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THRESHOLD EFFECT OF ICT INVESTMENT ON ELECTRICITY CONSUMPTION IN CHINA

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Abstract. *It lacks empirical studies about the effect of information communication technology (ICT) on energy consumption in developing countries. Although China will step into the junior stage of an information society in around 2020, the impact of ICT on electricity consumption has not been studied. To capture the relationship between ICT investment and electricity consumption, we introduce a STIRPAT model and apply a panel database of 30 provinces in mainland China from 2003 to 2012. The main conclusions are: The panel vector error correction (PVEC) model results reveal that ICT investment is the granger cause of electricity consumption in both long run and short run in mainland China. Besides, the Hansen threshold model results show that the threshold value for industrial share in China is 0.259, which implies that ICT investment significantly increases total electricity consumption in Beijing, while it would significantly reduce electricity cost in other provinces of mainland China.*
Keywords: ICT investment, Electricity consumption, China, Threshold effect, Granger causality

1. **Introduction.** Since the introduction of the reform and opening policy in 1978, China has been experiencing a rapid economic growth which poses a big energy demand pressure. The amount of total energy consumption in China exceeded that of U.S. in 2010. To achieve a sustainable development, Chinese government claims that reducing energy consumption per GDP by 16% with the 2010 level is one of their main goals in the outline of 12th Five-Year (2011-2015) Plan of China. Electricity plays an important role in energy consumption in China during these recent decades. Since electricity is directly consumed by operating ICT products and systems, and ICT reduces electricity consumption for its replacement of physical procedures and its potential to optimize the production process, the net effect of ICT on electricity consumption is worthy to be studied.

ICT has already been acknowledged to be one possible way of driving economic growth with less energy. Thanks to a technological leapfrogging process and ICT industry policies introduced by Chinese government, ICT expanded rapidly since the twenty-first century. China is predicted to step into the junior stage of an information society in around 2020; exploring the impact of ICT investment on electricity consumption is an urgent problem to be solved.

Many researchers studied the association between ICT and energy consumption from an empirical perspective. From the macro level, Takase and Murota [1] drew conclusions that the substitution effect is dominant in Japan and the income effect is dominant in the US. Ishida [2] revealed that ICT investment contributed to a moderate reduction in energy consumption in Japan over 1980-2010. Additionally, Schulte et al. [3] concluded that ICT significantly reduces total energy demand in OECD countries. Furthermore, it is concluded that ICT is not associated with a significant change in the demand for electric energy. Sadorsky [4] argued there is a positive relationship between ICT and electricity consumption by 19 emerging countries from 1993-2008. Salahuddin and Alam [5] drew different conclusions that the Internet usage has a long run significantly positive effect on electricity consumption while the effect in short run is insignificant in Australia. From the industrial level, Collard, Fève et al. [6] found that electricity intensity increased with computers and software capital increasing while decreased with communication device diffusion in the service sector of France. By employing the similar factor demand model, Bernstein and Madlener [7] further illustrated a negative effect of communication technology on electricity intensity in five major European manufacturing industries (chemical, food, metal, pulp and paper, textile) and the industry-specific impact of computers and software. Further study concluded that ICT investment increases electricity consumption in the service sector and most manufacturing sectors while decreases in some specific manufacturing sectors in South Korea [8]. From a micro level, Watch [9] provided the company case studies to prove the electricity consumption reduction effect of ICT.

Our research contributes to the existing literature as follows. First, when compared with the literature about ICT investment's impact on energy consumption in developed countries, little attention has been paid to the effect in developing countries, especially from the empirical perspective, because of the short time ranges and inaccessible data on ICT investment. The example of China is used to fill this gap. Second, many scholars do not realize that the dominant effect (negative effect or positive effect) of ICT investment on energy consumption could change with industrial structure development at the macro level. This means that few try to capture the threshold effect of ICT investment on electricity consumption. This paper introduces a Hansen threshold model to fill this gap. Third, to the best of our knowledge, it is the first time to detect the granger causal link running from ICT investment to electricity consumption.

The paper is organized as follows. Section 2 describes the models and methods. Section 3 presents the empirical results. Section 4 discusses the results. Section 5 concludes.

2. **Methods and Data.**

2.1. **The basic framework.**

To assess the environmental impact, a STIRPAT model is given ($I = a \cdot P^b \cdot A^c \cdot T^d \cdot e$ where a is the constant term, e is the error term and b, c, d corresponds to the elasticity of population (P), affluence (A) and technology (T) with respect to the environment (I), respectively). To investigate the association between ICT investment and electricity consumption, the model is rewritten and taken the logarithm form as below:

$$\ln ELC_{it} = \alpha_0 + \alpha_1 \ln POP_{it} + \alpha_2 \ln PGDP_{it} + \alpha_3 \ln INV_{it} + \alpha_4 \ln SV_{it} + \alpha \ln ICT_{it} \quad (1)$$

where ELC represents electricity consumption, POP denotes population, PGDP represents GDP per capita, T is measured by the share of industry sector in GDP (denoted by INV) and the share of service sector in GDP (denoted by SV) [10], and ICT measures ICT investment. The coefficients α_i ($i \neq 0$) correspond to the elasticity of every variable. α_0 is the fixed intercept. i represents the province dummies and t is the year dummies.

2.2. **Data.**

The sample covers 2003-2012 of 30 provinces (except Tibet) in mainland China. The data comes from China Statistical Yearbook of 2004-2013.

Table 1. Data sources

Variables	Description	Units
ELC	Total consumption of electricity of various kinds by the production sectors of the economy and by households	100 million kilo watt hour
POP	Total population at the end of a year	Persons
PGDP	GDP divided by total population	RMB and at 2003 constant prices
INV	Second industrial value added divided by GDP	Percentage
SV	Tertiary industrial value added divided by GDP	Percentage
ICT	Investment in fixed assets in the sector of information transmission, software and information technology	RMB and at 2003 constant prices

2.3. **Methodology.**

2.3.1. *Unit root test.* This study uses Choi [11] and Im-Pesaran-Shin (IPS) [12] unit root tests to check the stationary properties of the sample data. The null hypothesis is the non-stationary distribution. If it is rejected, the panel variable is stationary in level. Otherwise, the variable is non-stationary in level, in which case we differenced the series of the variable and repeat the stationary tests.

2.3.2. *Co-integration test.* Once we determine the degree of stationary of each variable, we then turn our attention to check if the variables as a group share one or more unit roots, in which case they become co-integrated and possess a long-run equilibrium relationship [13]. The Pedroni [14] approach is applied. Its null hypothesis is that no co-integration relationship exists. If the results reject the null hypothesis, it means at least one co-integration relationship among these variables exists.

2.3.3. *Panel granger causality test.* Although the panel variables are co-integrated, the long-run relationship may be out of balance in the short run. So the PVEC model is introduced to connect the short-run and long-run relationships together. The long-run granger causality is examined by the elasticity of ECT_{t-1} and the short-run granger causality is measured by the coefficient of Δx. The following econometric model is used:

$$\Delta y_{it} = \sum_{k=1}^{p_1} \alpha_k \Delta y_{i(t-k)} + \sum_{k=1}^{p_2} \beta_k \Delta x_{i(t-k)} + \theta ECT_{i(t-1)} + \varepsilon_{it} \tag{2}$$

where Δ is the first difference operator, t is the year subscript, i is the province subscript, and ε_{it} is the fixed intercept. k is the lag length, and p_1, p_2 are the maximum lag lengths. α_k, β_k, θ are the parameters to be estimated, ECT_{t-1} is the lagged error correction term which is derived from the co-integration equation and corrects the deviation occurring in the short-run return to the long-run equilibrium.

The representation of PVEC for Equation (1) is:

$$\begin{aligned}\Delta \ln ELC_{it} = & \sum_{k=1}^{p_1} \alpha_k \Delta \ln ELC_{i(t-k)} + \sum_{k=1}^{p_2} \beta_k \Delta \ln POP_{i(t-k)} + \sum_{k=1}^{p_3} \gamma_k \Delta \ln PGDP_{i(t-k)} \\ & + \sum_{k=1}^{p_4} \eta_k \Delta \ln INV_{i(t-k)} + \sum_{k=1}^{p_5} \lambda_k \Delta \ln SV_{i(t-k)} + \sum_{k=1}^{p_6} \phi_k \Delta \ln ICT_{i(t-k)} \\ & + \theta ECT_{i(t-1)} + \varepsilon_{it}\end{aligned} \tag{3}$$

α_k, β_k, γ_k, η_k, λ_k, ϕ_k, θ are the coefficients to be estimated. p_1, p_2, p_3, p_4, p_5, p_6 are the maximum lag lengths.

2.3.4. *Threshold model.* The regression is introduced after co-integration and granger causality tests. It has been acknowledged that the ICT's reducing effect on energy consumption mainly benefits from the substitution effect on energy-costing industries and replacement effect for other input factors. Based on the analyses and motivated by regional diversities of industrial structures in China, a threshold model is presented.

The Hansen [15] non-dynamic threshold model can effectively avoid the shortcomings that group estimations could not estimate the threshold value and the disadvantages that cross-term model cannot test the significance of the threshold effect. It means that the Hansen model we use estimates the exact threshold values of the threshold variable, examines their significances, and can test the significance of the threshold effect. The basic representation is given:

$$\begin{cases} y_{it} = u_t' + \mu_1 x_{it}, & q_{it} \leq \omega \\ y_{it} = u_t'' + \mu_2 x_{it}, & q_{it} > \omega \end{cases} \tag{4}$$

An alternative intuitive way of writing (4) is:

$$y_{it} = u_t + \mu_1 x_{it} * I(q_{it} \leq \omega) + \mu_2 x_{it} * I(q_{it} > \omega) \tag{5}$$

y is the dependent variable. i represents the individual dummy and t is the time dummy. u_t is the fixed intercept. x_{it} is independent variable. μ_i is the elasticity. $I(*)$ represents the indicator function. q_{it} is the threshold variable. ω is the threshold value.

In addition to single threshold of the above, there may be double threshold in the fact. The double threshold model takes the form:

$$y_{it} = u_t + \mu_1 x_{it} * I(q_{it} \leq \omega_1) + \mu_2 x_{it} * I(\omega_1 < q_{it} \leq \omega_2) + \mu_3 x_{it} * I(q_{it} > \omega_2) \tag{6}$$

where the thresholds are ordered so that $\omega_1 < \omega_2$.

In order to explore the impact of industrial structure on the relationship between ICT investment and electricity consumption, we further build a threshold model. The general representation for Equation (1) is as follows:

$$\begin{aligned} \ln ELC_{it} = {} & \gamma_0 + \gamma_1 \ln POP_{it} + \gamma_2 \ln PGDP_{it} + \gamma_3 \ln INV_{it} + \gamma_4 \ln SV_{it} \\ & + \gamma_5 \ln ICT_{it} * I(\ln \mathrm{INV} \leq \eta_1) + \gamma_6 \ln ICT_{it} * I(\eta_1 < \ln \mathrm{INV} \leq \eta_2) \\ & + \gamma_7 \ln ICT_{it} * I(\ln \mathrm{INV} > \eta_2) \end{aligned} \tag{7}$$

where η_1, η_2 are the threshold values and $\eta_1 \leq \eta_2$. When $\eta_1 = \eta_2$, it is a single threshold model; otherwise, it is a double threshold representation. γ_i $(i \neq 0)$ correspond to the elasticity of every variable. γ_0 are the fixed intercepts.

3. **Estimation Results.** Table 2 presents the results of unit root tests. Almost all statistics accept the null hypothesis at the level. However, when the test is applied in the first difference, the null hypothesis for each series is rejected at a 1% significance level. So, all variables are non-stationary in level while stationary in the first difference.

Table 2. Panel unit root test results

Statistics	Fisher-ADF		IPS	
	Level	First difference	Level	First difference
ln ELC	29.585(0.9997)	152.975*(0.0000)	2.916(0.9982)	−5.456*(0.0000)
ln POP	46.904(0.7423)	98.308*(0.0000)	1.538(0.9379)	−3.658*(0.0001)
ln PGDP	52.450(0.7450)	107.858*(0.0001)	1.3621(0.9134)	−3.117*(0.0009)
ln INV	78.926*(0.0512)	92.505*(0.0045)	−0.905(0.1827)	−2.466*(0.0068)
ln SV	75.493*(0.0857)	101.395*(0.0007)	−1.203(0.1145)	−2.391*(0.0084)
ln ICT	66.476(0.2638)	115.871*(0.0000)	−0.666(0.2526)	−3.725*(0.0001)

* represents significance at a 1% level. P value is shown in bracket.

Table 3 reports the co-integration test results. The results mostly reject the null hypothesis at a 1% significance level, which indicates there is at least one co-integration relationship among these variables.

Table 4 shows the granger causality results. ΔICT_{t-1} is statistically significant at a 5% level, which shows ICT investment is the granger cause of electricity consumption in short run. The positive coefficient results from ICT's direct usage of electricity. Besides, ΔECT_{t-1} is significantly negative at a 1% level, which reveals a long-term causal link from ICT investment to electricity consumption. It conforms to what one would expect.

Table 5 presents the regression results. According to it, the F-test value of robust standard error regression significantly rejects the null hypothesis at a 1% level, which implies the representation of Equation (1) is reasonable. The coefficient of ln ICT is significantly negative, which indicates ICT investment would reduce electricity cost.

The results of threshold models show: The coefficients of ln ICT with different industrial shares are significant at a 1% significance level, which means the threshold effect is obvious. The threshold value for single threshold model is calculated to be $\ln INV_{it} = -1.35$, namely the industrial share equals 0.259. It reveals that when industrial share is below 0.259, 1 unit of ICT investment increases 0.16 unit of electricity consumption. Afterwards, 1% of ICT investment reduces electricity consumption by 0.04%. The double thresholds for $\ln INV_{it}$ are -0.89 and -1.35, respectively, which means the industrial shares are

Table 3. Pedroni co-integration test results

	Statistics		Statistics
Panel v	−5.298910(1.0000)	Group rho	9.004165(1.0000)
Panel rho	7.040756(1.0000)	Group PP	−13.36147*(0.0000)
Panel PP	−6.968527*(0.0000)	Group ADF	−6.405985*(0.0000)
Panel ADF	−2.897818*(0.0019)		

* represents significance at a 1% level. P value is shown in bracket.

Table 4. PVEC model results

Model	short-run					long-run
	ΔPOP_{t-1}	$\Delta PGDP_{t-1}$	ΔINV_{t-1}	ΔSV_{t-1}	ΔICT_{t-1}	ΔECT_{t-1}
Equation (1)	−0.828*	0.072	−0.141	0.084	0.032*	−0.264**
	(0.029)	(0.624)	(0.259)	(0.203)	(0.016)	(0.000)

**,* represent significance at 1% and 5% levels, respectively. P value is shown in bracket.

Table 5. Regression results

Variables	Robust standard error	Single threshold	Double threshold
$\ln POP_{it}$	0.995***(0.0000)	0.9264***(0.0000)	0.8974***(0.0000)
$\ln PGDP_{it}$	0.764***(0.0000)	0.7596***(0.0000)	0.7677***(0.0000)
$\ln INV_{it}$	0.379***(0.0001)	0.3928***(0.0000)	0.5474***(0.0000)
$\ln SV_{it}$	0.1970*(0.0607)	0.1667(0.1052)	0.1583(0.1109)
$\ln ICT_{it}$	−0.0346**(0.0396)	–	–
$\ln ICT_{it} * I(\ln \mathrm{INV} \leq \eta_1)$	–	0.1626***(0.0059)	–
$\ln ICT_{it} * I(\ln \mathrm{INV} > \eta_1)$	–	−0.0435***(0.0060)	–
$\ln ICT_{it} * I(\ln \mathrm{INV} \leq \eta_1)$	–	–	0.1800***(0.0002)
$\ln ICT_{it} * I(\eta_1 < \ln \mathrm{INV} \leq \eta_2)$	–	–	−0.0395***(0.0085)
$\ln ICT_{it} * I(\ln \mathrm{INV} > \eta_2)$	–	–	−0.0428***(0.0048)
F-value	149.11***(0.0050)	10.5156***(0.0050)	12.0464***(0.0000)
Number of bootstrap	–	1000	1000
threshold value	–	−1.35	−0.89, −1.35

***,**,* represent significance at 1%, 5% and 10% levels, respectively. P value is shown in bracket.

0.411 and 0.259. So when a province's industrial share is between 0.259 and 0.411, ICT investment reduces electricity consumption by 0.0395%, and if the industrial share is higher than 0.411, the electricity reduction effect of ICT investment would be 0.0428%. Because of the similarity of the two elasticities (-0.0395 and -0.0428), we suggest that the single threshold model is more convictive than the double threshold model.

With regard to other variables, it is indicated that 1% increase of population size, income and industrial share would significantly increase electricity consumption by 0.926%, 0.760% and 0.393%, respectively.

4. **Discussion.** As presented in Table 6, the average industrial share of Beijing is below 0.259, which indicates that Beijing's ICT investment increases electricity cost. We argue the main causes are shown as follows. First, the substitution effect would do little because of the low share of energy-intensive industries. Second, the rebound effect increases electricity consumption. It means the electricity freed up by increasing electricity utilization is used in other electricity-intensive activities, in which way the electricity is consumed more in turn. Third, Beijing is the innovation centre of China; the technical development activities would cost lots of electricity by running giant computer systems and software programs. Additionally, the income effect of ICT investment also allows people in Beijing to have a greater capacity to consume more products and services, which also increases total electricity consumption. Therefore, the negative effect could be offset by the obvious increasing effect, so that ICT investment increases electricity cost in Beijing.

The average industrial share of China's provinces except Beijing from 2003 to 2012 is higher than 0.259, which indicates that ICT investment significantly reduces electricity consumption in most Chinese regions. The main conclusions are: Industrial electricity consumption accounts for almost 70% of total level in these provinces. And ICT's reducing effect on energy consumption mainly benefits from the substitution effect of ICT industry on energy-costing industries [1]. So ICT could provide an efficient way of reducing electricity consumption in China's provinces except Beijing. Besides, integrating ICT systems into the heavy industries increases the electricity efficiency, in which way electricity also could be saved up.

Table 6. Average level of industrial share during 2003-2012

Province	Value	Province	Value	Province	Value	Province	Value
Anhui	0.39	Hainan	0.27	Jilin	0.41	Shanghai	0.40
Beijing	0.21	Hebei	0.47	Liaoning	0.45	Shanxi	0.50
Chongqing	0.42	Heilongjiang	0.45	Inner Mongolia	0.43	Sichuan	0.38
Fujian	0.43	Henan	0.49	Ningxia	0.38	Tianjin	0.49
Gansu	0.37	Hubei	0.39	Qinghai	0.42	Xinjiang	0.38
Guangdong	0.46	Hunan	0.36	Shaanxi	0.44	Yunnan	0.35
Guangxi	0.36	Jiangsu	0.48	Shandong	0.49	Zhejiang	0.47
Guizhou	0.34	Jiangxi	0.40				

5. **Conclusions.** To the best of our knowledge, it is the first time to empirically explore the effect of ICT investment on electricity consumption in China. The findings suggest a short- and long-run causal link from ICT investment to electricity consumption. Besides, ICT investment would significantly increase electricity cost in the Chinese province where the industrial share is below 0.259, namely Beijing. Meanwhile, ICT investment significantly reduces electricity consumption in other provinces. According to the results, the Chinese government should invest more money on ICT to realize a sustainable reduction of electricity cost in provinces except Beijing.

For further researches, hardware is expected to be included, because ICT sector in this research refers to the sector of information transmission, software and information technology. Besides, the threshold effect of ICT investment on other kinds of energy consumption is an another direction which should also be investigated.

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