Chinese Journal of Population, Resources and Environment 20 (2022) 136–146

Contents lists available at ScienceDirect

Chinese Journal of Population, Resources and Environment

journal homepage: www.keaipublishing.com/cjpre

The effect of human capital on energy consumption: Evidence from an extended version of STIRPAT framework

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ARTICLE INFO

Keywords:
Energy consumption
Human capital
Scale effect
Structural effect
Technical effect

ABSTRACT

Human capital is an important aspect of energy consumption, exerting crucial effects on economic growth, technological progress, and economic restructuring. This paper presents an in-depth investigation of the effect of human capital on energy consumption using an extended version of the Stochastic Impacts by Regression on Population, Affluence, and Technology framework. The estimated results using a panel dataset covering China's 30 provincial regions during the period 1997–2018 and applying fixed effects with instrumental variables and the generalized method of moments indicated that an increase in human capital significantly drove energy consumption. A 1% increase in human capital increased energy consumption by approximately 0.3%. A two-step channel analysis to test scale, technical, and structural effects revealed that the positive effect of human capital on energy consumption is based primarily on the scale effect. However, highly educated human capital alleviates the energy pressure of this effect. In contrast to the scale effect, both the technical and structural effects of human capital reduced energy consumption, and this reduction is primarily correlated with enterprises' utility-oriented technological progress. Finally, we present strategic energy control policy implications related to human capital.

1. Introduction

The reliable provision of energy is an important driver of economic growth. Benefiting from the reform and opening up, China has become the largest developing country and the second largest economy in the world following four decades of rapid economic prosperity since 1978. However, at the same time, the nation's energy consumption dramatically increased. As early as 2009, China surpassed the U.S. as the world's largest energy consumer. Because China is still undergoing industrialization and urbanization, energy consumption is expected to continue to increase. The nation's massive energy consumption not only places considerable pressure on energy security but also generates serious environmental pollution challenges (Liddle, 2013; Dong et al., 2018; Huang et al., 2021b). Subsequently, controlling energy consumption is of great significance for policymakers and has become an important goal of national economic macrocontrol (Ma et al., 2017), and is exemplified by the Strategy for Revolution in Energy Production and Consumption (2016–2030), declaring that the country's total energy consumption will be controlled to under 6 billion tons of standard coal equivalent by 2030.

A substantial body of literature investigates the driving factors of energy consumption based on the impact, population, affluence, and technology (IPAT) framework or its extended version—the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model (Dietz and Rosa, 1997; York et al., 2003; Huang et al., 2021a). Most researchers determine that economic growth, technological progress, and industrialization have significantly contributed to the overall increase in energy consumption. For instance, based on the IPAT framework, Wang and Li (2016) calculated the effects of population, affluence, and technology on energy consumption in the world's two largest developing countries, attributing China's increasing energy consumption to rapid income growth and the reversal of a decline in technological progress. By contrast, for India, rapid population increase, rather than income or technological progress, is found to be the major cause of increasing energy consumption. Song et al. (2011) found energy consumption to be driven primarily by the rapidity of China's economic growth using the IPAT model. Liddle (2013) applied the STIRPAT model to examine how population, income, and population density influence energy consumption in private transport. With a large, city-level panel dataset, the researcher demonstrates that population density is negatively and significantly related with energy consumption in private transport. The insightful

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https://doi.org/10.1016/j.cjpre.2022.06.004
Received 23 July 2021; Accepted 8 March 2022

studies above uncover the driving forces of changing energy consumption.

In the past few decades, along with the rapid growth in the economy and energy consumption in China, human capital has also exhibited an increasing trend①, as shown in Figure 1②. Along with technological progress and economic restructuring, human capital has a substantial impact on economic growth, prompting the questions: Has human capital significantly contributed to increased energy consumption in China? If so, how? This study attempts to answer these compelling questions.

Human capital generates significant fluctuations in energy consumption. Its influence occurs primarily through three main channels. First, according to neoclassical theory (Lucas, 1988) and endogenous theory (Romer, 1990), economies grow from the accumulation of human capital through education and learning-by-doing. Congruent with economic development, resource consumption, an important element of production, also generally increases. Thereby, economic growth, also referred to as the scale effect or income effect, is an important mechanism for human capital's influence on energy consumption. Along with increased environmental awareness and higher incomes, higher-educated human capital is more inclined to choose resource-saving appliances and consume less energy (Broadstock et al., 2016). By contrast, higher income, lower-educated cohorts who value the environment less can afford more energy and are more likely to exhibit resource-oriented consumption behavior.

Second, in line with endogenous theory (Romer, 1990), human capital can drive technological progress, which can lead to reductions in the energy input required for a unit output by improving efficiency. Intuitively, human capital reduces energy consumption through technological progress, and such technological progress conducted by different performers for various purposes has heterogeneous impacts on energy mitigation. For example, compared with colleges and research institutes, because enterprises access more effective real-world information on energy consumption in production processes, enterprises' technological progress is more practical and result-oriented. Consequently, human capital reduces energy consumption more probably through enterprises' technological progress. Similarly, as utility-oriented technological progress has more practical value, it is expected to have a stronger effect on energy mitigation than invention-oriented technological progress.

Third, studies have demonstrated that industrial structure optimization lowers energy consumption by degrees through the development of more energy-efficient industries and supporting tertiary industries (Feng et al., 2009; Hu et al., 2011). Accordingly, structural effects are another mechanism through which human capital affects energy consumption.

As discussed above, human capital significantly affects energy consumption through scale, structural, and technical effects. The scale effect is generally positive, whereas a negative effect is demonstrated for higher-educated human capital, and both technical and structural effects are negative. We seek an answer to the question: Is the total effect of human capital on energy consumption positive or negative? The following discussions may clarify the drivers of energy consumption.

The primary research question of this study endeavors to answer how human capital influences energy consumption in China. Unlike previous studies (Fang and Chang, 2016; Salim et al., 2017), we do not employ average years of education as a proxy for human capital. This proxy was favored in prior work because it is easy to calculate and the data are readily available. However, this method discounts important factors that affect human capital, such as training quality or work experience, and therefore fails to comprehensively encompass the breadth of human capital. We introduce a more suitable measurement for human capital following the China Center for Human Capital and Labor Market Research (CHLR) and applying the improved Jorgenson–Fraumeni method (J–F method)③ (Jorgenson and Fraumeni, 1992a, 1992b). Compared with conventional methods, our approach comprehensively considers educational experience as well as work experience, health, and life cycle (Li, 2012). More notably, we selected this metric because it scientifically and systematically reflects the circumstances regarding Chinese human capital.

Moreover, considering the channels of scale, technical, and structural effects, we apply two-step analysis to explore how human capital influences energy consumption, referencing Nguyen and Phan (2020). In the first step, we examine the direct relation between human capital and the three effects. In the second step, we re-examine the relationship between human capital and energy consumption in the low and high terciles of the three effects. The advantage of this method is its ability to clearly verify both the direct impact of the

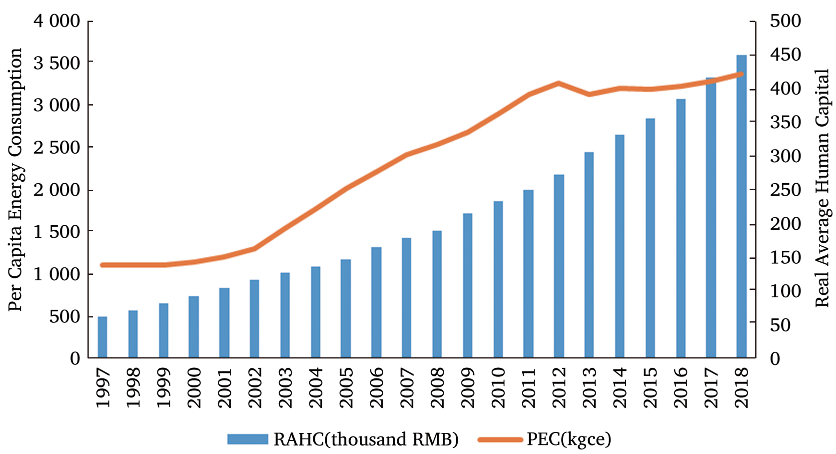

Figure 1. The trend of real average human capital in China (1997–2018)

①According to the Organisation for Economic Co-operation and Development (OECD,2001), human capital refers to the knowledge, skills, abilities, and qualities that individuals possess to create personal, social, and economic well-being.
②The data for real average human capital are from the China Center for Human Capital and Labor Market Research (CHLR), and per capita energy consumption is calculated by taking energy consumption as a percentage of the population data from China Provincial Statistical Yearbooks.
③Detailed information can be found at: http://humancapital.cufe.edu.cn/en/Human_Capital_Index_Project/Introduction.htm.

three effects on energy consumption and their indirect impact on human capital and energy consumption, enabling an assessment of whether the mechanism is evident in the subsamples at low and high terciles.

Through quantitative analysis of energy consumption across China's provinces, our primary contributions to the literature are threefold. First, we focus on human capital, particularly its effect on energy consumption through scale, technical, and structural effects. Second, a distinctive two-step analysis is applied in our mechanism analysis. With this method, we further demarcate the three effects to obtain more detailed and comprehensive results. Third, to identify the effect of human capital on energy consumption accurately, we employ a comprehensive measurement for human capital following the CHLR.

The remainder of this paper is structured into four sections. Section 2 presents the theoretical analysis and research hypotheses, Section 3 introduces the methodology, including the empirical models and data, and Section 4 reports the empirical results, followed by the conclusions and policy implications in Section 5.

2. Human capital effect on energy consumption: Conceptual channels and research hypotheses

According to Grossman (1993), pollution is correlated with economic activity. Following this view, economic activities primarily influence resource consumption through scale, structural, and technical effects. In the following section, we demonstrate how human capital influences energy consumption through these three effects.

2.1. Scale effect

Human capital may affect energy consumption through an economic growth effect, which is referred to as the scale effect. Many studies use cointegration and causality analysis to investigate the relationship between energy consumption and economic growth (Bloch et al., 2015; Ozturk, 2010; Smyth and Narayan, 2015), but their conclusions are contradictory. For instance, some studies find that economic growth accounts for energy consumption (Kraft and Kraft, 1978; Zhang and Cheng, 2009; Fang and Wolski, 2021), whereas others determine causality in the opposite direction, from energy consumption to growth (Bowden and Payne, 2009; Ho and Siu, 2007). Other studies do not detect any causality (Payne, 2009; Soytas and Sari, 2009) or bicausality (Bloch et al., 2015; Mahadevan and Asafu-Adjaye, 2007). Although no consensus has been reached regarding the economic growth–energy consumption relationship in current research, extensive literature reviews suggest that energy consumption is positively correlated with economic growth in most developing countries (Smyth and Narayan, 2015; Ozturk, 2010).

Endogenous theory suggests that human capital determines the speed of economic growth (Romer, 1990). Gregory et al.'s (1992) augmented Solow model recognized the significance of human capital for economic growth; some literature has also verified this significance. Using a panel of 100 counties from 1965 to 1995, Barro (2001) found economic growth to be positively correlated to human capital and to adult males with secondary school education and above in particular. Similarly, Benos and Zotou (2014) applied a meta-regression analysis, demonstrating that human capital is essential to economic growth. Based on the above discussion, human capital may increase energy consumption through the scale effect, leading to the following hypothesis:

H1: Human capital increases energy consumption through the scale effect.

The uncertain relationship between economic growth and resource consumption depends on the position in the environmental Kuznets curve (EKC) (Grossman and Krueger, 1995). The existence of a conventional inverted U-shaped EKC and whether the turning point has been reached are important indicators of the relationships between income level, energy consumption, and environmental quality. Generally, higher-educated human capital will reflect higher income and will value the environment more (Broadstock et al., 2016). These educated cohorts are more willing to buy environment-friendly products, continuously advocate environmental protection, and accept strict environmental regulations (Pachauri and Jiang, 2008; Broadstock et al., 2016). Higher-educated human capital is more likely to cross the turning point, occupy the downward sloping section of the EKC, and consume less energy. Conversely, the lack of environmental awareness results in less-educated human capital that improves their ability to afford more energy with income growth, rarely exerting a negative effect between the scale effect and resource consumption similar to higher-educated human capital. Thus, we develop the following hypotheses:

H1a: Higher-educated human capital reduces energy consumption through the scale effect.

H1b: Lower-educated human capital increases energy consumption through the scale effect.

2.2. Technical effect

In the energy field, technological progress (or the technical effect) can reduce the energy input required for unit output by reducing trade costs and improving production efficiency. Energy-saving technology presents an important breakthrough in the quest to reduce energy consumption (Li and Lin, 2016; Huang et al., 2020). A considerable number of Chinese scholars focus on the impact of the technical effect on energy consumption. For example, on the basis of a provincial panel dataset covering 2000–2015 in China, Dong et al. (2018) used research and development (R&D) investment as a proxy for technological progress, finding that technological progress could decrease energy consumption, but they also reveal differences across China's eastern, central, and western regions. From an industry perspective, Lin and Xie (2015) applied a cointegration model to study long-term equilibrium relationships among energy consumption, energy price, and technological progress in China's oil industry. Their results demonstrate that technological progress slows down energy consumption. In the most recent study, Shen and Lin (2020) focused on China's manufacturing industry using the two-stage least squares method. Their results also demonstrate that the technical effect and its spillover effect can significantly lower energy consumption.

Regarding the impact of human capital on the technical effect, endogenous growth theory maintains that human capital can strongly drive technological progress (Romer, 1990; Vandenbussche et al., 2006; Barro, 2001), primarily promoting two forms of technological progress, including independent innovation (direct form) and the imitation and absorption of technology from other regions (indirect form). In terms of the direct form, human capital is shown to be of great importance to creating new technology. Du et al. (2014) used a panel dataset from 30 Chinese provinces from 2002 to 2010, demonstrating that human capital can promote self-innovation and can contribute to economic growth. Similarly, Liu et al. (2008) found that human capital has a major influence on direct independent innovation. Regarding the indirect form, human capital is assumed to improve capacities for technological absorption, resulting in technology spillovers of innovation to one area from other areas. Scholars have conducted valuable research on this topic. Lai et al. (2005) introduced technology absorption capacity into the endogenous growth model, establishing the positive role of human capital in technology spillover, correlating to technology absorption capacity. Similarly, Zhao and Wang (2006) verified the importance of human capital in technology absorption capacity from the perspective of import trade. Hence, we propose our second hypothesis:

H2: Human capital reduces energy consumption through the technical effect.

Technical effect can be further categorized according to different performers and purposes. The reason for this decomposition is that not all technical effects driven by human capital can effectively influence energy consumption. For example, in terms of technical performers, Hart's (1995) natural resource-based perspective suggests that enterprises tend to leverage an environmentally conscious strategy that includes green technology and products to maintain sustainable competitive advantage. As enterprises are fully aware of energy consumption in production processes, technological progress is more effective, practical, and results-oriented to maximize profit. By contrast, colleges and research institutes are unable to identify the real causes of energy consumption in production accurately; more importantly, academic research activities tend to be less practical than enterprises. Thus, the impact of human capital on the technical effect achieved by enterprises, rather than colleges and research institutes, is expected to alleviate energy pressure. Regarding different purposes, technological progress can be bifurcated into utility-oriented and invention-oriented purposes. Similarly, compared with theoretically oriented inventions, utility-oriented technical effect driven by human capital has more practical value, and it could be more efficient on energy mitigation. To investigate this, we propose the following hypothesis:

H2a: The reduction of technical effect on energy consumption driven by human capital primarily comes from enterprises, rather than colleges and research institutes.

H2b: Compared with invention-oriented technical effect, the utility-oriented technical effect of human capital alleviates energy pressure.

2.3. Structural effect

As noted above, human capital is a significantly influential factor of China's industrial structure upgrading and optimization, driving the evolution of energy consumption. Amid the flow of labor and capital across sectors, the industrial structure is continuously adjusted and optimized. In this process, energy resources are transferred from sectors with high use to those with minimal resource use or nonenergy-dependent sectors (such as consumer services), resulting in a tendency toward decreased energy consumption (Luan et al., 2021). The higher the education level of human capital is, the more conducive it is to industrial structural optimization. First, as a generator of technology, human capital has a direct and positive role in improving industrial sector production efficiency, which promotes industrial structure upgrading and optimization. Second, with the increase in human capital, which is treated as a production input, the economy will also continue to accumulate physical capital. This accumulation effect will generate comparative advantage for industrial sectors with high human capital, thus promoting the transfer of factors of production among sectors and optimizing the industrial structure (Zhang et al., 2011). Accordingly, there is a reasonable chance that human capital affects energy conservation through the structural effect. The final hypothesis of this study is as follows:

H3: Human capital reduces energy consumption through the structural effect.

3. Methodology

3.1. Empirical models

We apply the STIRPAT model (Dietz and Rosa, 1997) to empirically examine the effect of human capital on energy consumption. The STIRPAT model is an extension of the IPAT method (Ehrlich and Holdren, 1972) and offers a flexible framework for hypothesis testing without imposing prior proportionality in the functional relationship between variables (Yao et al., 2020). The conventional model is given as follows:

$$I = aP^b A^c T^d e \tag{1}$$

Where, I is the measure of resource consumption; P, A, and T indicate the population, affluence (usually denoted by GDP), and technological progress, respectively; a represents a constant term; b, c, and d represent the resource consumption elasticity of population, affluence, and technological progress, respectively; and e is the random error term. As noted in Section 2, apart from the population, the level of human capital is also an essential factor for determining energy consumption. Furthermore, investigating the driving factor of energy consumption per capita, rather than total energy consumption, is more practical for policymakers' understanding of the regional characteristics of future energy change. Consequently, we present an extension of the STIRPAT framework by introducing the level of human capital and using energy consumption per capita as the explained variable:

$$PEC = a \times RAHC^b \times PGDP^c \times ETP^d \cdot e \tag{2}$$

Where, *PEC* denotes energy consumption per capita; *RAHC* represents real average human capital; *PGDP*, which stands for GDP per capita, is employed to reflect the scale effect on energy consumption; and *ETP* denotes technological progress in the energy field.

Apart from these influencing factors of energy consumption per capita, as shown in model (2), many other factors have important effects on energy consumption. First, as noted in Section 2, we include industrial structure optimization (defined as the Theil index) as a control variable in the energy consumption per capita model, and we expect to find that the higher the degree of industrial structure optimization is, the lower is the level of energy consumption.

Second, urbanization is regarded as an important driver of energy consumption (Ma et al., 2017). A higher urbanization rate implies greater energy consumption to sustain economic development and daily life. Therefore, referencing Huang et al. (2021a) and Zhang et al. (2011), the ratio of urban population to total population is included on the right-hand side of our model, with a positive effect anticipated.

Third, since China entered the World Trade Organization in 2001, its global exports have experienced a huge leap, along with energy growth. According to General Administration of Customs, in 2019, China ranked first in exports, which were estimated at US$2.5 trillion. It is clear that exports have become an important engine of China's economic development. Referencing Yao et al. (2020), we add the proportion of exports to GDP as a control variable. Finally, we integrate energy price into our model, which should relate to energy consumption according to microeconomic theory (Hang and Tu, 2007).

Taking the logarithm of model (2), our main empirical specification is as follows:

$$\begin{aligned}\ln PEC_{i,t} = {} & \delta + \alpha_1 \ln RAHC_{i,t} + \alpha_2 \ln PGDP_{i,t} + \alpha_3 \ln ETP_{i,t} + \alpha_4 \ln TLL_{i,t} \\ & + \alpha_5 \ln URB_{i,t} + \alpha_6 \ln EX_{i,t} + \alpha_7 \ln EP_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{3}$$

Where, subscripts i (i = 1, 2, 3,⋯, N) and t (t = 1, 2, 3,⋯, T) denote provinces and years, respectively; *TLL*, *URB*, *EX*, and *EP* represent the Theil index, urbanization, export, and energy price, respectively; other variables are consistent with model (2); α_m (m = 1, 2, 3,⋯, 7) is the parameter to be estimated; and ε is the stochastic error term.

Considering that energy consumption has a strong time persistence, we add its lagged term into the right-hand side of the model so that it has dynamic explanatory ability (Huang et al., 2020). The dynamic model for energy consumption is as follows:

$$\begin{aligned}\ln PEC_{i,t} = {} & \lambda + \beta_1 \ln PEC_{i,t-1} + \beta_2 \ln RAHC_{i,t} + \beta_3 \ln PGDP_{i,t} + \beta_4 \ln ETP_{i,t} \\ & + \beta_5 \ln TLL_{i,t} + \beta_6 \ln URB_{i,t} + \beta_7 \ln EX_{i,t} + \beta_8 \ln EP_{i,t} + \mu_{i,t}\end{aligned} \tag{4}$$

Where, $\beta_1 \in (0, 1)$ represents the coefficient to be estimated on the lagged dependent variable. Other variables mirror model (3).

As the dynamic panel model contains more information on the evolution of energy consumption compared to a static panel model, it is used as the benchmark model in this study. Unfortunately, our model may have severe endogeneity issues due to the introduction of lagged terms of the explained variables. Energy consumption may also have a bidirectional causality relationship with GDP (Fang and Chang, 2016) and export (Li and Qi, 2011), further intensifying the endogeneity. To address this, we use the conventional generalized method of moments (GMM) and instrumental regression technique (Arellano and Bond, 1991).

3.2. Data source and management

Data for Tibet, Hong Kong, Macao, and Taiwan are unavailable, and Chongqing has been separated from the Sichuan province since 1997 and is now the youngest municipality directly under the central government. Hence, a panel dataset of 30 provincial regions in the Chinese mainland from 1997 to 2018 is included in our analyses.

We use the average energy consumption of the provinces' population as the explained variable. The data on energy consumption are sourced from the China Energy Statistical Yearbooks, and the population data come from China Provincial Statistical Yearbooks (CPSY).

The J – F method, which was improved by the CHLR(Jorgenson and Fraumeni, 1992a, 1992b; Li, 2012), is applied to measure human capital. The J–F method uses the present value of lifetime income expectancy to measure human capital. The advantage of this method is that it more accurately and reasonably reflects long-run investments, such as in education and health, which have a significant role in human capital accumulation. Presently, the *China Human Capital Report* from the CHLR presents the estimation results for real average human capital in various Chinese provinces by year.[④] Owing to data limitations, the sample data regarding population education are only available from the China Statistical Yearbook. We assume the proportion of the population with a college degree or above to the total population as higher-educated human capital and that of senior high school degree or below as lower-educated human capital.

As for other variables, *PGDP* is converted into 1997 prices using the GDP deflator index, which is calculated as real GDP divided by the total population obtained from the CPSY. The structure of human capital is also obtained from the CPSY. Considering technological innovation is a difficult process that depends on many factors as not all R&D inputs will succeed in generating new technology. Furthermore, R&D can be adopted in some fields that are unrelated to energy. Therefore, not all R&D efforts will contribute to energy use. Consequently, in contrast to existing literature, we use the number of energy-saving patents as a proxy for energy technology. Because the data on capital stock can better reflect energy technology than flow data, we calculate the stock data of energy patents considering both the diffusion and depreciation rate:

$$ETP_{i,t} = \sum\nolimits_{j=0}^{t} Patents_{i,t} \exp[-v_1(t-j)] \cdot \{1 - \exp[-v_2(t-j)]\}, \tag{5}$$

Where, *Patents* (base period = 1990) denotes energy-saving patents granted by the State Intellectual Property Office of China on the standard filing date. The data on energy-saving patents are obtained by retrieving the names of the provincial regions and the International Patent Classification codes published by the World Intellectual Property Organization. The data on different types of energy-saving patents are obtained based on the standard application date. v_1 and v_2 represent depreciation and diffusion rates and have values of 0.36 and 0.03, respectively, referencing Lin and Zhu (2019).

Referencing Cheng et al. (2017), we apply the Theil index to measure the optimization of the industrial structure, primarily reflecting the flow and reasonable allocation of essential production elements among various sectors. As the Theil index considers the heterogeneity among industries by introducing different weights for different industries, it is suitable for determining industrial structure optimization (Luan et al., 2021). Model (6) shows how it is calculated:

$$TLL = \sum\nolimits_{i=1}^{n} \left(\frac{Y_i}{Y}\right) \ln\left(\frac{Y_i}{L_i} / \frac{Y}{L}\right), \tag{6}$$

Where, Y denotes the economic output; $Y_i (i = 1, 2, 3)$ represents primary, secondary, and tertiary industries, respectively; and L is the number of labor inputs. The Theil index is negatively correlated with the level of industrial structure optimization (i.e., if *TLL* is equal to 0, the industrial structure is extremely unbalanced). The data on Y and L can be obtained from the CPSY.

The data on urbanization (*UR*) and export (*EX*) are defined as the ratio of the urban population to the total population and exports as a share of GDP, respectively. Both values are from the CPSY. Energy price (*EP*) denotes the price index of purchasing fuel and power; 1997 is set as the base year (i.e., the EP index in 1997 is set as 100) and is obtained from the Price Yearbook of China. Tables 1 and 2 present the definitions of all variables and descriptive statistics of core variables, respectively. We also provide a correlation coefficient matrix of the variables in Table 3.

4. Results and discussion

Before conducting empirical analysis, it is necessary to assess the effects of the spurious regression through unit root and cointegration tests. We then apply a series of methods to investigate how human capital influences energy consumption.

4.1. Primary test

In the first step, we perform a unit root test of the panel dataset to determine the data stability of core variables. IPS (Im et al., 2003) and Fisher tests are commonly applied to check for panel unit roots. In Table 4, based on either the IPS test or the Fisher test, the presence of a unit root cannot be rejected for most variables. Nevertheless, the variables are stationary at first-order differencing in panel B, and therefore, economic development may affect the integration of all variables in our models over time. We apply the methods of Pedroni (1999, 2004) and Kao (1999) to test for the presence of a cointegration relationship in Table 5. We conduct cointegration tests on *RAHC*, and all strongly reject the null hypothesis, indicating no cointegration among the variables. Panels A and B demonstrate that the cointegration relationship is verified with or without a homogenous long-run variance when using the Pedroni (1999, 2004) method. The test based on the Kao (1999) method also indicates a cointegration relationship with our selected variables in panel C. As demonstrated by the augmented Dickey–Fuller statistic, a strong long-run cointegration relationship exists in our variables.

We conclude that there is a robust, long-term relationship between human capital and energy consumption. In the following, we examine the effect of human capital on energy consumption.

4.2. Effect of human capital on energy consumption

After confirming the existence of a cointegration relationship, we estimate the coefficients of model (4). Fixed (FE) and random effects models are commonly used for panel data. Our result at the bottom of Table 6 indicates that FE using the Hausman test is more appropriate for estimation. In Table 6, energy consumption fluctuations through human capital are reported by the fixed effect (FE) method in column (1). In column (2), we report the FE-IV results to preliminarily weaken the endogeneity by employing the first-order lagged export and GDP values. Because the right-hand side of the model contains the lag term of the dependent variable and GDP and export are

④Available from: http://humancapital.cufe.edu.cn/en/Human_Capital_Index_Project.htm

Table 1
Definitionof all variables.

Variables	Definition	Unit
PEC	Energy consumption divided by the total population	TCE/person
RAHC	Real average human capital	RMB
HEHC	The ratio of the population with college degree or above in total population	%
LEHC	The ratio of population with senior high school degree or below in total population	%
ETP	The stock of energy-saving patents	-
ETPE	The stock of energy-saving patents carried by enterprises	-
ETPR	The stock of energy-saving patents carried by research institutions	-
ETPC	The stock of energy-saving patents carried by colleges	-
ETPI	The stock of invention-oriented energy-saving patents	-
ETPU	The stock of utility-oriented energy-saving patents	-
PGDP	GDP divided by the total people	RMB
TLL	Theil index	-
URB	The ratio of urban population divided by total resident population	%
EX	The ratio of export divided by GDP	%
EP	The price index of purchasing fuel and power	-
HES	The ratio of the original value of total assets in the most six high energy-consuming industries to that in the overall industrial sectors	%

Notes: TCE stands for the standard coal equivalent.

Table 2
Descriptive statistics of the core variables

Variables	Obs	Mean	Std. Dev.	Min	Max
ln *PEC*	660	0.8	0.609	-0.726	2.334
ln *RAHC*	660	12.006	0.619	10.515	13.559
ln *ETP*	660	0.031	3.523	-7.580	7.407
ln *PGDP*	660	9.676	0.785	7.696	11.468
ln *TLL*	660	3.011	0.737	0.477	4.466
ln *URB*	660	3.807	0.366	2.642	4.503
ln *EX*	660	2.182	0.983	-0.328	4.598

Table 3
Correlation matrix of the variables

Variables	ln *PEC*	ln *RAHC*	ln *ETP*	ln *PGDP*	ln *TLL*	ln *URB*	ln *EX*
ln *PEC*	1.000						
ln *RAHC*	0.686	1.000					
ln *ETP*	0.610	0.896	1.000				
ln *PGDP*	0.726	0.931	0.881	1.000			
ln *TLL*	-0.238	-0.534	-0.337	-0.568	1.000		
ln *URB*	0.713	0.794	0.670	0.838	-0.613	1.000	
ln *EX*	0.161	0.293	0.152	0.387	-0.582	0.419	1.000

Table 4
Panel unit root tests

	IPS test	Fisher test			
	T	P	Z	L*	Pm
Panel A: levels					
ln *PEC*	-0.702	39.588	1.981	1.873	-1.863
ln *RAHC*	-1.019	42.064	2.956	3.202	-1.637
ln *PGDP*	1.832	42.156	5.214	5.237	-1.629
ln *ETP*	1.317	59.356	0.711	0.852	-0.059
ln *URB*	-5.176***	109.834***	-3.759***	-4.014***	4.549***
ln *EX*	-1.810**	90.828***	-1.277	-1.646*	2.814***
ln *TLL*	2.081	68.693	-1.224	-1.284	0.794
Panel B: first difference					
D.ln *PEC*	-11.584***	420.033***	-16.054***	-21.128***	32.866***
D.ln *RAHC*	-13.490***	434.226***	-16.541***	-21.856***	34.162***
D.ln *PGDP*	-4.834***	177.966***	-7.611***	-8.289***	10.769***
D.ln *ETP*	-11.735***	394.312***	-15.252***	-19.749***	30.518***
D.ln *URB*	-16.466***	495.343***	-18.256***	-24.885***	39.741***
D.ln *EX*	-18.534***	76.324***	-22.884***	-38.657***	64.478***
D.ln *TLL*	-14.707***	502.448***	-18.417***	-25.346***	40.390***

Notes: *, **, *** respectively represent the 10%, 5% and 1% significance level. For the IPS test the lag length is selected by minimizing Akaike Information Criterion (AIC) and panel means and time trend are included. For the *Fisher* test the lag order is set to be 1 and only panel means are included.

mutually causal with energy consumption, any serious endogeneity issues should be eliminated. Considering that the difference GMM (DIFF-GMM) estimator effectively addresses endogeneity issues, column (3) of Table 6 presents the corresponding estimates. In the DIFF-GMM estimator, the second-order and subsequent lag terms of the endogenous variables and the first-order and subsequent lag terms of the predetermined variables are regarded as our instrumental variables.

As shown in Table 6, human capital has a significantly positive impact on energy consumption. When human capital increases by 1%, energy consumption rises significantly by approximately 0.3%. Energy technological progress had minimal statistical significance on energy consumption. We find no evidence of a positive relationship of per capita GDP with energy consumption. The relationship between economic development and energy consumption remains mixed. The coefficient of the Theil index is significantly positive, indicating that economic structure optimization can influence the evolution of energy consumption, consistent with our expectations. A 1% decrease in the Theil index is associated with a 0.05% decrease in energy consumption.

Regarding other factors, urbanization increases energy consumption to meet daily life and production needs. If the urbanization level rises by 1%, an increase of 0.08% in energy consumption is expected. By contrast, we do not find an obvious correlation between export

Table 5
Panel co-integration tests

Panel A:Within-dimension (Pedroni,1999, 2004)	
Panel v-Statistic	-7.765***
Panel rho-Statistic	5.302***
Panel PP-Statistic	-3.751***
Panel ADF-Statistic	-4.252***
Panel B:Between-dimension (Pedroni,1999, 2004)	
Group rho-Statistic	7.347***
Group PP-Statistic	-3.049***
Group ADF-Statistic	-4.124***
Panel C: Kao (1999)	
Modified DF-Statistic	-0.409
DF-Statistic	-0.765
ADF-Statistic	-2.785***
Unadjusted modified DF-Statistic	-0.307
Unadjusted DF-Statistic	-0.696

Notes: *** respectively represents the 1% significance level. For the within-dimension and between-dimension test(Pedroni, 1999; 2004) the lagged length is selected by minimizing AIC and panel means and time trend are included. For the Kao (1999) test the lagged order is set as 2 and only panel means are included.

Table 6
The effect of human capital on energy consumption

No.	(1)	(2)	(3)
Method	FE	FE-IV	DIFF-GMM
L. ln *PEC*	0.921***	0.974***	0.885***
	(0.023)	(0.030)	(0.046)
ln *RAHC*	0.113*	0.221***	0.300***
	(0.061)	(0.068)	(0.083)
ln *ETP*	-0.004	0.002	-0.023
	(0.011)	(0.011)	(0.015)
ln *PGDP*	-0.075	-0.219***	-0.125
	(0.058)	(0.068)	(0.089)
ln *TLL*	0.054***	0.055***	0.056**
	(0.017)	(0.021)	(0.026)
ln *URB*	0.067**	0.046	0.083**
	(0.029)	(0.035)	(0.032)
ln *EX*	0.016	0.007	0.012
	(0.011)	(0.015)	(0.013)
ln *EP*	0.049*	0.036	0.079**
	(0.024)	(0.028)	(0.031)
Constant	-1.218	-1.007	
	(0.719)	(0.665)	
N	630	630	600
Hausman(P)	58.21(0)	79.88(0)	
AR(1)-P			0.002
AR(2)-P			0.446
Hansen-P			1

Notes: Values in parentheses denote the robust std.error for the coefficient. *, **, *** respectively represent 10%, 5% and 1% significance level. ln *PGDP* and ln *EX* are treated as the endogenous variables in FE-IV and DIFF-GMM estimator and the instruments are selected by using the collapse sub-option.

and consumption in energy. This implies that the impact of exports on energy consumption in China, which is determined by the types of export-oriented products, technology spillover, and other factors, remains uncertain. Moreover, EP appears to have a significant and positive impact on energy consumption, suggesting that energy prices fail to mitigate energy consumption because they are partially regulated by the government, and cannot accurately reflect the market signal.

We present a series of relevant statistics at the bottom of Table 6. *AR(1)* and *AR(2)* represent the first- and second-order autocorrelation, which checks the sequence correlation in our estimators. All results strongly accept the null hypothesis, suggesting that no second-order autocorrelation is present in the model, and our results are viable. The result for the Hansen test, which is used to determine whether an overidentification restriction exists, is also listed, confirming that no overidentification restriction is present in our estimators.

4.3. The influencing mechanism of human capital in energy consumption

After confirming that human capital is a strong driver of energy consumption, we next examine the three main channels of scale, technical, and structural effects using (Nguyen and Phan, 2020) proposed two-step analysis to determine whether mechanism effects exist. In the first step, we run a regression of human capital on mechanism effects. As expected, human capital has a positive impact on scale and technical effects and a negative impact on the structural effect. We next sort the mechanism effects from smallest to largest, dividing them into five equal parts, taking the subsamples in the highest tercile (5th) and lowest tercile (1st) to re-estimate the impact of human capital on energy consumption. If effects are present, the coefficients of human capital will significantly differ between the two subsamples because they represent a strong or weak channel effect.

4.3.1. The scale effect analysis

In Table 7, we first estimate the scale effect in columns (1)–(3), followed by higher-educated human capital in columns (4)–(6) and lower-educated human capital in columns (7)–(9). First, in column (1), the positive and significant coefficient of human capital suggests that human capital promotes economic growth. In columns (2) and (3), the positive and strongly significant coefficient (0.006) of human capital on energy consumption is shown in the highest tercile subsample (5th ln *PGDP*), whereas an insignificant coefficient (−0.017) is observed in the lowest tercile subsample (1st ln*PGDP*). The chi-square test at the bottom of Table 7 rejects the assumption of no difference in subsample coefficient size, revealing a notable discrepancy between the two tercile subsamples. Thus, the scale effect is an important mechanism between human capital and energy consumption; **H1** holds. Second, although scale effect is generally positive for resource consumption, higher-educated human capital values the environment more and consumes less energy, as previously discussed in Section 2. To address this, the impact of the scale effect and higher-educated human capital on energy consumption is estimated in columns (4)–(6). Higher-educated human capital significantly promotes the scale effect, but there is a negative coefficient in the highest subsample, and a significant disparity with the lowest subsample indicates that higher-educated human capital consumes less energy through the scale effect. It also implies that higher-educated human capital is more environmentally conscious. **H1a** is verified. Finally, we test the impact of lower-educated human capital on energy mitigation through the scale effect. As expected, lower-educated human capital expands economic scale and increases resource consumption, which is consistent with **H1b**.

The relevant statistics at the bottom of Table 7 are similar to those in Table 6.

Table 7
The scale effect analysis

No.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep =	ln *PGDP*	ln *PEC*		ln *PGDP*	ln *PEC*		ln *PGDP*	ln *PEC*	
Sample	Full	5^{th} ln *PGDP*	1^{th} ln *PGDP*	Full	5^{th} ln *PGDP*	1^{th} ln *PGDP*	Full	5^{th} ln *PGDP*	1^{th} ln *PGDP*
L.ln *PGDP*	0.921***			0.885***			0.900***		
	(0.022)			(0.043)			(0.032)		
L.ln *PEC*		0.501***			0.561***			0.470***	
		(0.126)			(0.054)			(0.085)	
ln *RAHC*	0.090**	0.006**	-0.017						
	(0.036)	(0.003)	(0.012)						
ln *HEHC*				0.126**	-0.038***	-0.004			
				(0.005)	(0.014)	(0.008)			
ln *LEHC*							0.087**	0.012*	-0.073***
							(0.041)	(0.007)	(0.023)
ln *ETP*	-0.006	0.022**		0.239***	0.052***		0.014**	0.027**	
	(0.007)	(0.012)		(0.009)	(0.013)		(0.006)	(0.013)	
ln *TLL*	0.023*	0.173*		0.028**	0.013		0.064***	0.041*	
	(0.014)	(0.091)		(0.014)	(0.026)		(0.013)	(0.023)	
ln *URB*	0.006	0.057		-0.019	-0.126		-0.008	-0.015	
	(0.020)	(0.056)		(0.013)	(0.151)		(0.020)	(0.056)	
ln *EX*	0.007	0.005		0.017**	0.048***		0.031***	0.022	
	(0.005)	(0.024)		(0.007)	(0.018)		(0.006)	(0.024)	
ln *EP*	0.066***	0.092		-0.002	0.124***		0.069***	0.095***	
	(0.016)	(0.058)		(0.012)	(0.041)		(0.017)	(0.035)	
Chi-squared test(P)		3.48(0.062)			4.54(0.033)			10.73(0.001)	
N	600	600		600	600		600	600	
AR (1)	0.017	0.087		0.001	0.004		0.001	0.047	
AR (2)	0.328	0.981		0.883	0.116		0.102	0.326	
Hansen-P	1	0.692		0.057	0.742		1	0.790	

Notes: Values in parentheses denote the robust std. error for the coefficient. *, **, *** respectively represent 10%, 5% and 1% significance level. ln*PGDP* and ln*EX* are treated as the endogenous variables in DIFF-GMM estimator and the instruments are selected by using the collapse sub-option.

4.3.2. The technical effect analysis

Similarly, estimates of technical effects are presented in Table 8. As previously applied, we first estimate the overall impact of human capital on energy consumption through technical effect and then examine what type of technical effects are the main mechanisms in detail. In columns (1)–(3), human capital has a positive effect on technical effect, as indicated by a coefficient of 0.422 with a 5% significance level. The subsample regression results reveal that the coefficient of human capital in the largest subsample (5th ln *ETP*) is smaller than the smallest subsample (1st ln *ETP*) and the chi-square test for coefficient difference is rejected. Technical effect plays a key role in energy mitigation driven by human capital. **H2** is also verified.

To determine which technical effects are dominant, we next consider different performers and purposes. In this regard, technical effect is divided into three different performers, namely, enterprises (ln *ETPE*), colleges (ln *ETPC*), and research institutes (ln *ETPR*), and into two purposes of invention-oriented (ln *ETPI*) and utility-oriented (ln *ETPU*) innovation. First, columns (4)–(12) present the technical effect carried by enterprises, research institutes, and colleges. As shown in chi-square tests, although human capital promotes the threefold technical effect, only the technical effect of enterprises is significant, compared with the results of research institutes and colleges. This implies that technical effects on energy mitigation driven by human capital are primarily contributed by enterprises, verifying **H2a**. Second, the results of different purposes of technical effect are presented in columns (13) – (18), indicating that utility-oriented technical effect, rather than invention-oriented technical effect, reduces energy consumption caused by human capital, confirming **H2b**.

The statistics at the bottom of Table 8 confirm the validity of our results.

4.3.3. The structural effect analysis

Finally, the structural effect is analyzed in Table 9. The estimated results suggest that human capital optimizes industrial structure and consumes less energy by reducing the Theil index as the negative coefficient in the lowest (1st ln *TLL*, the strong structural effect) tercile subsample demonstrates. Thus, the structural effect has a role, and **H3** is verified.

In summary, on the basis of the results in Tables 7–9, the positive influence of human capital on energy consumption is primarily correlated with the scale effect. However, owing to valuing the environment more highly, higher-educated human capital reduces energy consumption through the scale effect, but lower-educated human capital does not. Compared to the scale effect, both the technical and structural effects of human capital reduce energy consumption. Moreover, the technical effects generated by enterprises and utility-oriented innovations have a dominant influence on energy mitigation from human capital.

4.4. Robustness tests

To check the robustness of our models, various tests, including replacement of control variables and eliminating crowding-out effects, are applied below.

First, in economic structure measurement, shifting from high-energy-intensive industries to high-tech industries is significant because the energy required to produce one unit of GDP in some

Table 8
The technical effect analysis.

No.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep =	ln *ETP*	ln *PEC*		ln *ETPE*	ln *PEC*		ln *ETPR*	ln *PEC*	
Sample	Full	5th ln *ETP*	1th ln *ETP*	Full	5th ln *ETPE*	1th ln *ETPE*	Full	5th ln *ETPR*	1th ln *ETPR*
ln *RAHC*	0.422** (0.172)	-0.006** (0.001)	-0.002** (0.001)	0.982* (0.580)	-0.005*** (0.001)	-0.001 (0.002)	0.954* (0.576)	-0.004*** (0.001)	-0.007*** (0.002)
Control variables	Yes	Yes		Yes	Yes		Yes	Yes	
Chi-squared test(P)		3.59(0.058)			3.81(0.051)			1.52(0.218)	
N	600	600		600	600		600	600	
AR (1)	0.008	0.008		0.011	0.007		0.010	0.003	
AR (2)	0.251	0.346		0.911	0.193		0.328	0.395	
Hansen-P	1	1		1	1		1	1	
No.	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Dep =	ln *ETPC*	ln *PEC*		ln *ETPI*	ln *PEC*		ln *ETPU*	ln *PEC*	
Sample	Full	5th ln *ETPC*	1th ln *ETPC*	Full	5th ln *ETPI*	1th ln *ETPI*	Full	5th ln *ETPU*	1th ln *ETPU*
ln *RAHC*	1.876* (1.102)	-0.006*** (0.001)	-0.003 (0.002)	0.659** (0.275)	-0.009*** (0.003)	-0.015*** (0.003)	0.426** (0.179)	-0.012*** (0.003)	-0.006*** (0.001)
Control variables	Yes	Yes		Yes	Yes		Yes	Yes	
Chi-squared test(P)		1.00(0.318)			1.82(0.177)			4.08(0.043)	
N	600	600		600	600		600	600	
AR (1)	0.004	0.002		0.026	0.001		0.008	0.001	
AR (2)	0.766	0.385		0.758	0.824		0.203	0.662	
Hansen-P	1	1		1	1		1	0.984	

Notes: Values in parentheses denote the robust std. error for the coefficient. *, **, *** respectively represent 10%, 5% and 1% significance level. ln*PGDP* and ln*EX* are treated as the endogenous variables in DIFF-GMM estimator and the instruments are selected by using the collapse sub-option. For brevity, control variables contain all dependent variables lagging terms, ln*PGDP*, ln*TLL*, ln*URB*, ln*EX* and ln*EP*.

energy-intensive industries is much higher than that in high-tech industries (Li and Tao, 2017). We subsequently introduce the proportion of the original value of total assets in the six highest energy-intensive industries to that of the overall industrial sectors (%) as a proxy for economic structure⑤. The DIFF-GMM estimators are used to estimate model (4), and the corresponding results are reported in column (1) of Table 10 and are consistent with the results in Table 6, once again confirming that our empirical results are robust and effective.

Second, energy consumption may have a crowding-out effect on human capital, particularly for energy-intensive provinces, and may influence our estimation technique and analysis scope. To address this, in columns (2)–(4) of Table 10, the influence of energy consumption on human capital outflow is estimated. The results of FE, FE-IV, and DIFF-GMM estimators reveal no significant evidence of energy consumption being responsible for human capital outflow. To illustrate this further, limiting our sample to the top 25% of provinces with the highest energy consumption, we re-estimate the impact of energy consumption on human capital in column (5). The negative coefficient denotes that there is indeed a crowding-out effect on human capital in energy-intensity provinces, but this effect is negligible and hardly affects the empirical results.

At the bottom of Table 10, we present other relevant statistics, similar to previous iterations.

5. Conclusions and policy implications

Facing the reality of enormous energy consumption, China urgently needs to identify its driving factors to implement accurate energy-saving strategies. Unlike previous literature, this paper focuses on the influence of human capital on energy consumption. The major conclusions and policy implications are presented below.

5.1. Conclusions

On the basis of an extended version of the STIRPAT framework, this study estimated the impact of human capital on energy consumption using a panel dataset of China's 30 provincial regions from 1997 to 2018. Our research demonstrated that human capital can increase energy consumption. In particular, the positive effect of human capital on energy consumption primarily stems from the scale effect, but higher-educated human capital consumes less energy through the scale effect. Moreover, both the technical and structural effects reduce energy consumption driven by human capital, and the technical effect contributed by enterprises and utility-oriented technical innovation have a dominant influence on energy mitigation from human capital.

5.2. Policy implications

The conclusions above lead to some important implications for policymakers. First, China should pay considerable attention to accumulating and expanding its stock of human capital. The real average human capital presents an increasing trend on a national level during the period of 1985 – 2018. However, although China's development speed has been high, its human capital remains low compared to the rest of the world. Consequently, the government of China should initiate active measures to improve the quality of human capital (e. g., through education, training, practical experience, and other feasible approaches) as this also has a key role in energy consumption. Adjust-

⑤On the basis of the National Development and Reform Commission in China, the six most high-energy-consuming industries are petroleum processing; coking; nuclear fuel processing; production of raw chemical materials, chemical products, and nonmetallic mineral products; smelting and pressing of ferrous and nonferrous metals; and production and supply of electric and thermal power.

Table 9
The structural effect analysis.

No.	(1)	(2)	(3)
Dep =	ln *TLL*		ln *PEC*
Sample	Full	5^{th} ln *TLL*	1^{th} ln *TLL*
L.ln *TLL*	0.333*** (0.107)		
L.ln *PEC*			0.913*** (0.024)
ln *RAHC*	-0.546* (0.325)	0.001 (0.001)	-0.004*** (0.001)
ln *PGDP*	0.773** (0.395)		-0.071 (0.059)
ln *ETP*	-0.115 (0.070)		0.006 (0.010)
ln *URB*	-0.045 (0.101)		0.138*** (0.038)
ln *EX*	0.010 (0.043)		0.026* (0.014)
ln *EP*	0.112 (0.070)		0.069*** (0.026)
Chi-squared test(P)			8.82 (0.003)
N	600		600
AR (1)	0.095		0.001
AR (2)	0.547		0.327
Hansen-P	1		1

Notes: Values in parentheses denote the robust std. error for the coefficient. *, **, *** respectively represent 10%, 5% and 1% significance level. ln*PGDP* and ln*EX* are treated as the endogenous variables in DIFF-GMM estimator and the instruments are selected by using the collapse sub-option.

ing the structure of human capital should also be emphasized, rationalizing the distribution of human capital across regions to ensure that people of all social strata have equal rights to education. In particular, policies should focus on attracting high-quality human capital to inland regions. Furthermore, China should increase national investments in higher education to develop human capital, which will have a leading influence on energy conservation, and compulsory education should apply to the majority of the population.

Second, because technological progress promotes energy conservation, it is important for China to increase funding for technological R&D, particularly energy-saving innovation activities. Moreover, owing to the significant impact on technological progress generated by enterprises and utility-oriented innovation on energy mitigation, practical enterprise technological innovation should be encouraged.

Third, updating and optimizing the economic structure should be prioritized in the national development strategy, and it is essential for China to accelerate the transformation of its industrial structure to tertiary industry. At the same time, through restructuring, innovation, taxation, and other approaches, the production modes of energy-consuming industries should be transformed and the structure of exportation adjusted. In the future, China should reduce its dependence on energy for exportation, exporting high value-added and technology-intensive products.

Finally, urbanization is one of the most remarkable processes in China. Currently, over half of the total population resides in urban areas, exerting tremendous pressure on China's control of energy consumption. Given that high education is correlated with environmental concern, advocating an energy-saving urban lifestyle by increasing the use of public transportation instead of private cars could be popular.

Table 10
Robustness check

No.	(1)	(2)	(3)	(4)	(5)
Method	DIFF-GMM	FE	FE-IV	DIFF-GMM	DIFF-GMM
Dep =	ln *PEC*	ln *RAHC*	ln *RAHC*	ln *RAHC*	ln *RAHC*
L.ln *PEC*	0.866***				
	(0.047)				
L.ln *RAHC*		0.806***	0.805***	0.509***	0.683*
		(0.018)	(0.017)	(0.071)	(0.405)
ln *RAHC*	0.275***				
	(0.082)				
ln *PEC*		-0.009 (0.013)	-0.009 (0.012)	-0.003 (0.068)	-1.747*** (0.657)
ln *PGDP*	-0.097	0.096***	0.095***	0.412***	2.890**
	(0.086)	(0.019)	(0.016)	(0.153)	(1.413)
ln *ETP*	-0.022	0.006	0.006*	-0.016	-0.181
	(0.015)	(0.004)	(0.004)	(0.013)	(0.115)
ln *TLL*	0.051**	0.011	0.061	-0.034	-0.314*
	(0.025)	(0.006)	(0.044)	(0.029)	(0.162)
ln *URB*	0.086**	0.025	0.023	0.133	-0.445
	(0.033)	(0.016)	(0.016)	(0.126)	(0.453)
ln *EX*	0.014	0.003	0.006	-0.020*	0.112*
	(0.013)	(0.004)	(0.004)	(0.010)	(0.059)
ln *EP*	0.070**	0.008	0.007	-0.038**	0.221*
	(0.031)	(0.008)	(0.008)	(0.016)	(0.134)
ln *HES*	0.056				
	(0.042)				
Constant		1.295*** (0.250)	1.325*** (0.241)		
N	600	630	630	600	160
Hausman(P)		152.20(0)	147.7(0)		
AR(1)-P	0.001			0.005	0.009
AR(2)-P	0.473			0.508	0.144
Hansen-P	1			0.622	1

Notes: Values in parentheses denote the robust std. error for the coefficient. *, **, *** respectively represent 10%, 5% and 1% significance level. ln *PGDP* and ln *EX* are treated as the endogenous variables in DIFF-GMM estimator and the instruments are selected by using the collapse sub-option.

Disclosure statements

No potential conflict of interest was reported by the authors.

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