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ICT Development and Sustainable Energy Consumption: A Perspective of Energy Productivity

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Abstract: The information and communication technology (ICT) is closely related to the future of global energy consumption, not only because the ICT equipment itself increasingly consumes energy, but also because it is a general-purpose technology which may affect energy use of almost all sectors. Given the controversy over the net energy-saving effect of ICT, this paper focuses on a new perspective, i.e., energy productivity, to investigate the relationship between ICT development and energy consumption. Using a data panel of 50 economies over the period of 1995 to 2013, results of the Malmquist energy productivity index generally indicate an unbalanced development of energy productivity across the globe, while results of the patent-based ICT knowledge stock indicate a huge gap of ICT development comparing the high-income economies with the others. Furthermore, regression results indicate that ICT development is significantly related to energy productivity improvement. Finally, this paper suggests accelerating ICT development in underdeveloped economies, given the global common task of sustainable energy consumption.

Keywords: ICT; knowledge stock; energy consumption; sustainability; energy productivity

1. Introduction

The information and communication technology (ICT, henceforth) has been playing a significant role in modern society. With the rapid development and diffusion of ICT, the energy consumption of ICT equipment and services is surging. For instance, the ratio of electricity consumption of ICT equipment and services (e.g., communication networks, computers, and data centers) to global electricity consumption has risen from 3.9% in 2007 to 4.6% in 2012 [1,2]. Especially, some recent developments of ICT involve booming energy demand and potentially hinder the global energy sustainability. For example, cloud computing, as the interaction between telecommunications technology and a data center, transfers massive data between devices and data centers and consumes a large amount of energy [1]. Therefore, it is even warned that the widespread use of ICT equipment would make it one of largest energy-use categories [3,4]. Given the global target of energy-use control, the relationship between ICT development and sustainable energy consumption is vital for the world's sustainable future.

However, the ICT is more than just an emerging energy consumer, it is currently reshaping the economic production process as well as residential life across the globe. Since it brings about "dematerialization" in various sectors [5], the ICT is able to control the rising energy demand by improving energy-use efficiency or energy productivity. Such an indirect impact of ICT can potentially save much more energy than the direct impact of ICT itself [6]. However, existing studies typically focused on the direct impact of ICT on gross energy consumption, with only a few exceptions discussing the indirect impact in theory.

Given these above theoretical and policy meanings, this paper aims to empirically investigate the relationship between ICT development and sustainable energy consumption, by observing an energy productivity index rather than the traditional indicator of gross energy consumption. The contributions of this paper are twofold. Firstly, this paper is among the first to explore the relationship between ICT development and energy productivity, which is fundamental to understand whether ICT can benefit energy-sustainability goals. Referring to the literature, the change of key environmental indicators roots in three effects, i.e., income effect, composition effect (substitution effect), and direct technological effect [7,8]. While the total effect, income effect, and substitution effect were intensively discussed [9], the technological effect is worth investigating but is typically neglected. Secondly, regarding the methodology, this paper observes the ICT development with a patent-based knowledge stock indicator, which provides a new way of measuring ICT development.

The rest of the paper is organized as follows. In Section 2, we review the existing literature. In Section 3, we explain the method of measurements of ICT development and energy productivity, construct the data panel and corresponding econometric model for observing the relationship between the two variables. Section 4 shows the results. Section 5 concludes the paper.

2. Literature Review

The ICT's impact on environmental sustainability is an emerging issue. Recently, some developments in ICT (e.g., cloud computing and blockchain) received attention not only from researchers in engineering and economics [10–12], but also from researchers on energy issues [13]. It is widely concerned that the future development and diffusion of ICT like cloud computing and blockchain will come along with booming energy demand, which will be a big challenge for the world's sustainable energy goals. For instance, according to Aste, et al. [14], estimated electrical consumption of mining in the Bitcoin blockchain is around 1 gigawatt (GW) per second at May 2017, and the figure is still rising rapidly.

To the best of our knowledge, the ongoing development of ICT being on the road of energy saving is still under debate. While many studies revealed that the ICT had an energy saving effect [15–17], there are also some studies argued that it could stimulate energy use through various mechanisms [18–21], and some studies noted the differences of ICT's impacts among sectors [22] or groups of economies [23]. According to Takase and Murota [24], the overall impact can be divided into an income effect and a substitution effect. Regarding the income effect, the ICT, as a type of general purpose technology, is broadly related to production activity and residential life which involve energy use, so that its development can induce energy demand by stimulating economic growth [25]. Regarding the substitution effect, the ICT sector may reduce energy use by replacing the traditional sectors, given that the ICT sector and its products are relatively less energy-intensive [24–26]. Moreover, Hilty and Hercheui [27] argued that, while the above effects happened in short and medium term, the most meaningful impact of ICT on human behavior and society might happen in the long run. Therefore, it is noted that ICT has the potential to fundamentally change the historical "economic growth-booming energy demand" relationship and lead to a "win-win" situation between economy (In this paper, the definition and classification of economies are directly sourced from the World Bank. "The term country, used interchangeably with economy, does not imply political independence but refers to any territory for which authorities report separate social or economic statistics". For more details, see https://datahelpdesk.worldbank.org/knowledgebase/articles/378834-how-does-the-world-bank-classify-countries/) and energy [1,23,26].

Why do the macro-level impacts of the ICT development on energy consumption differ in many existing studies? The reason may have roots in the impact mechanisms. Specifically, the impact of ICT can be disaggregated into positive effects (e.g., income effect) and negative effects (e.g., substitution effect and direct technological effect). For different economies at different development stages, the relative magnitudes of these disaggregated effects may vary so that the dominant effects would represent the direction of ICT's overall impact [4,25]. Thus, the so-called controversy over the role of ICT in reducing energy demand is reasonable, since the complicated impact mechanism and varying dominant factors would make both positive net effect and negative net effect possible in theory [4].

The existing literature provides fruitful discussions on the differential relationships between ICT development and macro-level energy consumption, but the detail of these relationships still needs further investigations. To be specific, the energy productivity improvement is one of the fundamental paths of ICT's negative impact on gross energy consumption. That is, through energy monitoring and management applications, ICT can promote energy efficiency improvement in production as well as in residential life [6,17]; through substitution and optimization of energy (or material), ICT brings about the dematerialization process with potential of energy saving in many industrial sectors [23,27]. Recently, some studies on cloud computing or blockchain emphasized the important role of ICT in improving energy efficiency and/or market efficiency in certain application fields [11,28,29].

Hence, it is necessary to understand whether the ICT development can stimulate economic growth with less-than-proportionate increase of energy use, i.e., energy productivity improvement. If the ICT does not relate to energy productivity improvement, we should reconsider its role in achieving our sustainable development goals and should initiate corresponding policies. However, to the best of our knowledge, existing studies seldom focused on such a perspective. Although some researchers noted that ICT could improve energy productivity [30,31], unfortunately such a point of view currently lacks support from empirical studies.

To sum up, whether ICT can promote energy savings at the macroeconomic level is still an important under-debate issue. To understand the relationship between ICT and energy consumption, previous studies provided with different impact mechanisms. Among these mechanisms, energy productivity improvement is a key measure to achieve sustainable energy consumption in the theory. Hence, empirical investigations on the relationship between ICT and energy productivity can provide with new evidences regarding the above debate.

3. Method and Data

3.1. Method

3.1.1. Econometric Model

Given the perspective from energy economics as introduced in the last section, this paper constructs the following econometric model to investigate the impact of ICT development on energy productivity [32]:

$$\begin{aligned} MEPICM_{it} = \beta_0 MEPICM_{it-1} + \beta_1 \ln ICT_{it} + \beta_2 \ln HC_{it} + \beta_3 \ln EI_{it} + \beta_4 INVEST_{it} \\ + \beta_5 GOV_{it} + \beta_6 TRADE_{it} + \beta_7 FDI_{it} + \beta_8 INDUSTRY_{it} + (\alpha_i + \nu_{it}) \end{aligned} \tag{1}$$

where the subscript i and t denote economy and year respectively, $MEPICM$ represents the accumulated energy productivity index, ICT represents the development of ICT, thus the parameter β_1 is of interest and represents the relationship between energy productivity and ICT development. Besides, Equation (1) also takes account of other control variables that may have impacts on the energy productivity. Specifically, HC denotes human capital, given that a highly educated population may stimulate knowledge spillover and hence may relate to the improvement of productivity [33,34]. EI denotes energy intensity, since an intensive energy use is typically related to relatively low performance of energy productivity. $INVEST$ denotes the domestic investment level, since the investment is generally realized by replacing old facilities with new ones and hence may stimulate more efficient use of energy [32]. GOV denotes the economic intervention of local government. According to the theory of political economics, the design and quality of institution can influence economic productivity as well as environmental performance that includes energy productivity [35]. $TRADE$ denotes the foreign trade level, FDI denotes foreign direct investment level. We use these two variables to control the impact of trade and openness, which is widely concerned by studies with cross-economy samples and still under debate in existing studies [36,37]. On one hand, international merchandise trades may benefit the productivity by learning from trade partners and their latest technologies, or by competing in the global market; on the other hand, foreign direct investment may lead to bad environmental performance due to the transfer of low-efficient and high energy-consuming industries across countries. $INDUSTRY$ denotes the industry development level, since a higher ratio of secondary industry may rely on more use of energy. Parameters from β_0 to β_8 represent the impacts of corresponding variables, α_i is the economy-specific intercept, and ν_{it} is the unobserved disturbance term that is assumed to be i.i.d., $\nu_{it} \sim (0, \sigma^2)$.

Given that the existence of lagged dependent variable $MEPICM_{it-1}$ in Equation (1) makes traditional within estimator and least-squares dummy variable (LSDV) inconsistent and biased, this paper employs a bootstrap-based bias corrections for LSDV estimator (henceforth, BCFE) proposed by Everaert and Pozzi [38]. As suggested by Everaert and Pozzi [38], BCFE also have some advantages over traditional estimators (e.g., GMM estimator) in terms of estimation and inference, especially when the research samples have a small T (i.e., time period) and small N (i.e., number of cross-sections). To get the BCFE estimator, we first obtain the original biased LSDV estimator, then search over the parameter space using an interactive bootstrap method to find the unbiased estimates [38].

3.1.2. Measurement of ICT Development: A Patent Approach

To measure the development of ICT, this paper employs a patent-based indicator that is widely used in recent studies on technological innovation [39,40]. For a specific technology domain, the activity of a patent application typically indicates marginal improvements in some technological characteristics over the existing technology. Typically, a large number of patent applications in a field (e.g., ICT) indicates that the inventive activity is highly active. Thus, a sustained growth of patent counts in a field may reflect the ongoing development of that technology [41,42], as introduced in the database of OECD Statistics (see https://stats.oecd.org/fordetails). Though it is argued that the patent-based indicator might have flaws in innovation measurement since "not all inventions are patentable, not all inventions are patented and the inventions that are patented differ greatly in 'quality', in the magnitude of inventive output associated with them" [43], it at least can reflect the extent to which the research is active in a given field [44]. Compared with the widely used indicator of research and development (R&D) inputs, the patent-based indicator focuses on the output of knowledge production and has advantages in data availability and comparability across economies [45]. Besides, patent-based indicators can be subdivided according to patent classification system [41], which is unique among almost all innovation indicators.

This paper constructs an ICT knowledge stock indicator based on patent-quality selection, taking account of the following two aspects. First, technology development is closely related to knowledge accumulation and hence is a concept of stock, while the patent application number is a concept of flow [46]. Second, a great number of low-quality patents may lead to bias in measuring the dynamics of technological frontier [44]. Therefore, based on perpetual inventory method [47,48], the ICT knowledge stock indicator is calculated as:

$$ICT_{i,t} = PAT_{i,t} + (1 - \delta) ICT_{i,t-1} \quad (2)$$

where $ICT_{i,t}$ denotes the knowledge stock of ICT in economy i at year t, $PAT_{i,t}$ denotes the patent application number of "IP5 patent families", i.e., patents that have been filed in at least two intellectual property offices worldwide, one of which among the Five IP offices (namely the European Patent Office, the Japan Patent Office, the Korean Intellectual Property Office, the US Patent and Trademark Office and the State Intellectual Property Office of the People Republic of China) (see https://stats.oecd.

org/fordetails). As noted by Haščič, Silva and Johnstone [41], the "IP5 patent families" can guarantee the quality of patents application to some extent, because firms will seek property protections in two or more patent offices, only if there are commercial values or technological improvements in their inventions. Equation (2) indicates that, the sustained patent applications can contribute to the increase of knowledge stock, while the knowledge also depreciate over time at a given rate δ since new technology will replace the old one. Besides, the calculation of Equation (2) requires the initial value of knowledge stock ICT_{i,t_0} that is set as:

$$ICT_{i,t_0} = \frac{PAT_{i,t_0}}{(\overline{g}_s + \gamma)} \tag{3}$$

where $\overline{g}_s$ is the average growth rate of patent application numbers in the first five years, i.e., from t_0 and t_0 + 5, and γ is set to 0.1 according to existing studies [47,49,50].

3.1.3. Measurement of Energy Productivity: A Parametric Malmquist Index Approach

To estimate the performance of energy use, this paper follows Du and Lin [51] and focuses on the perspective of total-factor energy productivity, rather than traditional single-factor energy productivity such as the economic product of per unit energy use (i.e., GDP/energy use). For a decision making-unit (henceforth, DMU), the production technology can be written as:

$$P = \{(K, L, E, Y) | (K, L, E) \text{ can produce } Y\} \tag{4}$$

which indicates that the DMU can produce the final product (Y) given the combination of input factors such as capital (K), labor (L) and energy (E). Referring to Boyd [52] and Zhou, et al. [53], this paper constructs a Shepherd energy distance function as:

$$D_E^t(K, L, E, Y) = \sup\{\theta \big| (K, L, E/\theta, Y) \in P^t\} \tag{5}$$

where $D_E^t(K, L, E, Y)$ denotes the maximum reduction of energy input when the output and other inputs remain unchanged under the given technology condition [54]. Thus, the energy efficiency can be defined as [55]:

$$EFF^t = \frac{1}{D_E^t(K, L, E, Y)} \tag{6}$$

which represents the ratio of optimal energy use to actual energy use [56]. It is obvious that EFF^t measures the energy use performance at time t and hence it is a static indicator. To observe the dynamics of energy use performance, we further construct a Malmquist energy productivity index (henceforth, MEPI) as:

$$MEPI_i^{t,t+1} = \left[\frac{D_E^t(K_i^t, L_i^t, E_i^t, Y_i^t) \times D_E^{t+1}(K_i^t, L_i^t, E_i^t, Y_i^t)}{D_E^t(K_i^{t+1}, L_i^{t+1}, E_i^{t+1}, Y_i^{t+1}) \times D_E^{t+1}(K_i^{t+1}, L_i^{t+1}, E_i^{t+1}, Y_i^{t+1})}\right]^{\frac{1}{2}} \tag{7}$$

where $D_E^t(K_i^t, L_i^t, E_i^t, Y_i^t)$ denotes using (K_i^t, L_i^t, E_i^t) to produce Y_i^t given the technology frontier of time t, $D_E^{t+1}(K_i^t, L_i^t, E_i^t, Y_i^t)$ denotes using (K_i^t, L_i^t, E_i^t) to produce Y_i^t given the technology frontier of time t + 1, $D_E^t(K_i^{t+1}, L_i^{t+1}, E_i^{t+1}, Y_i^{t+1})$ denotes using $(K_i^{t+1}, L_i^{t+1}, E_i^{t+1})$ to produce Y_i^{t+1} given the technology frontier of time t + 1, $D_E^{t+1}(K_i^{t+1}, L_i^{t+1}, E_i^{t+1}, Y_i^{t+1})$ denotes using $(K_i^{t+1}, L_i^{t+1}, E_i^{t+1})$ to produce Y_i^{t+1} given the technology frontier of time t + 1. As proposed by Wang, et al. [57] and Du and Lin [51], $MEPI_i^{t,t+1}$ denotes the change in energy use performance for DMU i between the periods t and t + 1.

The estimations of Equations (6) and (7) require further econometric specification of Shepherd energy distance function, since the technology frontier cannot be directly observed. To solve this issue, we employ a DEA-based method, i.e., sequential DEA model, that is widely used in existing studies [58,59]. Specifically, we construct the production technology as:

$$
\begin{aligned}
P^{\tau} = \{(K, L, E, Y) : \quad & \sum_{t=1}^{\tau} \sum_{n=1}^{N} \lambda_n^t K_n^t \leq K \\
& \sum_{t=1}^{\tau} \sum_{n=1}^{N} \lambda_n^t L_n^t \leq L \\
& \sum_{t=1}^{\tau} \sum_{n=1}^{N} \lambda_n^t E_n^t \leq E \\
& \sum_{t=1}^{\tau} \sum_{n=1}^{N} \lambda_n^t Y_n^t \geq Y \\
& \lambda_n^t \geq 0, n = 1, \ldots, N, t = 1, \ldots, \tau\}
\end{aligned}
\tag{8}
$$

Furthermore, the Shepherd energy distance function can be calculated by the following linear programming technique:

$$
\begin{aligned}
\left[D_E^{\tau}(K_i^s, L_i^s, E_i^s, Y_i^s)\right]^{-1} \quad & = \min\theta \\
s.t. \quad & \sum_{t=1}^{\tau} \sum_{n=1}^{N} \lambda_n^t K_n^t \leq K_i^s \\
& \sum_{t=1}^{\tau} \sum_{n=1}^{N} \lambda_n^t L_n^t \leq L_i^s \\
& \sum_{t=1}^{\tau} \sum_{n=1}^{N} \lambda_n^t E_n^t \leq \theta E_i^s \\
& \sum_{t=1}^{\tau} \sum_{n=1}^{N} \lambda_n^t Y_n^t \geq Y_i^s \\
& \lambda_n^t \geq 0, n = 1, \ldots, N, t = 1, \ldots, \tau\}
\end{aligned}
\tag{9}
$$

By combining Equation (9) with Equations (6) and (7), we are able to observe the energy efficiency of time t (i.e., EFF^t) and energy productivity during t and t + 1 ($MEPI_i^{t,t+1}$), respectively. Moreover, the accumulated energy productivity index can be calculated by assuming $MEPI_i^{0,1} = 1$ and sequentially multiplying the period-wise energy productivity:

$$
MEPI_i^{1,t} = \prod_{t=2}^{\tau} MEPI_i^{t-1,t}, \tau \geq 2 \tag{10}
$$

3.2. DATA

This paper constructs a data panel of 50 economies over the period between 1995 and 2013, the samples are selected according to data availability. Table 1 reports the descriptive statistics.

Table 1. Descriptive Statistics.

Variables	Obs	Mean	Std. Dev.	Min	Max
MEPICM	950	1.375	0.713	0.250	6.428
ICT	950	6733.420	24,140.040	0.014	203,104.000
HC	950	2.872	0.523	1.450	3.726
EI	950	3207.791	2159.791	386.471	18,178.100
GOV	950	0.185	0.059	0.060	0.446
TRADE	950	−0.024	0.115	−0.609	0.397
FDI	950	4.312	9.170	−43.463	198.074
INVEST	950	23.923	5.913	0.299	47.686
INDUSTRY	950	31.031	7.277	11.251	66.757

Specifically, *MEPICM* is measured by the estimated accumulated energy productivity index; *ICT* is measured by the calculated knowledge stock of ICT (in numbers of applicated patents); *HC* is measured by index of human capital per person (in years of schooling) [60]; EI is measured by energy intensity level of primary energy (in MJ/$2011 PPP GDP); $INVEST$ is measured by gross capital formation (in % of GDP); GOV is measured by share of government consumption (in % of GDP); $TRADE$ is measured by share of merchandise exports and imports (in % of GDP); FDI is measured by net inflows of foreign direct investment (in % of GDP); $INDUSTRY$ is measured by value added of industry sector (in % of GDP). Data of EI, $INVEST$, FDI, and $INDUSTRY$ is extracted from database of World Development Indicators. Data of HC, GOV, $TRADE$ and data required for estimating $MEPICM$ is extracted from database of PWT 90 [61]. The patent application data required for calculating ICT is from the OECD statistics [62].

4. Results

4.1. Global ICT Development Trend Analysis: A Patent Approach

Figure 1 depicts the annual change of worldwide ICT patent counts. In general, the gross number of global ICT patent applications fluctuates to increase during the research period. Specifically, there is a decrease of patents growth rate comparing the period before 2000 with the period over 2001 and 2003, which may relate to the 'dot-com bubble' that happened around 2000. And there is a decrease in total number of global ICT patent applications around 2008, which may root in global financial crisis over that period. Regarding the contribution of different economies, before 2005, OECD economies contribute to more than 90 percent of the total amount of global ICT patents. After 2005, there is a fast-growing ICT patent counts in emerging economies, e.g., BRICS economies (Brazil, Russia, India China and South Africa), while the ICT patent counts of OECD economies fluctuate and decrease in general. At the end of the research period, inventors from BRICS economies applied for 13 percent of the worldwide ICT patents and hence became an important force in global ICT innovation.

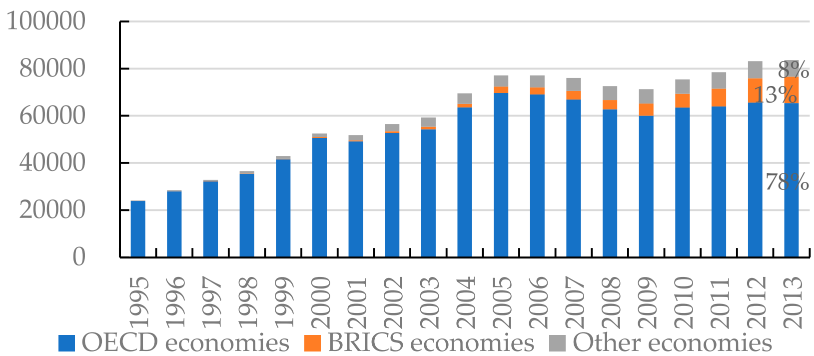

Figure 1. Information and communication technology (ICT) patent numbers of different groups of economies.

Figure 2 shows the dynamics of ICT knowledge stock, given that Figure 1 cannot reflect the stock characteristic of ICT knowledge which is essential to understanding the role of technological innovation in economic production. Figure 2 depicts changes in ICT knowledge stock of the top five inventor economies in the ICT field from 1995 to 2013. For the five economies as a whole, the ICT knowledge accumulated at a faster speed before 2007 than after 2007. Moreover, the United States and Japan contributed to more than 80 percent of the five economies' ICT knowledge stocks before 2002, then Korea and China have experienced fast growth rates of ICT technology and contributed to 17 percent and 8 percent of the five economies' ICT knowledge stocks in 2013, respectively. In general, the relative importance of the United States and Japan decreased and the development of ICT shows a balanced trend across the top inventor economies.

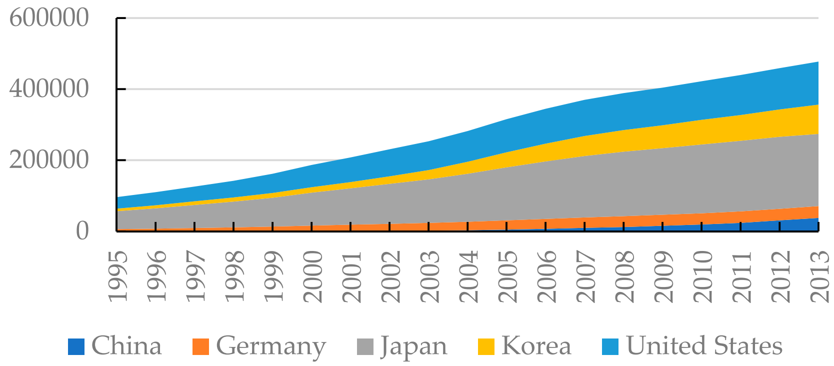

Figure 2. ICT knowledge stock of top five inventor economies.

In Figure 3, we show the group average of ICT knowledge stock by classifying the sample economies into three groups, i.e., high-income (HI) group, upper-middle-income (UM) group, and lower-middle-income (LM) group. Generally, the high-income economies have a much higher knowledge stock on average (e.g., 15,154 in 2013) compared with the other two groups (e.g., 2898 for UM group and 600 for LM group in 2013). Regarding the dynamics of ICT knowledge stock, the growth rate for the HI group slows down to a large extent after 2006, while for the UM group it shows an exponential growth trend.

To sum up, there is still a large gap in terms of ICT development between the high-income economies and the relatively poor economies, although a part of the latter (e.g., the upper-middle-income economies) have experienced a fast accumulation of ICT stock in the last two decades.

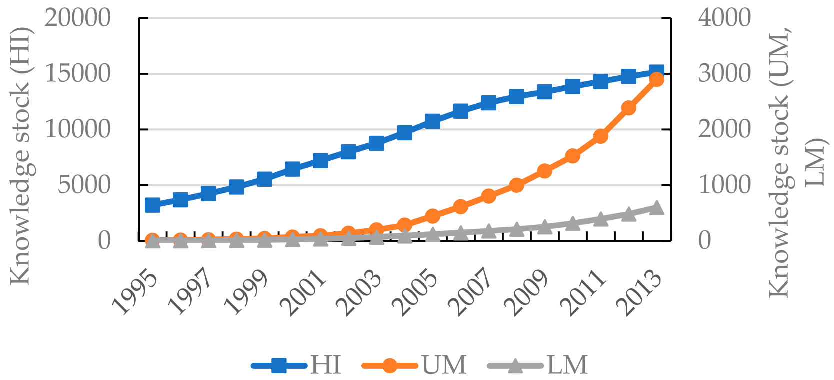

Figure 3. Average ICT knowledge stock of economies grouped by income level. Note: the classification of economies is sourced from the World Bank, see https://datahelpdesk.worldbank.org/knowledgebase/articles/906519 for details.

4.2. Estimates of Energy Efficiency and Energy Productivity

Table 2 reports the annual mean value of energy efficiency score that represents the annual performance of energy use and the accumulated value of energy productivity index that represents the overall change of energy productivity from 1995 to 2013.

Table 2. Energy efficiency and energy productivity of 50 economies.

Economy	TFEE_Mean	MEPI_cm	Economy	TFEE_Mean	MEPI_cm
Bulgaria	0.345	0.615	Germany	0.820	1.649
Iceland	0.249	0.682	Iran	0.331	1.673
Thailand	0.474	0.778	Russia	0.205	1.755
Japan	0.667	0.990	Hungary	0.486	1.759
Egypt	0.619	1.008	Croatia	0.554	1.771
Brazil	0.578	1.049	Mexico	0.608	1.805
China	0.315	1.090	Sweden	0.476	1.818
Korea	0.425	1.125	Australia	0.498	1.825
Turkey	0.742	1.189	New Zealand	0.444	1.844
Malaysia	0.460	1.238	Italy	0.806	1.884
Pakistan	0.639	1.241	India	0.483	1.953
Argentina	0.617	1.250	Singapore	0.275	2.030
South Africa	0.286	1.290	The Netherlands	0.703	2.074
Philippines	0.881	1.302	Denmark	0.743	2.081
Chile	0.554	1.320	Poland	0.462	2.198
Israel	0.717	1.343	Estonia	0.665	2.293
Colombia	0.758	1.359	United Kingdom	0.851	2.437
Portugal	0.662	1.369	Switzerland	0.858	2.542
Greece	0.627	1.399	Ukraine	0.151	2.948
Czech Republic	0.461	1.442	France	0.632	3.445
Spain	0.653	1.471	Saudi Arabia	0.367	3.474
Austria	0.658	1.486	United States	0.640	3.501
Slovenia	0.458	1.541	Lithuania	0.421	3.824
Cyprus	0.509	1.567	Romania	0.398	4.432
Finland	0.451	1.611	Ireland	0.991	6.428
Total_mean	0.554	1.884	HI_mean	0.583	1.505
UM_mean	0.477	1.145	LM_mean	0.568	1.056

Taking the 50 economies as a whole, the mean value of annual energy efficiency during the research period is 0.554, the mean value of accumulated energy productivity is 1.884. Among the 50 economies, three economies (i.e., Bulgaria, Iceland, and Thailand) had experienced non-negligible decreases of energy productivity, two economies (Japan and Egypt) roughly remained unchanged in terms of energy productivity, and most economies had experienced increases of energy productivity. Moreover, Ireland was the best player among all sample economies for it had experienced the largest energy productivity growth during the research period (i.e., accumulated MEPI equals to 6.428). Almost all of the top five inventor economies enjoyed growths in energy productivity. That is, the United States and Germany had experienced sustained growths of energy productivity (i.e., accumulated MEPI equals to 3.501 and 1.649, respectively), the accumulated energy productivity scores of China and Korea are larger than one but their energy efficiency scores are below the average level, Japan's performance of energy productivity was almost unchanged but its energy efficiency score was above the average level.

Table 2 can only show the change in energy productivity compared the 1995 level with 2013 level. To provide more details, Figure 4 depicts the annual change of accumulated energy productivity index. According to Figure 4, the patterns of changes in accumulated energy productivity index are different across the three groups. Besides, the mean value for the HI group is relatively larger compared with the UM group and the LM group, and the gaps generally show enlarging trends during the whole period. Together with Figure 3, the descriptive statistics reflect the unbalanced developments of both ICT and energy productivity among economies grouped by income levels.

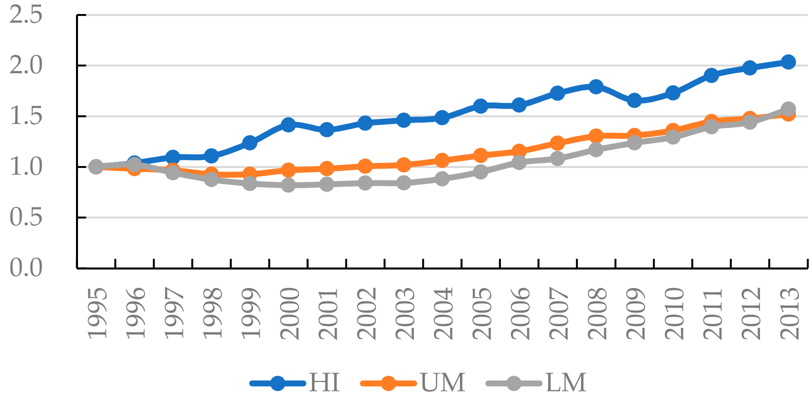

Figure 4. Accumulated energy productivity index of economies grouped by income levels.

4.3. Regression Results

Regarding the relationship between ICT development and energy productivity, Table 3 reports estimation results of Equation (1) using BCFE compared with estimation results of other two methods, i.e., ordinary least square (OLS) estimator and fixed-effect (FE) estimator. The coefficient of the lagged dependent variable $L.MEPICM$ is significant and equals to 0.9661, indicating that the energy productivity is closely related to its lagged term and that both the OLS estimator and the Fixed-effect estimator may be biased. Hence, we mainly focus on estimated parameters of BCFE in Column (3).

Table 3. Regression results of different models.

Variables	**(1)**	**(2)**	**(3)**
	OLS	**FE**	**BCFE**
ICT	0.0182 * (0.0096)	0.0842 ** (0.0332)	0.0285 *** (0.0107)
HC	0.2843 *** (0.0557)	1.5884 *** (0.4780)	0.0142 (0.0943)
$\ln EI$	−0.0251 (0.0420)	−1.3201 *** (0.3649)	−0.2356 *** (0.0748)
GOV	0.0158 (0.3653)	−0.1912 (0.9732)	−0.2975 (0.2329)
$TRADE$	1.9788 *** (0.4806)	1.5236 (1.0869)	0.4080 ** (0.1613)
FDI	0.0108 ** (0.0044)	0.0029 (0.0034)	0.0016 (0.0014)
$INVEST$	0.0124 ** (0.0048)	0.0294 ** (0.0139)	0.0040 (0.0026)
$INDUSTRY$	−0.0212 *** (0.0074)	−0.0185 (0.0246)	0.0068 (0.0050)
$L.MEPICM$			0.9661 *** (0.0258)
Intercept	1.0257 *** (0.3005)	6.6971 *** (2.3721)	
N	950	950	900

Note: *, **, and *** denote coefficient significant at 10%, 5%, and 1%, respectively.

We firstly focus on the key variable ICT. From Column (1) to Column (3), the parameters of variable ICT are consistently significant and positive, indicating a positive relationship between ICT development and energy productivity growth. According to Column (3), the coefficient of variable ICT is 0.0285 and significant at 1% level, which indicates that 1 unit increase of ICT knowledge stock is related to 0.0285 unit improvement in energy productivity. Although the principle of regression models cannot enable us to assert that the ICT development can promote energy productivity growth, such a positive relationship found in Table 3 may inspire the future studies on detailed impact investigations with different methods. As for the control variables, the coefficient of variable $\ln EI$ is significant and negative, indicating that energy intensity is negatively related to energy productivity. The coefficient of variable $TRADE$ is significant and positive, indicating that merchandise trades across countries may induce more efficient use of energy.

Why may ICT development, denoted by the patent-based knowledge stock indicator, promote energy productivity according to results, while the energy consumption in some fields still increases with ICT development? According to the theory of energy economics, the "rebound effect" phenomenon provides an interpretation. That is, due to the behavior change of economic agents, improvements in energy efficiency and/or energy productivity induced by ICT development may not lead to the expected energy-saving effects [63]. Taking the consumer side as an example, improvements in energy productivity may reduce the relative price of energy service compared with other goods. On one hand, the energy cost of the consumer decreases with the price, hence the consumer can use the remaining budget to buy more goods, which would inevitably cause energy consumption; on the other hand, relatively cheaper energy services may induce the consumer to purchase more energy services than other goods. The above two paths may, to some extent, offset the expected energy savings from the perspective of engineering, and may even cause the increase of energy use in some circumstances.

Compared with existing studies, this paper provides new evidences which help to understand the ongoing debate on whether ICT can lead to energy savings. Although we do not directly answer the above question, we empirically observe the relationship between ICT development and energy consumption from a new perspective of energy productivity. Regarding the existing different opinions on the net effect of ICT on energy consumption, we argue that both positive and negative effects are possible in the theory. Since the dominant impact factors, underlying the relationship between ICT and energy consumption, are different across time and/or economies, the net effects can also be differentiated for various research samples. Based on the results, we argue that it is in urgent need to empirically discover the impact mechanisms through which ICT development can potentially promote energy savings and to make corresponding policy implications, rather than continuous debate on the ICT's net effect on energy consumption across regions or times.

5. Conclusions

ICT has been playing a significant role in both modern life and modern economic production. While it is developing with a fast speed, ICT itself is related to many fields that consume a large amount of energy. To investigate whether the development of ICT relates to sustainable energy consumption, this paper empirically tests the relationship between ICT development and energy productivity. By using a data panel of 50 economies over the period from 1995 to 2013, the empirical results indicate that the ICT development is positively related to accumulation of energy productivity. Therefore, rather than debating whether ICT can lead to gross energy savings, we suggest that researchers should focus more on the impact mechanisms of ICT, e.g., the potential energy-saving paths and energy-consuming paths through which ICT affects economy-wide energy use. Besides, the statistics of ICT knowledge stock indicate that there is an unbalanced development of ICT across the world, especially when comparing the high-income economies with the other economies. Such a non-convergent phenomenon also happened in other technological fields related to energy savings and low-carbon development, referring to related studies [50]. Correspondingly, the development gap of energy productivity between the high-income economies and the other groups of economies doesn't show a narrowing trend. Thus, regarding the policy implication, it is necessary to initiate indigenous innovations on ICT in these underdeveloped economies as well as technology transfers from developed economies to underdeveloped economies. For future studies, it is worthwhile to investigate the definition, choice, combination and potential energy-saving effect of corresponding policy instruments.

The limitations of this paper are at least two-fold. Firstly, due to data availability, the patent statistics do not disaggregate the ICT patents, e.g., ICT patents with the potential of controlling energy use (or green ICT) and ICT patents without that potential. Without such detailed data, we cannot make judgement about which type of ICT can lead to energy savings, or which type of ICT has more potential in energy savings. Since the final target of this literature is to find a way to global energy-use reduction, we believe it would be an interesting topic investigating impacts of different types of ICT on energy consumption at the macroeconomic level. With the updating of the global patent database in the future, following studies may use the latest patent classification system to obtain the patent counts of green ICT, non-green ICT, and their subdivisions, and to implement more analyses on the relationship between ICT and environment [64]. Secondly, since this paper focuses on a macroeconomic perspective, the empirical section only obtains the relationship between the ICT development and energy productivity. However, the evidence is not enough for detailed policy implications on how to enable ICT's potential to promote energy productivity. Whether the impact of ICT development on energy productivity exists and what are the detailed impact mechanisms, the answers require further studies with micro-level data.

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