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Research Article

Investigating the Factors Affecting Energy Intensity in Iran with an Emphasis on the Information and Communications Technology Index

Maryam Ashouri, Hojat Parsa*, Ebrahim Heidari

Economics Department, Persian Gulf University, Bushehr, Iran

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Abstract
The purpose of this study is to investigate and analyze factors affecting the energy intensity in provinces of Iran with emphasis on information and communications technology (ICT) index, during the period from 2010-2015. Weighted Average Least Square (WALS) method and information criteria have been applied to select the model; so that, based on WALS method, six variables among various affective factors on energy intensity according to theoretical background and empirical studies have been chosen, and then based on information criteria, a Bayesian panel model was determined in order to evaluate the effect of each factor on energy intensity. Results from Monte Carlo simulation with Markov chains have indicated that among information and communications technology sub-indices, access to ICT equipment sub-index, reduces energy intensity, but, skill sub-index (the average years of schooling and enrollment rate in high school and university) has a positive effect on energy intensity. Per capita income and energy price have negative effects on energy intensity, and the share of industry sector in production and inventory of vehicles leads to an increase in energy intensity.

Keywords: Energy Intensity, Information and communications technology, Weighted Average Least Square, Monte-Carlo Stimulation, Provinces of Iran.

Introduction

Energy is one of important inputs of production which plays a significant role in economic development of countries. Energy-related issues, especially those related to the limitation of non-renewable resources and environmental effects and impacts of utilizing such resources like pollution and rising global warming, are among the most important challenges that human societies face with. Energy provides the necessary propulsion for transportation, production of heat and cold in different sections, production of crops and industrial products and etc.; but production and consumption of energy lead into an increase of greenhouse gases (Daryaei et al. 2019); and the greenhouse gases production leads to an increase in earth temperature, rising water levels, soil erosion, destroy of some of plant and animal species, and other terrible consequences for weather (Noorollahi et al. 2019).

Therefore, all countries, especially developing countries that experience an increase in energy demand in the process of their economic development, are seeking solutions in order to

* Corresponding author E-mail: hparsa@pgu.ac.ir

optimize energy production and consumption, and prefer to consume less energy to obtain specific level of gross domestic production (GDP) or reduce their energy intensity. But unlike what is happening in the world, Iran's economy not only is not in the direction of decreasing energy intensity (See Figure (1)), but also it consume more amount of energy than before with every economic growth unit and has relied its production process on the abundance of production inputs.

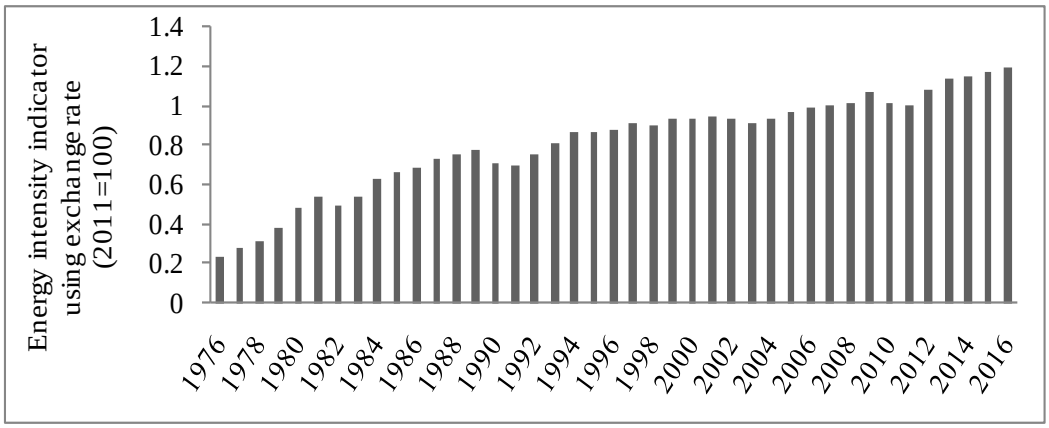

Figure 1. The trend of energy intensity in Iran

Nowadays, information and communications technology (ICT) has also grown dramatically in different countries, and this growth accompanies with numerous benefits like providing platforms for faster information exchange, reducing transaction costs and increasing productivity and efficiency. But study of official statistics published by World Telecommunication Union (WTU) shows that Iran has been 81th country among 176 countries in the field of information and communication technology (ICT) in 2017. Although this situation is 4 level higher that 2016, but it is still undesirable. (IDI, 2017).

Generally speaking, ICT development is considered as one of factors that reduce energy intensity, because information technology on one hand consumes less energy than traditional productions, and on the other hand it increases efficiency in all sectors of economy due to the existence of an inverse relationship between information and process time. Relying on this technology, developed countries also has been successful in optimizing energy consumption and consequently decreasing energy intensity. The study of Machado and Miller (1997) has shown that during 1963-1987, the economy of U.S. was more relevant to on information than energy. Studies like Cho et al. (2007), Sadorsky (2012) and Zhou et al. (2018) have also examined the effect of this indicator on energy intensity.

The impact of ICT on human life can be investigated from different aspects. From economic and environmental point of view, its impact on improving efficiency including energy efficiency has a significant importance. Using ICT equipment on one hand requires energy consumption, and on the other hand it is going to reduce energy consumption by increasing efficiency in various sectors of economy. Even it is argued that energy can be replaced by information in economic activities cycle and will create more economic value than the same amount of energy can do. Consequences like decrease in energy consumption at transportation sector and increase in energy efficiency as a result of computerization of production process are among the reasons which prove that information can be used in place of energy (Chen, 1994). ICT technology with ability to create electronic purchases, e-banking, e-commerce, virtual education, virtual meetings and etc. reduces the need for physical presence and mobility, and thus, it can be affective on energy consumption.

However, based on theoretical literature, there are numerous potentially factors affective on energy intensity, but, since conventional analysis methods do not have the capability of

examining the effect of wide range of variables on dependent variable, every researcher inevitably has to focus on several certain variables. For example, Adom (2015) considered energy intensity as a function of energy price, foreign investment, the value added of the industry sector and trade integration index. Mulder et al. (2014) examined the impact of energy price, ICT and climate conditions on energy intensity. Therefore, an important subject named as model selection is proposed. The importance of this issue arises from the fact that the effect of each variable on dependent variable relies on the combination of other variables that were used in the model (Draper, 1995).

By a general review of previous studies in this field, the variables which determine energy intensity can be classified into six groups (according to Table (1)) named as economic, communication and information technology, openness and Transportation, demographic, industrial and climate (which studies that have been conducted often chosen a subset of the variables in these groups). These variables have the most significant emphasis on energy intensity-related studies and can be effective on energy intensity through some channels.

Table 1. Variables explaining energy intensity in the empirical studies.

Category of factors	Representative empirical studies
Economic indicators	Yuxiang and Chen (2010), Song and Zheng (2012), Heidari et al. (2016), Farajzadeh and Nematollahi (2018)
ICT indicators	Takase and Murota (2004), Collard et al. (2005), Ishida (2015), Heidari et al. (2016), Park et al. (2018)
Openness and Transportation	Yu (2012), Herrerias et al. (2013), Zhang et al. (2016), Farajzadeh and Nematollahi (2018)
Demographic factors	Sajjad et al. (2010), Song and Zheng (2012), Mrabet et al. (2019)
Industrial characteristics	Papadogonas et al. (2007), Irawan et al.(2010), Li et al. (2013), Zhang et al. (2016), Guang et al. (2019)
Climate factors	Mulder et al. (2014)

For example, among economic factors, factors such as income, capital labor ratio, production structure and energy price are potentially variables affective on energy intensity. Income increase on one hand causes demand rise for various commodities including the energy which leads to an increase of energy intensity, and on the other hand increases awareness about environmental issues and therefore, it increases the tendency to utilize energy-saving technologies (Song and Zheng, 2012). The effect of capital per capita labor variable on energy intensity varies based on its relation to energy (complementary or substitute). This variable also is used as a measure of the level of technology (Wu, 2012) which is expected to have a negative impact on energy intensity. Regarding production structure changes, it can be expected that countries which are in development path face with higher share of services sector and lower share of agricultural and industrial sectors, and since service sector consumes less energy than other sectors, it leads to a decrease in energy intensity in economy. Energy price is also an important factor that its increase in short-term (due to stability of capital and technology) can cause a decrease in the rate of equipment utilization by energy consumer which leads to a downturn in economic activities; but in long-term the acceptance of energy-saving technologies by holders of capital also takes place.

Transportation sector not only in Iran, but also in the world has a great share in energy consumption and pollution emissions. In the field of trade, one can say that as a result of trade, countries first of all, find various fields for learning and imitation from external environment (Grossman and Helpman, 1993) and second, being placed in competitive environment and by that the basis for increasing the efficiency of energy usages has been provided.

In correlation to demographic variables, it can be said that with an increase in population, if infrastructures were improved the energy intensity is going to decrease, and if old infrastructures were used energy intensity will increase. Urbanization growth can also have a different effect on energy intensity because it on one hand causes existence of advantages regarding the scale based utilization, and on the other hand it leads to an increase in demand for energy related urban services such as transportation, waste disposal and wastewater and etc. (Jones, 1991).

Industrial factors such as investment in industry sector, the level of education of industrial workers, ownership and size of firms can also be affective on energy intensity. For example, it has been expected that the private sector works more efficiently about energy consumption. In correlation to the size of the firm it can be said that based on theory of existence of advantages regarding the scale of production, with an increase in firm size the average cost per unit of product decreases; therefore, it is expected that the energy intensity in larger firms be lower than in the smaller ones (Kleijweg et al., 1990). In relation to climatic variables, it has been expected that energy intensity in cold and warm regions would be higher in comparison to temperate regions.

This study seeks to investigate the effect of ICT development indicators on energy intensity, but first of all the effect of 20 potential affective variables on energy intensity including ICT development indicators on energy intensity has been investigated using non-standard Bayesian approach called Weighted Average Least Square (WALS), to study if ICT development indicators are significant or not in comparison to other variables. Then, in order to analyze the changes in energy intensity based on information criteria, a Bayesian panel model including the most important identified variables by WALS technique was elaborated and estimated using Monte-Carlo simulation with Markov chains.

It should be noted that this study has been carried out on 30 provinces of Iran during the period of 2010-2015. In the next section, the material and methods have been discussed. The third and fourth sections are assigned to Results and conclusion.

Material and Methods

Bayesian estimation

The Bayesian econometric basis is based on the Bayes' theorem, so that if Y considered as the set of available data (explanatory and dependent variables) and θ as the vector of parameters, the Bayes' law can be shown as equation (1). The probability of parameters in terms of available data set ($P(\theta|\, Y)$ can be written as follows:

$$P(\theta|\, Y) = \frac{P(Y|\, \theta)P(\theta)}{P(Y)} \tag{1}$$

$P(\theta)$ is a prior distribution function that is not dependent on data and represents the prior beliefs of researcher from parameters, before the data being observed. $P(Y|\, \theta)$ is likelihood function which indicates the density of data on the model's parameters and refers to the process of data generation. $P(\theta|\, Y)$ is also obtained using the combination of prior and likelihood

functions; therefore, the probability distribution of parameters after observation of data has been demonstrated and called posterior function (Magnus and Durbin, 1999).

Weighted average least square

In econometric models two types of explanatory variables are used. The first type is focus variables that their presence in model has been supported by official and solid theories such as price and income in demand function. The second type is auxiliary variables that their presence in the model is corrected based on unofficial theories and there is less certainty about their presence in the model.

The statistical framework that is applied in this study is a linear regression model which can be shown as equation (2).

$$y = X_1\beta_1 + X_2\beta_2 + u \tag{2}$$

Where, y is an $n \times 1$ vector of observations on the dependent variable. $X_{\mathrm{j}}(\mathrm{j} = 1, 2)$ are $\mathrm{n} \times k_j$ matrices of observations that are related to explanatory variables which are not random (X_1 contains focus variables and X_2 contains auxiliary variables). u is also an $n \times 1$ random vector of unobservable disturbances which is assumed to have $i.i.d\ N(0.\sigma^2)$ distribution.

Since the uncertainty of the model is limited to k_2 variable from X_2, the number of possible models (the number of models in model space) based on presence or absence of each of auxiliary variables is $\mathrm{I} = 2^{k_2}$. From now, M_i represents i^{th} model in model space.

Weighted Average Least Square is a Bayesian averaging method of model coefficients which is introduced by Magnus and Durbin (1999) and Danilov and Magnus (2004) in order to examine the statistical properties of estimators. The main idea of averaging estimators of model is that firstly, parameters would be estimated conditional on each model in model space and then computes an unconditional estimation as a weighted average of these conditional estimations. A model-averaging estimation of β_1 as the coefficient of one of the explanatory variables is given by equation (3).

$$\hat{\beta}_1 = \sum_{i=1}^{I} \lambda_i \hat{\beta}_{1i} \tag{3}$$

Where the λ_i are random nonnegative weights with sum equals to one.

In Weighted Average Least Square method, practically the usage of prior informative function for parameters is not possible so, the prior non-informative function is used for all models. If we assume that M_{i} model is correct, then the sample likelihood function used by the model can be written as (4):

$$P(y|\,\beta_1.\beta_{2i}.\sigma^2\,.M_i) \sim (\sigma^2)^{-n/2} \exp\left(-\frac{\varepsilon_i^T \varepsilon_i}{2\sigma^2}\right) \tag{4}$$

The prior knowledge about the parameters of M_{i} model were taken into account by using non-informative priors for β_1 parameters and σ^2 error variance, in addition to an informative function for β_{2i} auxiliary parameters (specifically $\beta_{2i}|\,\beta_1, \sigma^2, M_i \sim N(0, \sigma^2 V_{0i})$), lead to a conditional joint prior distribution that can be shown as (5):

$$P(\beta_1.\beta_2.\sigma^2|\,M_i) \sim (\sigma^2)^{(k_{2i}+2)/2} \exp\left(-\frac{\beta_{2i}^T V_{0\,i}^{-1} \beta_{2i}}{2\sigma^2}\right) \tag{5}$$

Where $V_{0\,i}^{-1}$ is variance-covariance matrix of β_{2i} prior distribution. (It should be noted that WALS method uses Laplace prior distribution function, because it is relevant to the more explicit concept of uncertainty about the role of auxiliary variables).

But the WALS method is based on preliminary orthogonal transformations of auxiliary regressors and their parameters. The first step in this method is to calculate orthogonal matrix P and diagonal matrix $\wedge$ with $k_2 \times k_2$ dimensions; so that, $P^{\mathrm{T}}\mathrm{X}_2^{\mathrm{T}}\mathrm{M}_1\mathrm{X}_2P = \wedge$. These matrices are used to define $Z_2 = \mathrm{X}_2P\wedge^{-1/2}$ and $\gamma_2 = \wedge^{-1/2}P^{\mathrm{T}}\beta_2$ matrices, also we have $Z_2\mathrm{M}_1\mathrm{Z}_2 = \mathrm{I}_{\mathrm{k}_2}$ and $Z_2\gamma_2 = \mathrm{X}_2\beta_2$. It is noteworthy that the principal vector of β_2 auxiliary parameters always can be obtained from $\beta_2 = P\wedge^{-1/2}\gamma_2$.

After applying these orthogonal transformations for the each model, the unrestricted OLS estimators β_1 and γ_2 from regression of y on X_1 and Z_2 can be calculated as equation (6):

$$\hat{\beta}_{1u} = \hat{\beta}_{1r} - R\hat{\gamma}_{2u} \tag{6}$$

Where $\hat{\gamma}_{2\mathrm{u}} = Z_2^{\mathrm{T}}\mathrm{M}_1\mathrm{y}$. Also, where $R = (X_1^T X_1)^{-1}X_1^T Z_2$, the multivariate OLS estimators of Z_2 regression on X_1 can be calculated using equation (7):

$$\hat{\beta}_{1i} = \hat{\beta}_{1\mathrm{r}} - \mathrm{RW_i}\hat{\gamma}_{2\mathrm{u}} \quad ,\hat{\gamma}_{2i} = W_i\hat{\gamma}_{2u} \tag{7}$$

Where $W_{\mathrm{i}} = \mathrm{I}_{\mathrm{k}_2} - \mathrm{S_i}\mathrm{S_i^T}$ is a diagonal matrix with $k_2 \times k_2$ dimensions, whose j^{th} element on its diagonal is equal to zero if γ_{2j} constrained to zero.

Based on these transformations, $\hat{\gamma}_{2i} \sim \mathrm{N}_{\mathrm{k}_2}(\gamma_2.\sigma^2\mathrm{I}_{\mathrm{k}_2})$. By considering some minimal regularity conditions on model weights (λ_i), the WALS estimator of β_1 is given by equation (8):

$$\tilde{\beta}_1 = \sum_{i=1}^{\mathrm{I}} \lambda_{\mathrm{i}}\hat{\beta}_{1\mathrm{i}} = \hat{\beta}_{1\mathrm{r}} - \mathrm{RW}\hat{\gamma}_{2\mathrm{u}} \tag{8}$$

Where $W = \sum_{i=1}^{I} \lambda_i W_i$ is a random diagonal matrix (because each λ_i is random) with $k_2 \times k_2$ dimensions. Therefore, if the model space contains 2^{k_2} models, the calculation burden of the WALS estimator of $\tilde{\beta}_1$ is of the order k_2, because it is only necessary to consider the diagonal elements on of W matrix (De Luca and Magnus, 2011).

Description of variable

This study has been conducted on 30 provinces of Iran during the period of 2010-2015. The dependent variable is the logarithm of energy intensity of provinces that has been represented by *Energy int* abbreviation and was calculated by dividing energy consumption (including electricity, natural gas, gasoline, kerosene, mazut and gas oil) on real production of provinces. The ICT development index includes three sub-indices named as access, use and skill that selection and calculation of these sub-indices have been conducted by The Ministry of Information and Communication Technology of Iran (2016) based on the availability of information, different statistical survey results, the conceptual framework of ICT and communication in 2007 and etc. These sub-indices are defined according to Figure (2) as follows.

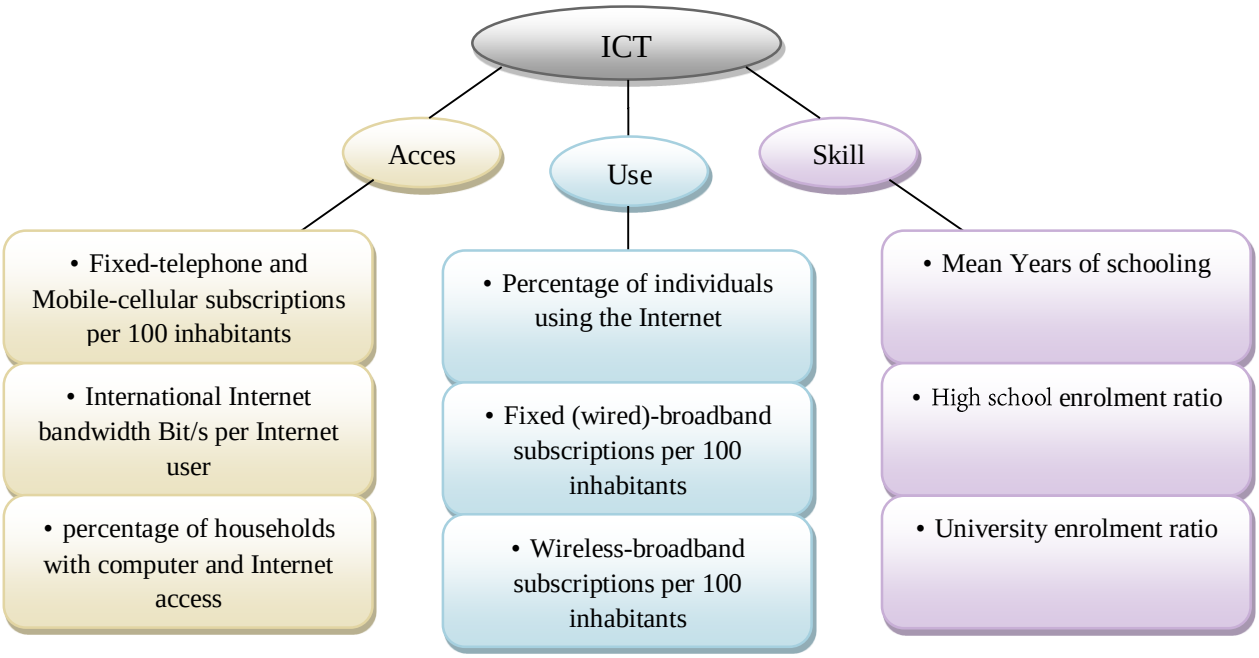

Figure 2. Sub-indices of ICT development

Status of the provinces of Iran from the perspective of ICT sub-indices during the period of 2010-2015 have been shown in Figure (3) using 10-point system.

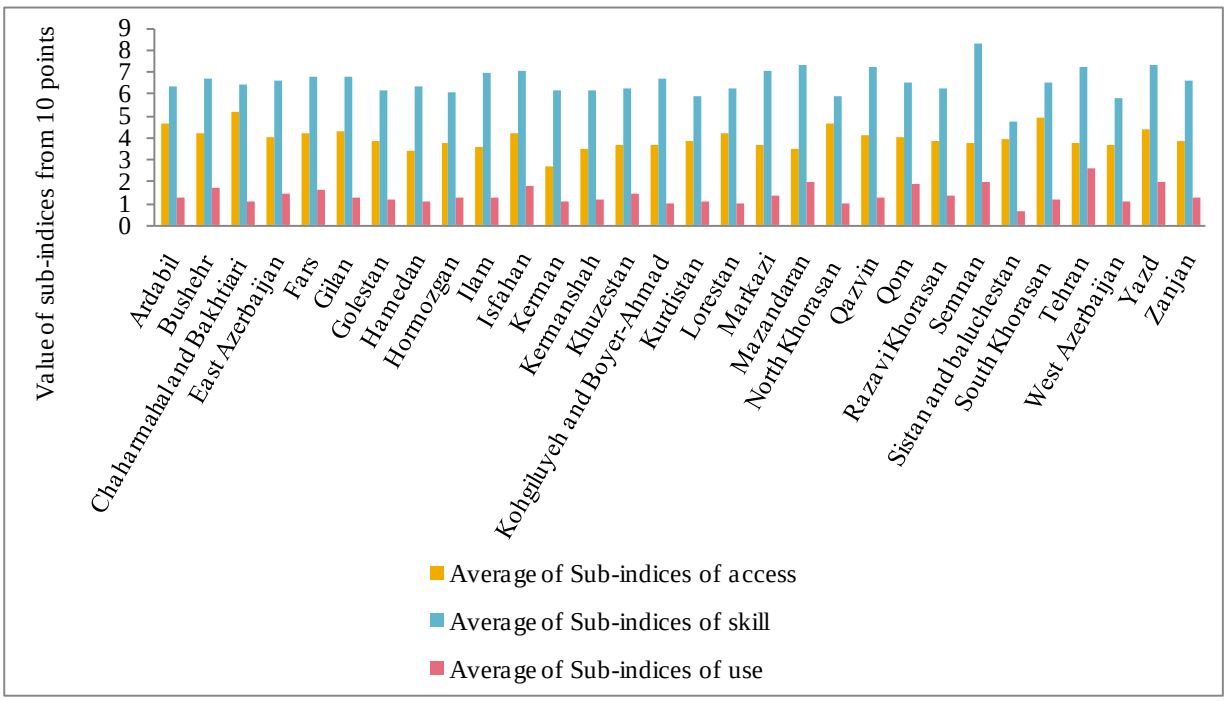

Figure 3. The average value of sub-indices of ICT in provinces of Iran during the period of 2010-2015 from 10 points

Other explanatory variables that were used to identify more important variables including various economic, openness and transportation, demographic, industrial and climate variables as described in Table (2).

Table 2. Variables used in study

Categories of factors	Variables	Explanations`
Economic	GRP	Logarithm of real per capita income
	G.GRP	Logarithm of growth of real per capita income (in %)
	K/L	Logarithm of the ratio of real capital to labor, which has been multiplied by capital stock of country to the ratio of GRP of province to the GRP of country in order to calculate the capital stock of each province.
	S Val	Logarithm of services share in GRP (in %)
	I Val	Logarithm of industry share in GRP (in %)
	Price	Logarithm of real energy price, which is the weighted average of real price of energy kinds (including electricity, natural gas, gasoline, kerosene, mazut and gas oil). Weights also represent the amount of energy carrier consumption from total amount of energy carrier consumption.
Openness and Transportation	Trade	Logarithm of the ratio of sum of the imports and exports to production (%)
	Car	Logarithm of the number of vehicles that has been licensed
Demographic	Pop	Logarithm of population (person per square kilometer)
	Urb	Logarithm of ratio of urban population to total population (in %)
Industrial	Private	Logarithm of the number of industrial workshops with private ownership to total of industrial workshops (in %)
	L Ind num	Logarithm of the number of major industrial workshops (with 50 or more workers) to total of industrial workshops (in %)
	S Ind num	Logarithm of the number of minor industrial workshops (with 10 to 40 workers) to total of industrial workshops (in %)
	Ind Edn	Logarithm of the number of workers in industrial workshops with high education to all the workers (in %)
	Inv	Logarithm of investment in industrial workshops
Climatic	Temp	Logarithm of average temperature
	Rain	Logarithm of average rainfall

Result and Discussion

Results of WALS estimation

For this estimation, the equation $y = a + X_1 b + X_2 c + e$ has been used, in which X_1 and X_2 represents the focus (logarithm of per capita income and logarithm of energy price) and auxiliary (contains 18 variables) regressors. Table (3) shows the results of WALS estimation using STATA software.

The importance criterion of explanatory variables in WALS method has been measured using t-statistics, based on this, logarithm of per capita income, logarithm of the share of industry in production, logarithm of the level of access to ICT equipment, logarithm of energy price, logarithm of vehicle inventory and logarithm of sub-index of skill are more significant as compared with other variables. Therefore, among the most important variables of this study, there are two sub-indices of ICT development.

Table 3. Results of WALS estimation

Variables	Coefficients	t	Lower bound	Upper bound
GRP	0.345	3.84	0.25	0.43
I Val	0.185	2.63	0.11	0.26
Access	-0.160	-2.81	-0.22	-0.10
Price	-0.138	-2.59	-0.19	-0.85
Car	-0.097	-2.47	-0.14	-0.06
Skill	0.044	1.97	0.02	0.07
Ind Edu	0.045	1.50	0.01	0.07
S Val	0.187	1.19	0.03	0.03
Urban	0.327	1.13	0.04	0.62
S Ind num	-0.056	-1.08	-0.11	-0.00
Private	-0.212	-1.05	-0.41	-0.01
G.GRP	0.135	1.01	0.00	0.27
Trade	-0.026	-0.99	-0.05	0.00
Temp	0.105	0.94	-0.01	0.22
K/L	-0.026	-0.86	-0.06	0.00
Pop	-0.229	-0.76	-0.53	0.07
Rain	-0.040	-0.53	-0.12	0.04
Inv	0.018	0.30	-0.04	0.08
L Ind num	-0.008	-0.04	-0.23	0.21
Use	0.002	0.04	-0.05	0.06

Note: In the first column, the variables are arranged according to their importance level. The second and third columns, respectively, demonstrate the estimated coefficients and t-statistics. In fourth and fifth columns, confidence intervals have been reported.

Select the optimal model

Now, in order to extract the optimal models which include various combinations of important variables, stepwise selection algorithms such as forward selection and backward elimination are performed, after selecting the best subset Leaps-and-Bounds algorithm is used and best subset for any number of explanatory variables based on Bayesian Information Criterion (BIC), Akaike's Information Criterion (AIC), Akaike's Corrected Information Criterion (AIC_C) and R^2_{ADJ} (adjusted) have been determined (Lindsey and Sheather, 2010). The results from this analysis indicate that based on the minimum value of AIC and AICC and maximum value of R^2ADJ, a model including six important explanatory variables is an optimal model. Informative criteria for this model have been reported in Table (4).

Table 4. report of information criteria for the optimal model

Information criterion	BIC	AIC	AICC	$\boldsymbol{R^2ADJ}$
Value of information criterion	-150.23	-340.93	170.73	0.43

After selecting the model that includes a subset of most important variables, it is necessary to determine the Bayesian modeling of these selected variables based on the minimum value of Deviance Information Criterion (DIC). Accordingly, after discussions and considering that the data used in this study is panel, a Bayesian model (9) with a value of DIC equals to -469.6 was chosen as the best Bayesian model.

$$\text{Energy int}_{it} = \beta_0 + \beta' X_{it} + u_i + \epsilon_{it} = \beta' X_{it} + \tau_i + \epsilon_{it},$$
$$X' = (GRP, IVal, Access, Price, Car, Skill)$$
$$\epsilon_{it} \sim i.i.d.\ N(0, \sigma_0^2)$$
$$\tau_i \sim i.i.d.\ N(\beta_0, \sigma_{id}^2) \qquad (9)$$

Where i and t represent the province and year, respectively. u_i represents the random effects of the ith province, σ_{id}^2 shows variance of random effects and σ_0^2 is variance of error. Regression coefficients ($each\ \beta$) have normal distribution with mean of zero and a variance of 100 and for variance parameters, inverse-gamma $(0.001\ .0.001)$ priors has been considered, so that all the prior functions which have been chosen, were non-informative (These prior functions are common in the Bayesian econometric literature, and the combination of normal and gamma priors when the distribution of likelihood function is normal, yields the conjugate prior function and normal-gamma posterior function).

It is noteworthy that the mean of prior distribution of random effects of τ_i is the constant term of regression, namely β_0 which has a normal prior distribution with mean of zero and a variance of 100; hence, this model is called hierarchical. Indeed, in case where $\tau_i s$ are independent and homogeneous and their common distribution depends on the unknown parameter of α_0, a hierarchical prior density function is demonstrated that can be used to obtain posterior distribution by combining it with likelihood function. Overall, this type of modeling based on intergroup independency and intragroup correlation in analysis or in other words, controlling the interchangeability between and within groups is an appropriate tool for analyzing panel data and increasing the accuracy of model estimation (For further study, Gelman and Hill, 2007; Goldstein, 2010).

Today, there are numerous statistical inference methods that can be used in statistical calculations of these models; Monte-Carlo integrated simulation method is one that has been used for this purpose. Monte-Carlo simulation method solves Bayesian computations of posterior density torques by sampling posterior distribution but, this method has some disadvantages which have been eliminated by using Markov chains to generate sequences of sample points from the domain of posterior density distribution at an acceptable rate.

estimation of optimal model

Since the most common distribution that is widely used in economy is normal distribution, in this study it has been assumed that the likelihood function has a normal distribution which has been based on normality of the dependent variable; so, in order to investigate this assumption Kolmogorov-Smirnov Test (1967) has been used. The results of this test have been demonstrated in Table (5).

Table 5. Results of Kolmogorov- Smirnov Test

Variable	Significance level	Error value	Test statistic	Result
Energy int	0.208	0.05	1.064	Normal

Table 6. Model estimation results

Variables	Mean	Std	MCSE	Median	Lower Bound	Upper bound	ESS	Efficiency
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GRP	-0.24	0.0125	0.0011	-0.2452	-0.271	-0.221	138	0.028
IVal	0.18	0.0112	0.0011	0.1884	0.167	0.210	098	0.020
Access	-0.07	0.0063	0.0005	-0.0661	-0.079	-0.055	182	0.036
Price	-0.90	0.0089	0.0007	-0.8997	-0.916	-0.881	140	0.028
Car	0.36	0.0049	0.0005	0.3616	0.352	0.371	097	0.019
Skill	0.26	0.0090	0.0008	0.2603	0.242	0.280	140	0.028
Cons	0.01	0.0130	0.0012	0.0094	-0.015	0.036	122	0.024
$\boldsymbol{\sigma_0^2}$	0.01	0.0004	0.0001	0.0041	0.003	0.005	075	0.015
$\boldsymbol{\sigma_{id}^2}$	0.99	0.0096	0.0009	0.9903	0.972	1.010	122	0.024

Table (6) shows the results of estimation in STATA software by using Metropolis-Hastings algorithm for 7500 iterations (Number of iterations obtained by MCMC simulator) and for samples that their size are 5000, were used.

According to the results demonstrated in Table (6), based on the posterior mean of explanatory variables coefficients (second column), it is obvious that there is inverse relation between per capita income and energy intensity; so that, one percent increase in per capita income leads to a decrease about 0.24 percent in energy intensity. As a result, it can be declared that Iran's provinces are at the phase of development where any increase in their income affect positively their awareness and willingness to use energy-saving technologies. With assuming other factors constant, regarding the impact of industry share in production, results have shown that one percent increase in such a share causes 0.18 percent increase in energy intensity. The abundance of energy resources in Iran has led to energy consuming structures in its provinces' industries. The existing time-worn technologies are another reason for the greater energy consumption in industry sector in comparison to the value added of production by this sector. Energy price has a negative impact on energy intensity, such that one percent increase in average energy price reduces energy intensity by 0.9 percent. This effect of price on energy intensity could have been the result of adopting energy-saving technologies. Vehicle inventory also has a positive impact on energy intensity and with one percent increase in such inventory 0.36 percent increase in energy intensity can be observed which suggests that the increase in demand and consumption of petroleum products is higher than production in transportation sector and consequently it causes inefficacies in road transportation sector.

As expected, the impact of access to ICT equipment on energy intensity was negative and one percent increase in access to ICT equipment leads to 0.07 percent decrease in energy intensity. By increasing availability of such equipment, transportation and similar sectors can be replaced by ICT and decrease the energy intensity in this way. The positive coefficient of the level of skill could be a result of inefficacy in education structure in Iran; such that if all other variables considered as constant, one percent increase in this skill leads to 0.26 percent growth in energy intensity.

The Monte-Carlo standard errors (the forth column) for all parameters is also smaller than the conventional standard errors of posterior distributions (If Monte-Carlo standard error is equal to 0.05 of conventional standard error of posterior distribution, it can indicate the convergence of algorithm in finding posterior marginal distribution). The proximity of median and mean posterior distribution of parameters indicates that parameters have a symmetric posterior distribution. Sixth and seventh columns of Table (6) show the 95% credible interval of estimated posterior mean for each parameter.

Another important criterion that should be considered is effective sample size which is denoted by ESS. For instance, the effective sample size for GRP variable is about 0.028 based on the sample size of 5000 that is obtained using MCMC simulation; it means that about 138 (0.028 * 5000) independent observations are available. As can be seen, the effective sample size for estimating the posterior density mean of all model's parameters is more than one percent; therefore, the results are considered as valid.

Also, in order to provide valid Bayesian inferences based on the sample obtained by MCMC simulation, Markov-chains convergence has been examined using the trace and autocorrelation graphs of posterior density of explanatory variables that were used in model. Graphs related to other variables' parameters, as in Figures (4) and (5), indicate the convergence of algorithm in the simulation of parameters.

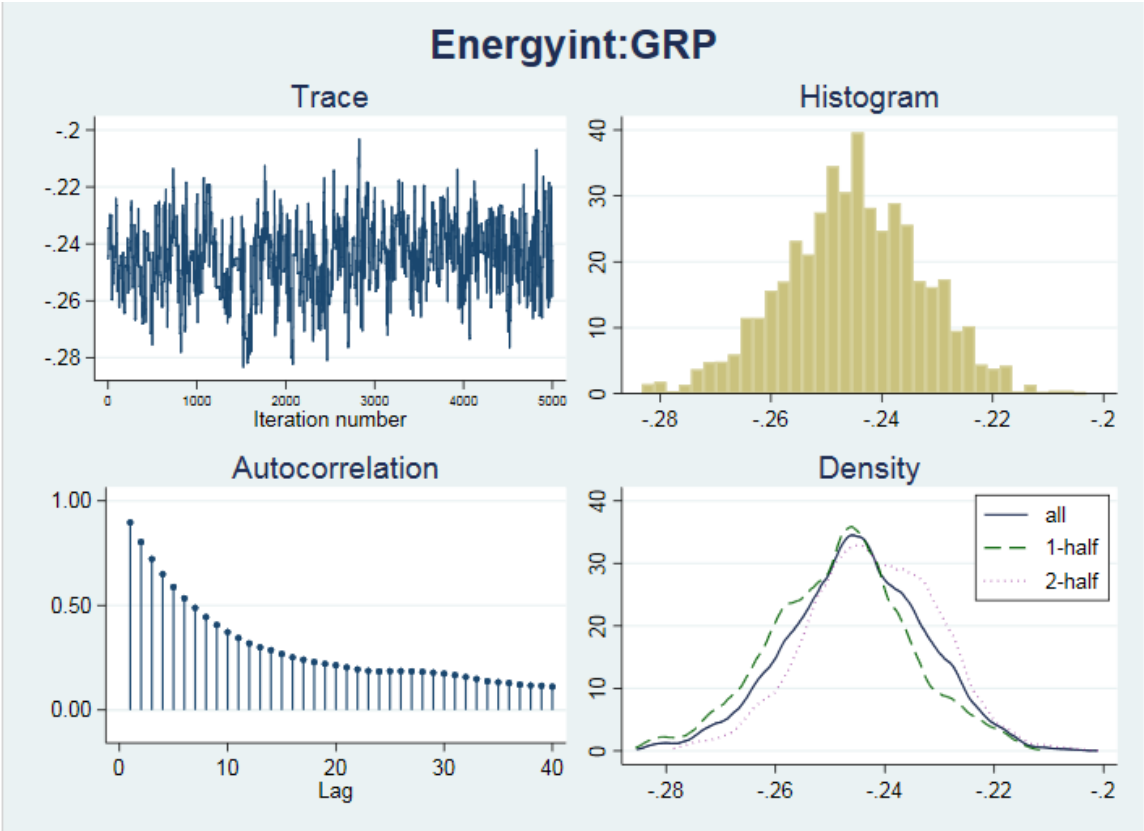

Figure 4. Multiple posterior density simulated by MCMC for logarithm of per capita income variable

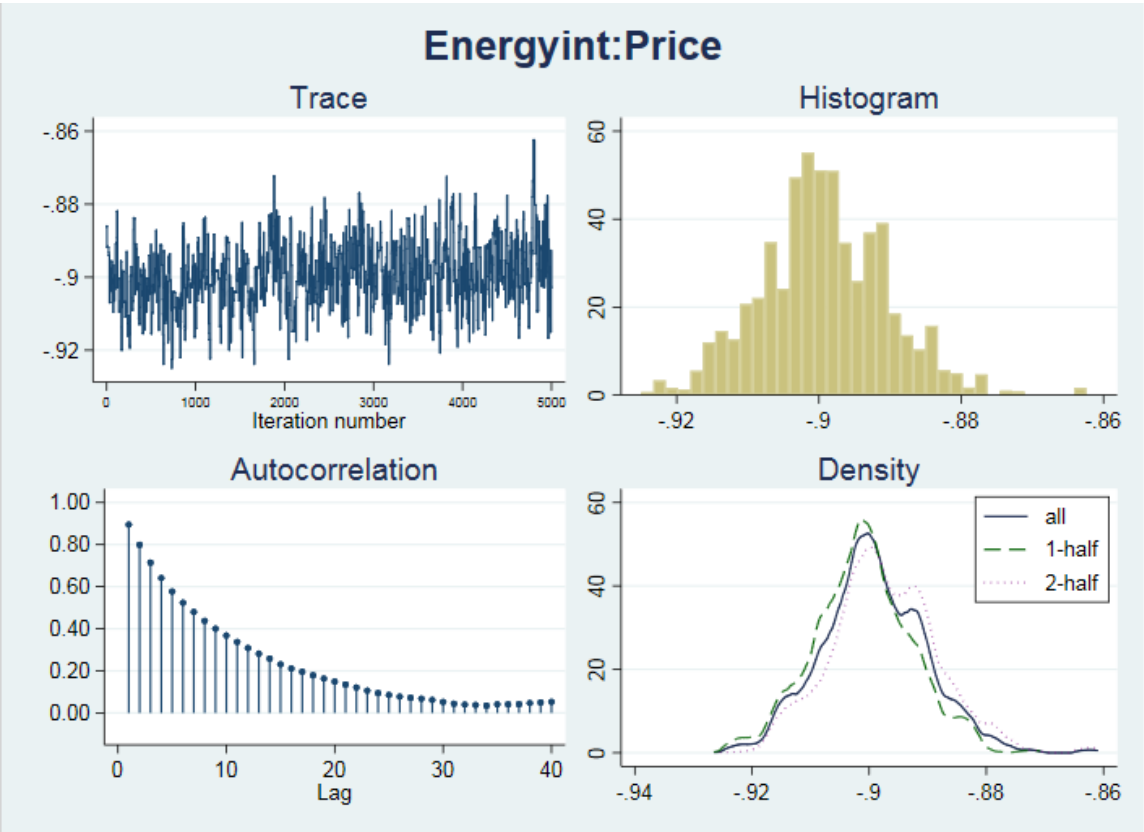

Figure 5. Multiple posterior density simulated by MCMC for logarithm of energy price variable

Conclusion and Recommendation

Although development and economic growth have not been possible without energy consumption and environmental degradation so far, developed countries have been able to use tools such as ICT to take steps toward optimizing energy consumption and thus decreasing energy intensity. In Iran, due to high energy intensity, the necessity of addressing this issue by policy makers is inevitable. Therefore, in this study, the ICT index has been considered as one of the key factors affecting energy intensity along with other important factors. There are numerous factors affecting energy intensity and conventional econometric models are not able to investigate the wide range of these factors' effects on energy intensity. Thus, this study in the first step has applied weighted average least square approach for selecting an optimal model and on this basis, among 20 explanatory variables (that have been classified in six different groups named as economic, communication and information technology, openness and Transportation, demographic, industrial and climate), variables of per capita income, sub-indices of ICT (access and skill), industry share in production, vehicle inventory and energy price were selected as the most effective variables on energy intensity in provinces of Iran. In the next step, based on information criteria, a hierarchical Bayesian panel model including selected variables has been determined and estimated. The results of the model estimation have shown that industry share in production, skill sub-index and vehicle inventory with coefficients of 0.19, 0.26 and 0.36, respectively, have a positive impact on energy intensity and per capita income, energy price and access to equipment sub-index with coefficients of -0.24, -0.9 and -0.07, respectively, have a negative effect on energy intensity.

According to findings of this study, the following policy recommendations have been made in order to help reducing the energy intensity in Iran:

- Since the industry share has a positive and significant effect on energy intensity, it can be indicated that existence of time-worn and energy consuming technologies in Iran's economy and Therefore, planning is necessary in order to make renovations in this sector.
- According to available capabilities to access to ICT equipment, the expansion of ICT infrastructures and special attention toward better and inexpensive access of target groups such as service and manufactures businesses, rural regions and deprived regions to this equipment with government's support could has a significant impact on the reduction of energy intensity.
- Expanding the utilization of advanced equipment like intelligent transportation systems, smart cities, establishment of e-government system, e-banking, online shopping and e-commerce and etc. could be effective in reducing energy intensity in provinces of Iran.
- As the estimations have shown, skill sub-index has a positive impact on energy intensity so that it is a result of weakness and inefficiency of country's educational system in the field of efficient usage of energy in schools and universities. Consideration and planning of policymakers in educational field can have a significant impact on the effectiveness of this factor.

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