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The impact of ICT investment on energy intensity across different regions of China

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There are few empirical studies concerning the impact of information communication technology (ICT) on energy intensity in developing countries. We introduce an expanded STIRPAT model and China's provincial data samples during 2003–2012 to fill this gap. This paper applies the Driscoll–Kraay econometric method to assess the long-term impact of ICT investment on energy intensity and employs a panel error correction model to explore the short-term influence. The results indicate that the ICT investment significantly reduces energy intensity in the long-run, while it does not in the short-run at a nationwide level. Concerning the regional diversities of China, the impact of the ICT investment on energy intensity is significantly negative in western and central regions, while is insignificant in the eastern sample. Furthermore, the negative impact grows as the ICT investment increases in central provinces. Additionally, the short-term energy intensity reduction effect exists only in eastern regions, while it does not in central provinces. The ICT investment increases the energy intensity in the short-run in the western sample. *Published by AIP Publishing.* [http://dx.doi.org/10.1063/1.4962873]

I. INTRODUCTION

Information communication technology (ICT) has been seen as one possible way to drive economic growth more efficiently (Sadorsky, 2012). However, there are widespread controversies regarding the effect of ICT on energy consumption and the environment (Coroama and Hilty, 2014). The effect of ICT investment on energy intensity in developing countries is one of these issues. On the one hand, energy is consumed by operating ICT products and integrating ICT systems into other industries. On the other hand, ICT reduces the energy cost for its replacement of physical procedures and its potential to optimize the production process. So, the net impact of ICT on the energy consumption is still ambiguous.

Attributed to a technological leapfrogging process and ICT policies introduced by the Chinese government, ICT has expanded rapidly in China, the largest developing economy in the world, since the beginning of the twenty-first century. In 2003, the subscribers' number for mobile phones surpassed that for fixed-line for the first time. The total ICT investment in 2014 is nearly 2.5 times than that in 2003. However, empirical research on the relationship between the ICT investment and the energy intensity in China is still lacking. As China is predicted to step into the junior stage of an information society in around 2020 (State Information Centre of China, 2015), exploring the impact of ICT investment on energy consumption is an urgent problem that needs to be solved.

The purpose of our paper is to explore the impact of ICT investment on energy intensity by using 30 provincial data sets in China from 2003 to 2012. We specify an expanded STIRPAT model that includes population, income, industrial structure, energy consumption structure, technology level, and ICT investment as explanatory variables which respond to energy intensity as the dependent variable. This paper not only helps Chinese decision-makers

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implement the lower energy intensity ICT instruments but also expands the existing literature regarding the association between ICT investment and energy consumption.

This research contributes to the existing studies as follows: there is little known about the impact of the ICT investment on energy consumption in developing countries. Furthermore, due to the inaccessible data on the ICT investment of developing economies, little attention has been paid to the empirical research at the macro level. This paper fills these gaps by using provincial panel samples in China. Besides considering the regional diversities in China, the energy intensity impact of the ICT investment may vary drastically. We explore the regional differences and analyse the reasons among the eastern, central, and western samples in China. Meanwhile, it has been ignored that the energy intensity reduction effect of the ICT investment would change as the ICT investment increases in previous studies. Our results reveal a growing marginal reduction effect of the ICT investment on the energy intensity with the ICT investments increasing in central China. Additionally, to the best of our knowledge, the short-term impacts are investigated for the first time in order to explore if the lagged effect of the ICT investment on reducing the energy intensity exists in China.

The paper proceeds as follows. Section II reviews the related literature. Section III describes the methods and data used in this paper. Section IV presents the empirical results. Section V discusses the reasons. Section VI concludes.

II. LITERATURE REVIEW

Although the total energy cost of ICT was calculated for the first time in the 1950s (Thirring and Miner, 1963), the topic of the relationship between ICT and energy consumption developed slowly from the mid-1980s (Sioshansi and Davis, 1989; Walker, 1985; and 1986). It has been acknowledged that the ICT development influences energy consumption from two perspectives: First, ICT reduces energy consumption. Wireless information technologies emphasise the potential energy savings that can be accrued from decreasing the need for reading newspapers and business travel (Hilty *et al.*, 2006; Ishida, 2015; and Toffel and Horvath, 2004). Barratt (2006) argued that education and training can be achieved through distance teaching via the Internet. E-business makes it possible for consumers to go shopping online instead of going to malls, which leads to cars being used less frequently (Collard *et al.*, 2005). Second, ICT consumes energy. Roth *et al.* (2002) suggested that office and communication equipment in the U.S. consume less than 3% of the delivered electricity nationwide. Owen (2007) even predicted that entertainment, computers, and gadgets will account for 45 per cent of the domestic electricity consumption by 2020. The International Energy Agency (2009) further argued that electronic devices have made a large contribution to the total growth in the residential electricity use and warned that electronic devices will become one of the largest end-use categories in the next few years. Generally speaking, in order to instal the ICT equipment it requires electricity (Sadorsky, 2012). Overall, ICT influences energy consumption from many perspectives. Until now, there have been two mainstreams of theoretical analysis about the impact of ICT on energy consumption.

The first mainstream is the substitution effect and income effect theory defined by Takase and Murota (2004). The income effect mainly means that the increasing economic growth and rising household incomes spurred by the ICT development increase the energy cost for households, transport, and construction. The substitution effect is mainly derived from the shift in industrial structure away from energy-costing industries towards energy-saving ones. In addition, the Global e-Sustainability Initiative (2008) also argued that using ICT to replace physical procedures is a channel for the replacement effect. For example, travelling via ICT enabled video conferences and e-commerce, and ICT could also replace labour or investment input (Masanet and Matthews, 2010 and Schulte *et al.*, 2014).

The second main theory was developed by the OECD (2010) and Hilty *et al.* (2006), who divided the impact of ICT into three orders. The first order (direct impact) is directly related to the lifecycle of ICT hardware, including ICT hardware research, production, application, recycling, and disposal. The second order of impact (enabling effect) is due to the ICT application, which could optimise the production and transport process, and even influence users' lifestyles. It is attributed to the energy-saving potentials of ICT in the use of smart grids, smart buildings, smart motor systems, smart logistic systems, intelligent heating, ICT-controlled process optimisation, and so on. The third order (systemic impact) is the long-term behaviour adaptation and the economic structure optimisation that arise from the following ICT availability and its services. Most of the existing researches are concentrated on the second order of impact and have concluded with optimistic results that ICT will help to reduce energy consumption (Erdmann and Hilty, 2010 and Masanet and Matthews, 2010).

The existing research on the relationship between ICT and energy consumption focuses on theoretical analysis, whereas less concern is given on empirical analysis. The results vary according to different research perspectives. Collard *et al.* (2005) found that electricity intensity increased as the use of computers and software capital increased, while it decreased with the diffusion of communication devices in the service sector in France. By employing a similar model, Bernstein and Madlener (2010) further illustrated a negative effect of communication technology on electricity intensity in five major European manufacturing industries and the industry-specific impact of computers and software. Cho *et al.* (2007) concluded that the ICT investment increases electricity consumption in the service sector and in the most manufacturing sectors, while it decreases it in some specific manufacturing sectors in South Korea.

At a country level, Sadorsky (2012) found that internet connections, mobile phones, and personal computers (PCs) increase electricity consumption in 19 emerging countries during 1993–2008. Similar results are found by applying different samples consisting of 67 countries from 1990 to 2012 (Saidi *et al.*, 2015). In addition, Salahuddin and Alam (2015) concluded that internet usage has a significant long-term increasing effect on electricity consumption, while the short-run effect is insignificant in Australia. Considering that electricity consumption is a part of energy cost and the usage of ICT infrastructures as ICT proxy excludes software and services, Schulte *et al.* (2014) further concluded that the ICT capital service significantly reduces energy demand in OECD countries. ICT is also negatively related to non-electricity energy demand and is not associated with a significant change in electric energy demand. Ishida (2015) revealed that the ICT investment contributed to a moderate reduction in energy consumption in Japan over the 1980–2010 period.

III. METHODS AND DATA

A. The basic framework

One of the classic models on the environment impact is the STIRPAT model, in which the environment impact (I) is the result of population (P), affluence (A), and technology (T). After taking the log-linear form, the model can be written as below

$$\mathrm{lnI} = a + b^{*}\mathrm{lnP} + c^{*}\mathrm{lnA} + d^{*}\mathrm{lnT}, \tag{1}$$

where a denotes the constant term and b, c, d correspond to the elasticity of every variable with respect to the dependent variable, respectively.

Considering that China is the largest developing economy in the world, energy intensity is chosen as "I" instead of total energy consumption. "P" and "A" have already been acknowledged to be measured by population size and gross domestic product (GDP) per capita, respectively. "T" is denoted by research and development (R&D) expenditure in GDP (Yu, 2012 and Lin and Zhao, 2015). Therefore, the representation below is obtained

$$\mathrm{lnEI} = a + b^{*}\mathrm{lnPOP} + c^{*}\mathrm{lnPGDP} + d^{*}\mathrm{lnRD}, \tag{2}$$

where EI denotes energy intensity, POP means total population, PGDP represents GDP per capita, RD denotes R&D investment intensity.

Following Grossman (1995) and Yang *et al.* (2014), energy intensity could be written as a function of scale effect, technique effect, and structure effect of the economic activities. The scale effect could be measured by two variables: population and GDP per capita instead of one variable—GDP in Eq. (2), because of the large population bonus to economic development in China. Meantime, the technique effect is represented by R&D in Eq. (2). As for the structure effect, it includes industrial structure and energy consumption structure, which are not revealed in Eq. (2). The two indicators shall be represented by industrial share and coal consumption share, respectively, because the industry consumes 70% of total energy and coal plays a major role in energy costs in China. Besides, to capture the relationship between ICT investment and energy intensity, the ICT investment should also be included as an important independent variable. By incorporating all the mentioned variables, the following model is derived:

$$\mathrm{lnEI}_{it} = \alpha_0 + \alpha_1 \mathrm{lnPOP}_{it} + \alpha_2 \mathrm{lnPGDP}_{it} + \alpha_3 \mathrm{lnRD}_{it} + \alpha_4 \mathrm{lnINS}_{it} + \alpha_5 \mathrm{lnCS}_{it} + \alpha_6 \mathrm{lnICT}_{it}, \quad (3)$$

where EI denotes energy intensity, POP means total population, PGDP represents GDP per capita, INS means industrial share, CS represents coal consumption share, RD denotes R&D investment intensity, and ICT represents ICT investment intensity. The coefficient α_{i} $(\mathrm{i} \neq 0)$ corresponds to the elasticity of each variable, where α_0 is the fixed intercept.

B. Methodology

1. Stationary tests

This study uses Augmented Dickey–Fuller (ADF) (Dickey and Fuller, 1979; 1981) and Im–Pesaran–Shin (IPS) (Im *et al.*, 2003) unit root tests to check the stationary properties of the data. The null hypothesis of the ADF and IPS tests is non-stationary distribution. If it is rejected, the time series variable is stationary. Otherwise, the variable is non-stationary. In this case, we differenced the series and repeat the stationary tests. The stationary order of a variable is defined by the number of times it is differenced until it is stationary.

2. Co-integration tests

Once we determine the stationary degree of each variable, we 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-term relationship (Darrat and Al-Sowaidi, 2010). The Pedroni approach is introduced to test the co-integration relationship (Pedroni, 1999 and 2004). The null hypothesis is that no co-integration among variables exists. If the results reject the null hypothesis, there is at least one co-integration relationship. Otherwise, no co-integration relationship exists.

3. Driscoll–Kraay (DK) estimation

If the panel variables are co-integrated, the regression could be further tested to check the long-term influence of every explanatory variable. Fixed-effect estimation with standard error is initially applied. Three tests have to be employed to check the robust fixed-effect estimation. First, we test for autocorrelation with the Wooldridge test (Wooldridge, 2002). The null hypothesis is that no first-order autocorrelation exists. If it is rejected, there is a first-order autocorrelation among these variables which would lead the panel regression bias. Second, we should confirm the presence of a group wise heteroscedasticity problem with the modified Wald statistic (Greene, 2000). The null hypothesis is homo nested in hetero. If the results reject the null hypothesis, there is a serious group wise heteroscedasticity problem. Third, cross-sectional dependence is tested with the Pesaran (2004) statistic, which is more suitable for the panel data of large cross-sectional dimensions and small time dimensions. The null hypothesis is that there is no cross-sectional dependence. If it is rejected, a cross-sectional dependence problem among these variables exists. Otherwise, it does not exist.

Then, Driscoll–Kraay (DK) estimation (Driscoll and Kraay, 1998) should be employed to avoid the first-order autocorrelation, heteroscedasticity, and cross-sectional dependence problems, with which the standard error estimates are robust to general forms of cross-sectional and temporal dependence (Hoechle, 2007). It has a good property when T is smaller than N in the panel data. DK estimates the coefficients with pooled ordinary least squares, weighted least squares, or fixed effects within regression (we use the fixed effects in this paper). The error structure is assumed to be heteroscedastic, auto-correlated up to some lag, and possibly correlated between the panels.

4. Panel error correction model (ECM)

According to Granger (1969), there must be an error correction model (ECM) representation if the variables share a co-integration relationship. The long-run relationship among these co-integrated variables may be out of balance in the short-run, so we need to connect the short-run relationship and long-run relationship together with ECM. The equation is shown as follows:

$$\Delta \ln EI_t = \sum_{k=1}^{p_1} \alpha_k \Delta \ln EI_{t-k} + \sum_{k=1}^{p_2} \beta_k \Delta \ln POP_{(t-k)} + \sum_{k=1}^{p_3} \gamma_k \Delta \ln PGDP_{(t-k)} + \sum_{k=1}^{p_4} \delta_k \Delta \ln INS_{(t-k)} + \sum_{k=1}^{p_5} \varphi_k \Delta \ln CS_{(t-k)} + \sum_{k=1}^{p_6} \lambda_k \Delta \ln RD_{(t-k)} + \sum_{k=1}^{p_7} \eta_k \Delta \ln ICT_{(t-k)} + \theta ECT_{t-1} + \varepsilon_t, \tag{4}$$

where Δ is the first difference operator, t is the time subscript, and ε_t is the stochastic error term. k is the lag length and $p_1, p_2, p_3, p_4, p_5, p_6, p_7$ are the maximum lag lengths of the corresponding variables, respectively. $\alpha_k, \beta_k, \gamma_k, \delta_k, \varphi_k, \lambda_k, \eta_k, \theta$ are the parameters to be estimated and ECT_{t-1} is the lagged error correction term derived from the co-integration equation; it can correct the deviation which may occur in the short-term return to the long-term equilibrium. The long-term equilibrium is measured by θ, which can be detected by using a T-test. The short-term dynamics of ICT investment are measured by η_k, which is tested with an F-test.

C. Data

The sample covers the 2003–2012 period for 30 provinces (except Tibet) in mainland China. The data are taken from the China Statistical Yearbook. The unit of energy intensity is tons of standard coal equivalents per China Yuan (RMB). Population is represented by the total population by the end of a year and its unit is person. GDP per capita is adjusted for the consumer price index at 2003 constant prices. Industrial share is computed by industry value added output divided by GDP. Coal consumption share is equal to the coal consumption divided by energy consumption. R&D investment intensity and ICT investment intensity are R&D investment per GDP and ICT investment per GDP, respectively. The units of industrial share, coal consumption share, RD investment intensity, and ICT investment intensity are all in percentages.

The eastern region includes Beijing, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin, and Zhejiang. The central provinces refer to Anhui, Heilongjiang, Henan, Hubei, Hunan, Jiangxi, Jilin, and Shanxi. The rest are in the west of China, including Chongqing, Gansu, Guangxi, Guizhou, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Sichuan, Xinjiang, and Yunnan.

IV. EMPIRICAL RESULTS

A. Results of panel unit root test

The results of the unit root tests are presented in Table I. These tests suggest that most of the variables are non-stationary in level, while stationary in the first difference.

B. Results of panel co-integration tests

The co-integration test results are reported in Table II. Most results reject the hypothesis of no co-integration at a 10% significance level or lower, which indicates that co-integration relationships among these variables exist. This reflects the long-term equilibrium of our model.

TABLE I. Panel unit root test results. ***, **, and * represent significance at a 1%, 5%, and 10% levels, respectively. P-value is in parentheses.

	Fisher–ADF		IPS	
	Level	First difference	Level	First difference
lnEI	26.5496(0.9999)	214.790***(0.0000)	3.97673(1.0000)	−10.4307***(0.0000)
lnPOP	46.9038(0.7423)	98.3083***(0.0000)	1.53770(0.9379)	−3.65793***(0.0001)
lnPGDP	52.4502(0.7450)	107.858***(0.0001)	1.36208(0.9134)	−3.11687***(0.0009)
lnINS	78.9258*(0.0512)	92.5052***(0.0045)	−0.90531(0.1827)	−2.46576***(0.0068)
lnCS	90.9467***(0.0061)	118.668***(0.0000)	−1.52759*(0.0633)	−3.92564***(0.0000)
lnRD	51.4860(0.7751)	115.040***(0.0000)	3.17974(0.9993)	−3.51144***(0.0002)
lnICT	70.8248(0.1600)	116.609***(0.0000)	−0.24041(0.4050)	−3.77835***(0.0001)

TABLE II. Pedroni co-integration test results. ***, **, and * represent significance at a 1%, 5%, and 10% level, respectively. P-value is in parentheses.

	Whole sample	Eastern sample	Central sample	Western sample
Panel v	−4.606641(1.0000)	−3.155069(0.9992)	−1.750435(0.9600)	−3.431947(0.9997)
Panel rho	6.255756(1.0000)	4.331339(1.0000)	2.836522(0.9977)	4.484273(1.0000)
Panel PP	−13.41710***(0.0000)	−5.059942***(0.0000)	−6.077378***(0.0000)	−5.301149***(0.0000)
Panel ADF	−7.324235***(0.0000)	−2.007151**(0.0224)	−4.308540***(0.0000)	−1.644915**(0.0500)
Group rho	8.234006(1.0000)	5.636264(1.0000)	4.009301(1.0000)	5.943513(1.0000)
Group PP	−24.17739***(0.0000)	−7.486232***(0.0000)	−8.473461***(0.0000)	−9.810537***(0.0000)
Group ADF	−11.24278***(0.0000)	−3.712317***(0.0001)	−4.612720***(0.0000)	−1.535925*(0.0623)

C. Results of panel regressions

Table III shows the regression results for whole samples. Model 1 provides the linear specification to test the relationship between R&D investment intensity and energy intensity, and ICT investment intensity and energy intensity. The coefficient of lnRD is statistically significant at a 1% significance level, which means R&D significantly influences the energy intensity in mainland China. However, the positive sign is not in line with what we had expected.

TABLE III. Estimation results for whole samples. ***, **, and * represent significance at a 1%, 5%, and 10% level, respectively. P-value is in parentheses.

	Robust fixed-effect	DK (model 1)	DK (model 2)
lnPOP	−0.285(0.156)	−0.285***(0.000)	0.151(0.125)
lnPGDP	−0.370***(0.000)	−0.370***(0.000)	−0.344***(0.000)
lnINS	0.384***(0.000)	0.384***(0.000)	0.298***(0.000)
lnCS	0.029(0.629)	0.029(0.735)	0.003(0.955)
lnRD	0.109*(0.098)	0.109***(0.006)	−1.364***(0.001)
$(\ln RD)^2$	…	…	−0.057***(0.000)
lnICT	−0.019(0.262)	−0.019(0.101)	−0.023*(0.090)
C	1.345(0.734)	1.345(0.377)	−10.767**(0.012)
Autocorrelation	211.639***(0.0000)	…	…
Heteroscedasticity	2992.23***(0.0000)	…	…
Cross-sectional dependence	15.240***(0.0000)	…	…
R^2	0.7470	0.7470	0.7664
Observations	300	300	300

Therefore, motivated by the literature on the environmental Kuznets curve (EKC), we include the square term of lnRD to examine the possible non-linear influence of R&D investment in model 2. The results show that both lnRD and its quadratic term are significant at a 1% significance level, which means the impact of R&D investment on energy intensity is $-0.114\ln RD - 1.364$. This illustrates that the reduction impact of R&D investment on energy intensity grows when the R&D investment intensity increases. Meanwhile, the coefficient of lnICT is significantly negative. It is indicated that one unit of the ICT investment intensity reduces the energy intensity by 0.023 units. In addition, the coefficients of lnPGDP and lnINS are both statistically significant at a 1% significance level. The values of −0.344 and 0.298 illustrate that a 1% increase in income decreases the energy intensity by 0.344%, and that a 1% increase of industrial share in GDP increases the energy intensity by 0.298%. Furthermore, the insignificant elasticities of lnPOP and lnCS reveal that total population and coal consumption share do not help mainland China in reducing the energy intensity.

Table IV illustrates the regression results for the eastern samples. Model 4 shows that lnRD and $(\ln RD)^2$ are both significant, which demonstrates the specific relationship between the R&D investment intensity and the energy intensity as $-0.112\ln RD - 1.412$, which also shows the reduction effect of R&D changes as the R&D investment intensity increases. Meanwhile, models 3, 4, and 5 all show the insignificance of the lnICT coefficient and its square term. This reveals that energy intensity is not significantly influenced by the ICT investment in eastern provinces of China. Additionally, the elasticities of lnPGDP and lnPOP, namely, −0.200 and −0.357, are significant at a level of 5% or lower, which means that a 1% increase in income and population contributes to a 0.2% and 0.357% energy intensity reduction. Further, the coefficients of lnINS and lnCS, namely, 0.320 and 0.070, show that a 1% industrial structure and coal consumption share increases the energy intensity by 0.32% and 0.07%, respectively.

Table V shows the estimation results for the central provinces. The coefficient of lnICT is insignificant even at a 10% significance level in both models 6 and 7. This evidence does not conform to the facts and people's expectations. Therefore, the square term of lnICT is included in model 8. The estimation results of model 8 show that the influences of R&D investment and ICT investment are both negative. This indicates that the effect of R&D investment on energy intensity is shown as $-0.198\ln RD - 2.342$ and the impact of ICT investment on energy intensity is shaped as $-0.078\ln ICT - 0.395$. In addition, the coefficients of lnPOP and lnPGDP, −2.005 and −0.408, are statistically significant at a 5% and 1% significance level, respectively, which means that one unit of population and income significantly reduces the energy intensity

TABLE IV. Estimation results for eastern samples. ***, **, and * represent significance at a 1%, 5%, and 10% level, respectively. P-value is in parentheses.

	Robust fixed-effect	DK (model 3)	DK (model 4)	DK (model 5)
lnPOP	−0.628***(0.004)	−0.628***(0.005)	−0.357**(0.043)	−0.431*(0.076)
lnPGDP	−0.211(0.115)	−0.211***(0.000)	−0.200***(0.000)	−0.207***(0.000)
lnINS	0.375***(0.008)	0.375***(0.000)	0.320***(0.000)	0.292***(0.002)
lnCS	0.027(0.388)	0.027(0.731)	0.070*(0.075)	0.052(0.314)
lnRD	0.022(0.861)	0.022(0.517)	−1.412***(0.001)	−1.419***(0.001)
$(\ln RD)^2$	…	…	−0.056***(0.001)	−0.060***(0.001)
lnICT	−0.014(0.472)	−0.014(0.525)	−0.019(0.351)	−0.179(0.231)
$(\ln ICT)^2$	…	…	…	−0.014(0.228)
C	4.476(0.259)	4.476(0.170)	−9.465**(0.046)	−8.586(0.125)
Autocorrelation	65.312***(0.0000)	…	…	…
Heteroscedasticity	545.78***(0.0000)	…	…	…
Cross-sectional Dependence	5.512***(0.0000)	…	…	…
R^2	0.8237	0.8237	0.8478	0.8500
Observations	110	110	110	110

TABLE V. Estimation results for central samples. ***, **, and * represent significance at a 1%, 5%, and 10% level, respectively. P-value is in parentheses.

	Robust fixed-effect	DK (model 6)	DK (model 7)	DK (model 8)
lnPOP	−1.822(0.108)	−1.822**(0.031)	−1.816**(0.029)	−2.005**(0.025)
lnPGDP	−0.412***(0.000)	−0.412***(0.000)	−0.390***(0.000)	−0.408***(0.000)
lnINS	0.268**(0.038)	0.268***(0.003)	0.246***(0.006)	0.250**(0.020)
lnCS	−0.151(0.359)	−0.151(0.255)	−0.167(0.308)	−0.192(0.242)
lnRD	0.125*(0.074)	0.125**(0.016)	−1.932*(0.100)	−2.342*(0.065)
$(\ln RD)^2$	…	…	−0.082*(0.086)	−0.099*(0.056)
lnICT	0.0001(0.997)	0.0001(0.990)	0.0005(0.963)	−0.395*(0.052)
$(\ln ICT)^2$	…	…	…	−0.039*(0.060)
C	−29.130(0.152)	−29.130**(0.046)	−15.881**(0.025)	−16.033**(0.023)
Autocorrelation	22.056***(0.0022)	…	…	…
Heteroscedasticity	196.90***(0.0000)	…	…	…
Cross-sectional Dependence	3.751***(0.0002)	…	…	…
R^2	0.8643	0.8643	0.8697	0.8821
Observations	80	80	80	80

by 2.005 and 0.408 units in central provinces. The elasticity of lnINS is also significant at a 5% level, which shows that a 1% increase in industry output significantly increases the energy intensity by 0.25%. The association of coal consumption share and energy intensity in the central regions is insignificant.

Table VI presents the estimation results for the western regions. It is shown that the coefficients of lnRD and its square term are both insignificant in models 10 and 11. The elasticity of $(\ln ICT)^2$ is also insignificant in model 11. Therefore, the energy intensity impacts of the R&D investment and the ICT investment are linear, which are shown in model 9. It is indicated that a 1% increase in the ICT investment intensity significantly reduces the energy intensity by 0.032% and that one unit increase of the R&D investment intensity significantly increases the energy intensity by 0.087 units in western provinces. It is also illustrated that a 1% income increase reduces the energy intensity by 0.353% and that 1% population and industry output growth increases energy intensity by 0.777% and 0.379%, respectively.

TABLE VI. Estimation results for western samples. ***, **, and * represent significance at a 1%, 5%, and 10% level, respectively. P-value is in parentheses.

	Robust fixed-effect	DK (model 9)	DK (model 10)	DK (model 11)
lnPOP	0.777**(0.030)	0.777***(0.001)	0.780***(0.001)	−0.778***(0.000)
lnPGDP	−0.353***(0.000)	−0.353***(0.000)	−0.351***(0.000)	−0.359***(0.000)
lnINS	0.379***(0.003)	0.379***(0.000)	0.375***(0.000)	0.388***(0.000)
lnCS	−0.086(0.488)	−0.086(0.434)	−0.088 (0.422)	−0.083(0.442)
lnRD	0.087(0.325)	0.087***(0.000)	−0.004 (0.994)	0.050(0.924)
$(\ln RD)^2$	…	…	−0.003(0.870)	−0.001(0.956)
lnICT	−0.032***(0.008)	−0.032***(0.001)	−0.032***(0.001)	−0.127*(0.051)
$(\ln ICT)^2$	…	…	…	−0.009(0.135)
C	−17.139**(0.022)	−17.139***(0.000)	−17.804***(0.001)	−17.625***(0.000)
Autocorrelation	93.814***(0.0000)	…	…	…
Heteroscedasticity	61.59***(0.0000)	…	…	…
Cross-sectional dependence	3.683***(0.0002)	…	…	…
R^2	0.7614	0.7614	0.7614	0.7429
Observations	110	110	110	110

TABLE VII. Panel ECM results. ***, **, and * represent significance at a 1%, 5%, and 10% level, respectively. P-value is in parentheses.

	Whole sample	Eastern sample	Central sample	Western sample
$\Delta \ln POP_{t-1}$	0.145(0.343)	0.576*(0.063)	0.255 (0.242)	−0.299(0.341)
$\Delta \ln PGDP_{t-1}$	0.373***(0.000)	0.252**(0.018)	0.144(0.167)	0.364***(0.003)
$\Delta \ln INS_{t-1}$	−0.027(0.595)	−0.083(0.283)	0.087(0.286)	0.032(0.749)
$\Delta \ln CS_{t-1}$	−0.034(0.151)	0.009(0.817)	−0.024(0.591)	−0.091*(0.064)
$\Delta \ln RD_{t-1}$	2.173**(0.016)	1.087(0.345)	−0.846(0.834)	0.152(0.204)
$\Delta(\ln RD)^2_{t-1}$	0.084**(0.016)	0.046(0.303)	−0.037(0.821)	…
$\Delta \ln ICT_{t-1}$	0.001(0.927)	−0.012*(0.076)	0.110(0.466)	0.025*(0.093)
$\Delta(\ln ICT)^2_{t-1}$	…	…	0.011(0.480)	…
ΔECT_{t-1}	−0.717***(0.000)	−0.791***(0.000)	−0.905***(0.000)	−0.678***(0.000)

D. Results of panel ECM

Table VII presents the panel ECM results. The elasticity of $\Delta \ln ICT_{t-1}$ is statistically significant at a 10% significance level in the eastern and western samples. This reveals a short-term impact of the ICT investment on energy intensity in these regions, while none in the other samples. Specifically, the ICT investment reduces energy intensity in short-run in the eastern region, while increases it in western provinces. The coefficients of ΔECT_{t-1} are significantly negative at a significance level of 1% and the absolute value is less than one, which conforms to the error correction mechanism. Therefore, a long-term equilibrium among the variables exists in all samples. It is also indicated that it would take more than one year to return to long-term equilibrium from a short-term shock of the energy intensity in China. With regard to the other variables, it is reported that income affects the energy intensity in short-term in all samples except the central one. Furthermore, coal consumption share only benefits short-term energy intensity reduction in the western regions. In addition, the association between R&D and energy intensity in the short-term exists in the whole sample. The total population would increase energy intensity in the short-run in eastern provinces.

V. DISCUSSION

The ICT investment contributes to reducing energy intensity at a national level in China, which is consistent with previous studies. As reviewed in Section II, the ICT investment significantly reduces energy consumption in Japan (Ishida, 2015) and OECD countries (Schulte *et al.*, 2014). We suggest that China's energy intensity reduction effect mainly benefits from the following channels: the substitution effect of the ICT industry on energy-costing industries (Takase and Murota, 2004); the replacement of physical procedures, such as travelling via ICT (Global e-Sustainability Initiative, 2008), the replacement effect of ICT technology for low-skilled labour (Schulte *et al.*, 2014), and the enabling effect of ICT technology, for example, ICT-controlled systems (OECD, 2010). In addition, as the ICT sector of China experiences a change from electronic manufacturing to software and computer services, ICT's reducing effect becomes more obvious.

The influences of the ICT investment on the energy intensity widely vary in different regions. It is widely admitted that the biggest potential of the ICT investment to reduce the energy intensity is its impact on industrial structure optimisation, which moves away from energy-costing industries to less energy-intensive industries. The share of energy-intensive industries in GDP in the central regions is acknowledged to be greater than that in the western provinces, which leads to a bigger energy intensity reduction influence of the ICT investment in the central provinces than that in western China. In addition, the growing marginal reduction effect in central samples shows the great potential of ICT industry's substitution effect on reducing energy consumption. Furthermore, the main cause of the insignificance in the eastern regions is their advanced industrial structure and the rebound effect. The high cost of producing energy-costing products and the environmental regulation policy introduced by the Chinese government lead to the advanced industry structure, which results in the small impact of the substitution effect. Meantime, changing behaviour means that eastern people are apt at using ICT in their daily lives. And the income effect also allows them to have a greater capacity to consume more products and services than those in the central and western regions. These evidences would result in an obvious rebound effect (Zhang and Liu, 2015). The energy freed up by increasing energy utilisation is used in other energy-intensive activities, which may also increase total energy consumption. Therefore, the negative effect of the ICT investment on total energy consumption is offset by its positive effect in the eastern regions. As for the western regions, the inconvenient geographical location determines the difficulties in connecting with other areas, in which case ICT would contribute to transportation and communication sectors. Furthermore, the ICT development helps western provinces achieve a technological leapfrogging process and industrial structure updating. Therefore, the energy intensity can be significantly reduced in western provinces.

It is concluded that the short-term impact of the ICT investment on the energy intensity exists in the eastern and western samples, which is as we expected. We argue that the main causes are: the eastern regions have prior access to ICT talent, infrastructure, and other excellent resources, while, due to the relatively low development of the ICT talents in the central provinces, software and information service investment there would have an obvious lagged effect. Therefore, the effect in the central provinces could not be revealed in a short period. As for the western provinces, the ICT infrastructure is the least developed among three Chinese regions, in which case investing software and information services would increase GDP by consuming much energy. So, the ICT investment increases the energy intensity in western China in short-run.

VI. CONCLUSIONS AND POLICY IMPLICATIONS

This paper studies the relationship between the ICT investment and the energy intensity from an empirical perspective, considering the regional diversities in China. We apply a STIRPAT model and a panel data set of 30 provinces in mainland China from 2003 to 2012. The panel ECM results illustrate that a short-term link between ICT investment and energy intensity exists in eastern and western regions. Meanwhile, the DK estimation results indicate that the long-run impact of ICT investment on energy intensity reduction in the central regions is greater than that in the west of China, while that in the eastern provinces is insignificant. Furthermore, the reduction effect grows as ICT investment increases in central China.

According to the conclusions we draw, the Chinese government should value the potential of ICT investment to realise the sustainable lowering of energy intensity. We provide some policy recommendations for policy makers in this paper.

First, the Chinese government should provide more investment and other consistent support for ICT. On the one hand, because the ICT industry is the fifth largest sector responsible for energy consumption (Wu, 2008), green ICT should be especially invested to avoid a large amount of energy cost by producing and running ICT equipments. Furthermore, the software and information service sectors instead of hardware manufacturing are preferred in attracting investments. On the other hand, the ICT systems should be further introduced into other industries, such as monitoring system and production optimizing system in the manufacturing industry, and intelligent locating and managing system in the transportation sector. Additionally, the ICT energy-saving projects, such as "energy-net by ICT" should be given a prior consideration when making decisions on investment.

Second, the regional differences should be considered when the ICT energy-saving policies are introduced. Eastern governments should encourage more energy-saving projects and concentrate on exploring green technologies. Furthermore, some guidance about green lifestyle from the governments is supposed to be provided, such as using green ICT products and taking the public transportations. The lifecycle management of the ICT products should be valued. Meanwhile, energy-costing activities should be limited. It is crucial for the central provinces to introduce more ICT products to the heavy industries in order to increase the energy efficiency and lower total energy consumption. Meanwhile, it is also very much necessary to promote the industrial structure optimisation process from the heavy energy-costing sectors towards the energy-saving industries by applying the ICT systems. Overall, the policy-makers in central regions should encourage to promote the transition from a production-oriented traditional manufacturing to a service-oriented one by implementing the ICT instruments. When compared with the share of heavy industries in central China, the energy-costing sector share is relatively low in the west, which is a big advantage and opportunity to achieve a technology leapfrogging. In this case, developing ICT industry is a possible and efficient way for western regions to achieve a sustainable development. Western governments should focus on the construction of the ICT infrastructural facilities and attracting ICT talents. Meantime, the ICT products and systems could be further introduced, such as video conferences and e-commerce.

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