The entry of I(2) variables in the analysis should be avoided since the ARDL model only provides critical boundary values for the I(0) and I(1) series. Therefore, this research conducts ADF and P.P. tests to determine the order in which targeted variables were integrated. These two tests in econometric literature have been widely used. The results of both root unit tests have been included in Table 3 below. All the variables were checked by both the unit root checks I(1). In Table 4, the outputs of LMDI analysis in percentage-based of increasing and decreasing for each decomposition variable.

By reformulating Eq. (5) above as an ARDL(p, q., q) model. ARDL model as forecasting model for HES effect, can be written as follows:

$$\Delta \mathrm{HES}_{\mathrm{it}} = \alpha + \varnothing \Delta \mathrm{HES}_{\mathrm{it}-1} + \sum\nolimits_{j=1}^{k} \beta_{\mathrm{j}} \mathrm{X}_{\mathrm{j.t}-1}$$

$$+ \sum\nolimits_{j=1}^{p} \alpha_{\mathrm{i}} \Delta \mathrm{HES}_{it} + \Sigma_{j=1}^{k} \Sigma_{i=0}^{q} \delta_{j}{,}_{\mathrm{t}}\, \Delta \mathrm{X}_{\mathrm{j.t}-1} + \lambda_3 \mathrm{ECT}_{\mathrm{t}-1} + u_{it} \tag{6}$$

$$\text{And } \lambda_1 \mathrm{ECT}_{\mathrm{t}-1} = \mathrm{Y}_{\mathrm{t}-1} - \beta_0 - \beta_1 \mathrm{X}_{\mathrm{t}-\mathrm{t}} \tag{7}$$

Note:

k−1= Optimal lags (−1)

β_1, α_1, δ_j= Short-run, dynamic coefficient and& long-run equilibrium

λ_1= Speed of adjustment

ECT_{t-1}= The error correction term

U_{it}= Error.

4.4. Lags Selection

Based on Table 5, The Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) obtained two optimal lag lengths. The authors selected the max second lags for deploying the Panel VEC Model.

4.5. Validity and Stability Test

Several diagnostic tests were used, such as the residual serial correlation problem in the estimated model. The authors used Breusch-Godfrey Serial Correlation L.M. The test obtained a serial correlation test that the value of Probability F 0.4924 >0.05. L.M. resulted can be concluded that serial correlation between

Table 1: Descriptive analysis

	HE'S Effect	Pop Effect	GDP Effect	EPC Effect	REC Effect	FFC Effect	GFC Effect	Labour Effect	Household Effect	House-Cons Effect
Mean	30209120	4952221	14509699	−9170448	8698135	−9016813	12815734	−15876970	−1930085	647547,5
Median	21041329	2856252	7591553	−95749,43	456413,1	−471094,5	1302592	−9949280	8415,172	−144685,6
Max	1,50E+08	13285659	37905078	18724760	1,71E+08	2,05E+08	1,09E+08	23109964	21790706	45749729
Min	−1,59E+08	186603,8	−8182137	−1,14E+08	−1,98E+08	−1,77E+08	−22775590	−52692724	−58472865	−35395223
Std. Dev.	61695414	4711390	15230182	26324912	62401589	64650186	28579408	20072421	13132476	15053197
Skewness	−0,973	0,514	0,365	−2,635	−0,389	0,389	1,831	−0,133	−2,942	1,237
Kurtosis	5,193	1,711	1,559	10,640	7,336	7,347	6,459	2,238	14,270	6,837
Jar-Bera	9,667	3,058	2,937	96,895	21,829	21,936	28,548	0,733	181,84	23,448
Prob	0,008	0,217	0,230	0,000	0,000	0,000	0,000	0,693	0,000	0,000
Sum	8,16E+08	1,34E+08	3,92E+08	−2,48E+08	2,35E+08	−2,43E+08	3,46E+08	−4,29E+08	−52112307	17483783
SumSq.Dev	9,90E+16	5,77E+14	6,03E+15	1,80E+16	1,01E+17	1,09E+17	2,12E+16	1,05E+16	4,48E+15	5,89E+15

Table 2: Bounded cointegrated test

F-Bounds test		Null Hypothesis: No levels relationship		
Test statistic	Value	Sign in.	I (0)	I (1)
			Asymptotic: n=1000	
F-statistic	57,320	10%	1,800	2,800
k	9	5%	2,040	2,080
		2,50%	2,240	3,350
		1%	2,500	3,680

Table 3: Individual unit root

Series	Level						1st differences					
	ADF test AIC		ADF test SIC		Phillips-Perron test Bartlett Kernel		ADF test AIC		ADF test SIC		Phillips-Perron test Bartlett Kernel	
HES-effect	0,619		0,001	*	0,001	*	0,000	*	0,000	*	0,000	*
Pop-effect	0,207		0,207		0,936		0,563		0,563		0,123	
GDP-effect	0,925		0,925		0,948		0,000	*	0,000	*	0,000	*
EPC-effect	0,994		0,064		0,064		0,657		0,001	*	0,000	*
REC-effect	0,045	**	0,000	*	0,000	*	0,000	*	0,000	*	0,000	*
FFC-effect	0,045	**	0,000	*	0,000	*	0,000	*	0,000	*	0,000	*
GFC-effect	0,987		0,026	*	0,026	**	0,001	*	0,001	*	0,000	*
Labor-effect	0,766		0,766		0,145		0,000	*	0,000	*	0,000	*
Household-effect	0,001	*	0,001	*	0,000	*	0,001	*	0,000	*	0,000	*
House-Cons-effect	0,002	*	0,001	*	0,003	*	0,006	*	0,006	*	0,000	*
Group Statistik												
ADF - Fisher Chi-square	0,001	*	0,000	*	-		0,000	*	0,000		-	
ADF - Choi Z-stat	0,162		0,000	*	-		0,000	*	0,000		-	
P.P. - Fisher Chi-square	-		-		0,000	*	-		-	*	0,000	*
P.P. - Choi Z-stat	-		-		0,000	*	-		-	*	0,000	*

independent variables did not occur, which means there was no correlation between independent variables. Meanwhile, the normality test was conducted by testing independent and dependent variable data on the resulting regression equation, whether normally distributed or abnormally distributed. Regression equations were good if they had independent variable data and dependent variable data near-normal or normal. The test showed a probability of 0.2258, meaning normally distributed data.

The CUSUM test was based on the total sum of 5 percent regression equation errors with critical lines. As the sum of recursive errors gets within the two critical lines, the equation parameters are stable. The overall results were deemed stable based on the CUSUM test. The Squares CUSUM test was similarly measured and interpreted as the CUSUM test, except that we use recursive duplicated errors instead of recursive errors. According to this test, the equation's values were not stable; see Figure 3 below.

Hence, the authors took another test, i.e., test the stability—this test ascertained whether the estimated model was linear or correctly specified. Based on the reset test, see Table 6—the result showed that the model was correctly specified.

Authors also need to satisfy the homoscedasticity assumption for the valid regression results. White's Heteroscedasticity test was the last validity test. The null hypothesis of the test stated that there was no current heteroscedasticity. Based on Table 7, the result showed Breusch-Pagan-Godfreyin occurred symptoms of heteroscedasticity due to prob values. F and Prob. Chi-Square Sig < 0.05. However, different results occurred when the authors used the Harvey and ARCH-LM methods. Hence, based on the tests, it was assumed that heteroskedasticity does not affect the stated ECM. The authors preferred to use arch-LM output because it was more reliable than another test.

Figure 3: CUSUM of Square and CUSUM

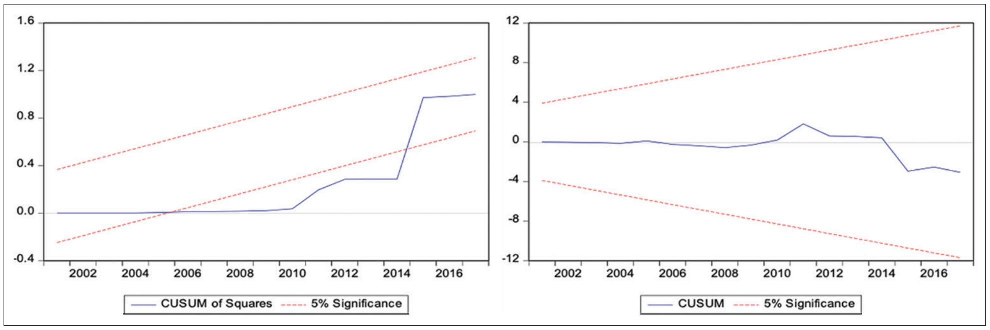


Table 4: Energy consumption subsidy decomposition per unit variable

Year	Household Subsidy	Pop effects	GDP effect	EPC effect	REC effect	FFC effects	GFC effects	Labour effect	Household effect	House-Cons effect	HES effect
1990-1991	−4,05%	1,70%	4,85%	1,41%	2,29%	−2,37%	−1,69%	−2,20%	−1,26%	−0,89%	−5,89%
1991-1992	12,07%	1,79%	4,88%	3,16%	15,34%	−15,92%	−4,15%	−0,94%	−1,21%	−0,73%	9,85%
1992-1993	13,22%	1,75%	4,95%	−0,81%	−13,58%	14,10%	−0,51%	−2,96%	0,05%	−1,60%	11,83%
1993-1994	7,49%	1,65%	5,89%	−0,59%	−11,14%	11,52%	6,05%	−10,52%	0,06%	−1,08%	5,67%
1994-1995	25,59%	1,73%	7,14%	−1,77%	3,18%	−3,28%	7,71%	−11,62%	0,06%	−0,47%	22,91%
1995-1996	37,44%	1,76%	7,10%	−1,27%	−0,41%	0,42%	8,35%	−12,86%	0,81%	−1,96%	35,48%
1996-1997	77,02%	1,96%	4,23%	4,99%	−46,50%	47,78%	−1,37%	−7,50%	−0,52%	0,91%	73,04%
1997-1998	43,51%	1,71%	−18,66%	14,72%	57,95%	−59,66%	−44,31%	52,70%	−1,73%	−0,17%	40,96%
1998-1999	53,59%	1,74%	−0,76%	9,94%	−4,94%	5,12%	−36,19%	29,42%	0,18%	0,62%	48,44%
1999-2000	21,00%	1,52%	3,77%	3,97%	−4,97%	5,15%	7,61%	−15,55%	0,22%	2,05%	17,23%
2000-2001	17,36%	1,48%	2,40%	2,28%	12,53%	−12,99%	1,11%	−6,38%	4,27%	−3,31%	15,96%
2001-2002	14,79%	1,46%	3,26%	−0,01%	−14,29%	14,80%	−0,31%	−5,11%	1,61%	−0,94%	14,31%
2002-2003	16,56%	1,46%	3,59%	2,97%	−13,31%	13,73%	−7,80%	0,33%	2,08%	−1,36%	14,87%
2003-2004	33,39%	1,56%	4,13%	−6,25%	7,43%	−7,66%	16,67%	−13,62%	1,03%	−1,49%	31,59%
2004-2005	38,76%	1,58%	4,97%	−3,64%	4,12%	−4,26%	9,45%	−12,53%	3,65%	−3,76%	39,17%
2005-2006	27,93%	1,51%	4,56%	−4,44%	−8,63%	8,90%	1,00%	−0,69%	−1,03%	−1,54%	28,30%
2006-2007	21,84%	1,46%	5,34%	1,03%	5,14%	−5,30%	2,19%	−4,25%	−13,44%	9,59%	20,08%
2007-2008	17,92%	1,44%	4,91%	−7,71%	10,18%	−10,52%	13,91%	−9,94%	−0,89%	−2,33%	18,87%
2008-2009	−16,71%	1,21%	2,92%	−0,88%	0,58%	−0,60%	−0,27%	−1,59%	3,49%	−5,66%	−15,90%
2009-2010	16,46%	1,45%	5,08%	3,60%	17,99%	−18,68%	−0,63%	−6,38%	−0,78%	−2,96%	17,78%
2010-2011	28,37%	1,53%	5,27%	2,96%	−32,67%	33,86%	−1,31%	−7,37%	0,41%	0,95%	24,74%
2011-2012	16,03%	1,46%	4,86%	−0,70%	−3,28%	3,38%	3,70%	−6,71%	−1,91%	5,88%	9,34%
2012-2013	6,53%	1,38%	4,20%	−2,80%	14,24%	−14,70%	2,72%	−4,25%	0,57%	1,20%	3,97%
2013-2014	10,96%	1,38%	3,77%	−11,85%	2,33%	−2,41%	11,37%	−3,09%	−0,14%	0,87%	8,73%
2014-2015	−14,40%	1,17%	3,24%	−5,25%	−3,49%	3,61%	5,24%	−3,33%	−0,04%	−0,62%	−14,94%
2015-2016	3,38%	1,24%	3,75%	−2,29%	18,67%	−19,37%	2,45%	−3,35%	0,14%	−0,45%	2,60%
2016-2017	3,63%	1,20%	3,84%	−1,10%	2,87%	−2,99%	2,27%	−3,18%	−1,70%	0,20%	2,23%

Table 5: Lags selection analysis

Lag	Lo		loLRFPO	AIC	SC	HQ
0	−4458,38	NA	8,90E+136	343,7216	344,2055	343,8609
1	−4082,57	433.6273*	9.6e+127*	322.5054*	327.8281*	324.0381*

*Indicates lag order selected by the criterion. L.R.: sequential modified L.R. test statistic (each test at 5% level). FPE: Final prediction error. AIC: Akaike information criterion. SC: Schwarz information criterion. H.Q.: Hannan-Quinn information criterion

Table 6: RESET test

Description	Value	df	Probability
t-statistic	0,277	16	0,785
F-statistic	0,077	(1, 16)	0,785
Likelihood ratio	0,130	1	0,719

4.6. Causality Analysis Test

Based on Table 8, statistically, there were only two bi-direct granger causality between GFC and Population and Household and Labour on the Pair-wise Granger Causality tests. The several variables had a Uni-direct granger causality.

In Tables 9 and 10, respectively, long-term and short-term results were published. The long-term results show that nine variables harmed energy subsidy (ΔHES). There was almost a negative impact on the 1st lag for all nine variables see Table 9. However, it was partly pointed out that all independent variables, such as GDP-effect, EPC-effect, GFC-effect, Labour-effect, Household-effect, and House-Cons-effect, had no insignificant impact on the ΔHES. The empirical result above showed that all variable effects have a significant impact at the 0.01 level and 0.05 for GFC-effect in the long-run causality. Except for Population-effect had a positive effect with coefficient 1.595 has a significant impact at 0.05. It did

Table 7: Hetereocadasity test

	Breusch-Pagan-Godfrey	Harvey		ARCH	
F-statistic	4,600	0,288		0,229	
Obs*R-squared	19,140	3,567		0,245	
Scaled explained SS	12,034	9,459		-	
Prob. F (9,17)	0,003	0,969	*	0,637	*
Chi-Square (9)	0,024	0,938	*	0,620	*
Chi-Square (9)	0,211	0,396		-	

Table 8: Granger causality

	Pop Effect	GDP Effect	EPC Effect	REC Effect	FFC Effect	GFC Effect	Labour Effect	Household Effect	House-Cons Effect	HE'S Effect
Pop-effect		1,417	3,312	3,312	3,335	5,429	4,923	0,688	1,683	0,178
		0,266	0,057	0,057	0,056	0,013**	0,018**	0,514	0,211	0,838
GDP-effect	3,158		2,980	6,247	6,255	4,892	9,546	0,350	0,382	0,962
	0,064		0,074	0,008*	0,008*	0,019**	0,001*	0,709	0,687	0,399
EPC-effect	17,669	2,314		13,385	13,425	0,137	0,480	0,141	0,197	21,760
	0,000*	0,125		0,000*	0,000*	0,873	0,625	0,870	0,823	0,000*
REC-effect	0,291	0,280	1,420		0,990	0,264	0,181	0,376	1,607	1,122
	0,751	0,759	0,265		0,389	0,771	0,836	0,691	0,225	0,345
FFC-effect	0,288	0,280	1,408	1,001		0,261	0,181	0,377	1,608	1,114
	0,753	0,759	0,268	0,385		0,773	0,836	0,691	0,225	0,348
GFC-effect	11,303	4,280	0,271	12,913	12,967		0,468	1,356	0,729	12,935
	0,001*	0,028**	0,765	0,000*	0,000*		0,633	0,280	0,495	0,000*
Labor-effect	0,278	3,161	1,684	2,093	2,093	1,732		3,877	1,796	0,097
	0,760	0,064	0,211	0,150	0,150	0,202		0,038**	0,192	0,908
Household-effect	2,993	3,447	1,018	1,276	1,273	1,875	4,385		2,698	2,705
	0,073	0,052	0,379	0,301	0,302	0,179	0,026**		0,092	0,091
House-Cons	8,467	6,789	10,188	2,580	2,570	6,579	4,013	0,179		4,034
	0,002	0,006*	0,001*	0,101	0,102	0,006*	0,034**	0,838		0,034&&
HES	4,565	0,103	0,832	18,691	18,686	1,373	0,135	0,965	1,158	
	0,023**	0,903	0,450	0,000*	0,000*	0,276	0,875	0,398	0,334	

Table 9: ARDL – short run causality

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
HE'S(−1)	−1,056	0,049	−21,723	0,000*
Pop-effect	152,192	4,197	36,261	0,000*
Pop-effect(−1)	−148,912	4,805	−30,990	0,000*
GDP-effect	0,051	0,582	0,088	0,933
GDP-effect(−1)	−4,375	0,632	−6,918	0,001*
EPC-effect	0,183	0,598	0,306	0,770
EPC-effect(−1)	−2,981	0,786	−3,792	0,009*
REC-effect	−41,910	11,270	−3,719	0,010*
REC-effect(−1)	−67,742	15,958	−4,245	0,005*
FFC-effect	−40,519	10,903	−3,716	0,010*
FFC-effect(−1)	−65,627	15,382	−4,266	0,005*
GFC-effect	0,443	0,501	0,885	0,410
GFC-effect(−1)	−2,440	0,725	−3,367	0,015**
Labour-effect	0,246	0,464	0,530	0,615
Labour-effect(−1)	−2,660	0,682	−3,899	0,008*
Household-effect	−−0,033	0,185	−0,176	0,866
Household-effect(−1)	−1,497	0,153	−9,797	0,000*
House-Cons-effect	−0,054	0,133	−0,408	0,698
House-Cons-effect(−1)	−0,719	0,229	−3,148	0,020**
C	157275,5	749739,6	0,209774	0,8408
R-squared	1	Mean dep. var		31395840
Adjusted R-squared	0,999216	SD dep. var		62602172
SE of regression	1752473	AIC		31,66308
Sum squared resid	1,84E+13	Schwarz-criterion		32,63085
Log-likelihood	−391,62	HQ criterion		31,94176
F-statistic	1678,73	Durbin-Watson		2,719588

Table 10: ARDL - long run causality

Variable	Coefficient	Std. error	t-statistic	Prob.
Pop-effect	1,595	0,635	2,514	0,046 **
GDP-effect	−2,103	0,334	−6,300	0,001 *
EPC-effect	−1,361	0,277	−4,915	0,003 *
REC-effect	−53,339	12,730	−4,190	0,006 *
FFC-effect	−51,634	12,295	−4,200	0,006 *
GFC-effect	−0,971	0,316	−3,072	0,022 **
Labor-effect	−1,174	0,313	−3,757	0,009 *
Household-effect	−0,744	0,106	−6,997	0,000 *
Household-Consumption	−0,376	0,089	−4,250	0,005 *
C	76505,230	364714,100	0,210	0,841

* significant level at the 0.01 level, ** at 0.05 level

Table 11: Error correction model

Variable	Coefficient	Std. error	t-statistic	Prob.
D (Pop-effect)	152,192	0,919	165,546	0,000 *
D (GDP-effect)	0,051	0,154	0,334	0,750
D (EPC-effect)	0,183	0,078	2,334	0,058
D (REC-effect)	−41,910	1,510	−27,763	0,000 *
D (FFC-effect)	−40,519	1,457	−27,802	0,000 *
D (GFC-effect)	0,443	0,078	5,701	0,001 *
D (Labour-effect)	0,246	0,082	3,018	0,023 **
D (Household-effect)	−0,033	0,040	−0,808	0,450
D (House-Cons-effect)	−0,054	0,028	−1,960	0,098
CointEq(−1)*	−2,056	0,007	−296,959	0,000 *
R-squared	1,000	Mean dep. var		834112,4
Adjusted R-squared	1,000	S.D. dep. var		86174523
S.E. of regression	1073166	AIC		30,89385
Sum squared resid	1,84E+13	Schwarz criterion		31,378
Log-likelihood	−391,620	Quinn criterion		31,033
Durbin-Watson	2,720			

mean that 1% change in Population-effect increased 1.595% in energy subsidy. On the other hand, for all nine variables that had adverse effects, 1% change in every nine variables decreased as much as the coefficient stated.

In Table 11, The result showed that the models' approximate results showed that the ECT coefficient was almost negative, −2.056, with long-term statistical causality. It has been shown that the long-term balance of ΔHES was valid significant with 0.01%. It means that the previous period's imbalance shocks reconnected into a long-run equilibrium. In other words, there was a long-term causality between ΔHES with the other nine variables.

5. CONCLUSION

In the study, we have investigated the dynamic causal linkages of household energy subsidy with nine other variables in Indonesia from 1990 to 2017. The study of decomposition decoupling measured how much energy was used relative to an activity measure. The elements of decomposition depend on the structure of the economy and the environment of the country. This type of indicator aimed to quantify how effectively we use energy and how decomposition factors differ. Comparing decomposition factors and energy used in the household was valuable when decomposing energy subsidy consumption. Based on LMDI results, we found out that the GDP and Population effect were the most significant factors aggravating energy consumption change for the household subsidy. Energy efficiency has been the cornerstone in controlling the rising energy used in the household subsidy.

On the other hand, reducing the labor force effect for household and industrial sectors contributed to the lowest change to the energy used for both sectors. The negative sign of subsidy energy signifies the decreasing significance of less energy subsidy. The result showed that the models' approximate results show that the ECT coefficient was almost negative, -2.056, with long-term statistical causality. It had been shown that the long-term balance of **Δ**HES was valid significant with 5.73%. It meant that the previous period's imbalance shocks reconnected into a long-run equilibrium. In other words, there was a long-term causality between **Δ**HES with the other nine variables.

Under Time Series ECM, there were no anomalies in the CUSUM test. We established that the models were stable. The equation parameters were stable for households as the entire total of recursive errors gets within the two critical lines. The CUSUM test was based on 5 percent regression equation errors with critical lines. The equation parameters were stable as the entire sum of recursive errors gets within the two critical lines. Based on the CUSUM measure, the overall outcomes were considered stable. The Squares CUSUM test was calculated and interpreted similarly to the CUSUM test, except that we use recursive duplicate errors instead of recursive errors. Moreover, the RESET test was an additional test was deployed to confine the result of the squares of CUSUM since the test was based on the total sum of 5 percent regression equation errors outside the critical lines. According to this RESET test, the general aspects were considered stable. The last validity test was White's Heteroscedasticity Test. The test's null hypothesis states that no existing heteroscedasticity exists. Based on the outcome, the null hypothesis of heteroscedasticity should not be discarded since the p-value carried out approaches the significance stage. It was, therefore, presumed that heteroscedasticity does not impact the specified ECM.

The waste of spending caused by wrong subsidy targets has long been a problem for the Indonesian economy. It has become a trap for almost decades - fuel subsidies have always been difficult to solve. The current government's political courage was indispensable to advancing strategic actions in managing the bloated fuel subsidy budget. The reduction of subsidies periodically, Pertamina's LPG prices, and periodic electricity tariff adjustments for specific groups by PT PLN were subsidy reforms undertaken by the government. The decline was expected to support the Ministry and other governments' spending needs in other sectors. These subsidy reforms were acceptable based on environmental considerations because low-cost fuels tend to cause people to buy more fuel (rebound effect), boosting CO_2 emission. Moreover, Increasing the construction of coal-fired power plants was contrary to reducing greenhouse gas emissions. Nevertheless, then the subsidy savings expected to drive renewable energy generation were not proven. Many renewables exist, such as geothermal, solar energy; micro-hydro was generally converted into electrical energy but not easily used as fuel. Only Biofuels (BBN) or biofuels, namely biodiesel, and bioethanol were quickly converted into fuel.

REFERENCES

Ang, B.W. (2015), LMDI decomposition approach: A guide for implementation. Energy Policy, 86, 233-238.

Cansino, J.M., Roman-Collado, R., Merchan, J. (2019), Do Spanish energy efficiency actions trigger JEVON'S paradox? Energy, 181, 760-770.

de Freitas, L.C., Kaneko, S. (2011), Decomposing the decoupling of CO_2 emissions and economic growth in Brazil. Ecological Economics, 70, 1459-1469.

Kojima, M., Bacon, R. (2009), Changes in Co_2 Emissions from Energy Use. Washington, DC, United States World Bank.

Krstic, B., Krstic, M. (2015), Models of irrational behaviour of household and firm. Ekonomika, 61(4), 1-10.

Ma, C., Stern, D.I. (2008), Biomass and China's carbon emissions: A missing piece of carbon decomposition. Energy Policy, 36, 2517-2526.

Ma, M., Cai, W. (2018), What drives carbon mitigation in the Chinese commercial building sector? Evidence from decomposing an extended Kaya identity. Science of the Total Environment, 634, 884- 899.

Ma, M., Cai, W., Cai, W. (2018), Carbon reduction in China's commercial building sector: A bottom-up measurement model based on Kaya-LMDI methods. Energy, 165, 350-368.

Ministry of Energy and Mineral Resources Republic of Indonesia. (2018), Energy and economic statistics of Indonesia. In: Handbook of Energy and Economic Statistics of Indonesia. Indonesia: Ministry of Energy and Mineral Resources Republic of Indonesia.

Moutinho, V., Madaleno, M., Silva, P.M. (2015), Which factors drive Co_2 emissions in EU-15? Decomposition and innovative accounting. Energy Efficiency, 9(5), 1087-1113.

Nasip, I., Sudarmaji, E. (2018), Managing tax dispute due to IFRS-16 on the retrofits implementation in Indonesia. International Journal of Engineering and Technology, 7(3.21), 200-208.

Pui, K.L., Othman, J. (2019), The influence of economic, technical, and social aspects on energy-associated Co_2 emissions in Malaysia: An extended Kaya identity approach. Energy, 181, 468-493.

Sadikova, M., Faisal, F., and Resatoglu, N.G. (2017), Influence of energy use, foreign direct investment, and population growth on unemployment for the Russian federation. Procedia Computer Science, 120, 706-711.

Saunders, H.D. (2015), Recent evidence for large rebound: Elucidating the drivers and their implications for climate change models. The Energy Journal, 36(1), 23-48.

Sudarmaji, E., Thalib, S. (2020), To nudge or not to nudge households: Energy efficiency case in Indonesia. International Journal of Production Economics, 24(6), 3225-3241.

Toba, A.L., Seck, M. (2016), Modeling social, economic, technical And environmental components in an energy systems. Procedia Computer Science, 95, 400-407.

Wang, W., Liu, X., Zhang, M., Song, X. (2014), Using a new generalized LMDI (logarithmic mean Divisia index) method to analyze China's energy consumption. Energy, 67, 617-622.

World Bank Group. (2016), The Role of Cities in Sustainable Economic Development. Washington, DC, United States: World Bank Group.

Wu, J. (2014), Urban ecology and sustainability: The state-of-the-science and future directions. Landscape and Urban Planning, 125, 209-221.

Zhang, M., Su, B. (2016), Assessing China's rural household energy sustainable development using improved grouped principal component method. Energy, 113, 509-514.

Zhang, Y. (2019), Energy rebound effect analysis based on technological progress. In: IOP Conference, Series Earth and Environmental Science No. 300.

Zhao, X., Zhang, X., Li, N., Shao, S., Geng, Y. (2017), Decoupling economic growth from carbon dioxide emissions in China: A sectoral factor decomposition analysis. Journal of Cleaner Production, 142, 3500-3516.