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# Energy Poverty, Internal Immigration, and Sustainable Development: Empirical Evidence from China

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**Abstract:** This study examines the impact of energy poverty on internal immigration based on the current situation in which reducing energy poverty is a necessary condition for ensuring sustainable development. The threshold effects model is applied to verify the significance of energy poverty in the prediction of internal immigration. The main results suggest that energy poverty significantly and negatively affects internal immigration. A heterogeneity analysis between coastal and non-coastal regions shows that the effects are more pronounced in non-coastal regions than in coastal regions. Further analysis reveals that there exists a kink in the threshold effects. The results remain robust using the specification of the kink threshold effects model. The policy implication is that a balanced development of energy infrastructure in different regions is required to achieve better social welfare for migrants.

**Keywords:** energy poverty; internal immigration; threshold effects; China

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## 1. Introduction

Energy poverty is one of the most critical issues associated with sustainable development. Reducing energy poverty can promote residents' health and quality of life and can balance the relationship between economic development and environmental pressure, which meets the United Nations Sustainable Development Goals [1,2]. From a global perspective, the problem of energy poverty is much more serious in developing and underdeveloped countries than in developed countries because of imbalanced economic development. China, the second-largest economy, faces a more complicated and more severe situation of energy poverty. Even though China has made remarkable achievements in providing energy services, such as achieving complete electrification in 2014 [3], the distributional mismatch between energy resources and consumption is still a crucial problem. By the end of 2020, the western regions of China accounted for about 80% of national energy resources, while less than 30% of national energy was consumed. However, the eastern regions (e.g., the Yangtze River Delta and the Pearl River Delta) consumed more than 33% of national energy, while the energy resources only accounted for 5% of the whole country [4]. This inconsistency is rooted in the uneven and enormous disparities in the economic development of the Chinese territory.

The term energy poverty has two main factors, which are difficulties in energy accessibility and affordability. Energy inaccessibility refers to residents having difficulty obtaining modern clean energy services, such as domestic power; liquefied gas; natural gas; service of solar water heaters; service of solar houses; service of ventilators; and service of clean cookers [5]. Even though the problem of energy poverty has improved over recent years in China, there are still lots of people who rely on traditional energy for living. In addition, increasing research has begun to notice the affordability of clean energy. It is a complex and strict problem in China that relates to significant income disparities among areas. The best-known standard of energy affordability is the ten percent rule, which was introduced

by Boardman [6]. This explains that, if the total expenditure on energy in a household is more than 10 percent of the whole disposable income, the household may be in a dilemma of energy poverty.

Some stylized facts on energy poverty and internal immigration are presented. Figure 1 presents the geographic distribution of energy poverty in China, which shows that the western provinces have a much more severe energy poverty situation, especially Tibet and Qinghai. Meanwhile, the demographic structure in China is also changing rapidly in different regions. Based on the Seventh National Population Census, the number of migrants increased to 493 million in 2020, which is around two times higher than in 2010. Figure 2 shows the geographic distribution of immigrants in China, with Guangdong, Shanghai, Jiangsu, and Zhejiang having a higher attraction for migrants. Hence, it is an interesting and pertinent question to investigate how energy poverty affects immigration. To demonstrate their close relationship intuitively, Figure 3 plots the top 20 regions with the highest immigration rates and their energy poverty indexes in 2020, which shows that the provinces with a lower energy poverty level also have a higher immigration rate.




**Figure 1.** The geographic distribution of the energy poverty index in China. Source: calculated by authors.

The main contributions and novelties of this research are summarized as follows: First, to the best of our knowledge, it is pioneering to consider that energy poverty is a valid factor for predicting internal immigrant rates in China, which has never been explored in the existing literature. Today, migration is one of the most important economic and social issues facing the aging Chinese society. Although there exists a mass of literature on the determinants of migration, most previous studies mainly focus on traditional factors. An innovative interpretation based on the energy poverty perspective is urgently needed. Second, the most updated population census data and energy poverty index are utilized, which can provide comprehensive information to successfully achieve our research goals. Third, a novel panel threshold model is employed to find out the threshold effects of energy poverty on internal immigration. Fourth, the research findings have practical policy

implications, such as promoting accessible, affordable, and clean energy reforms to achieve sustainable development.

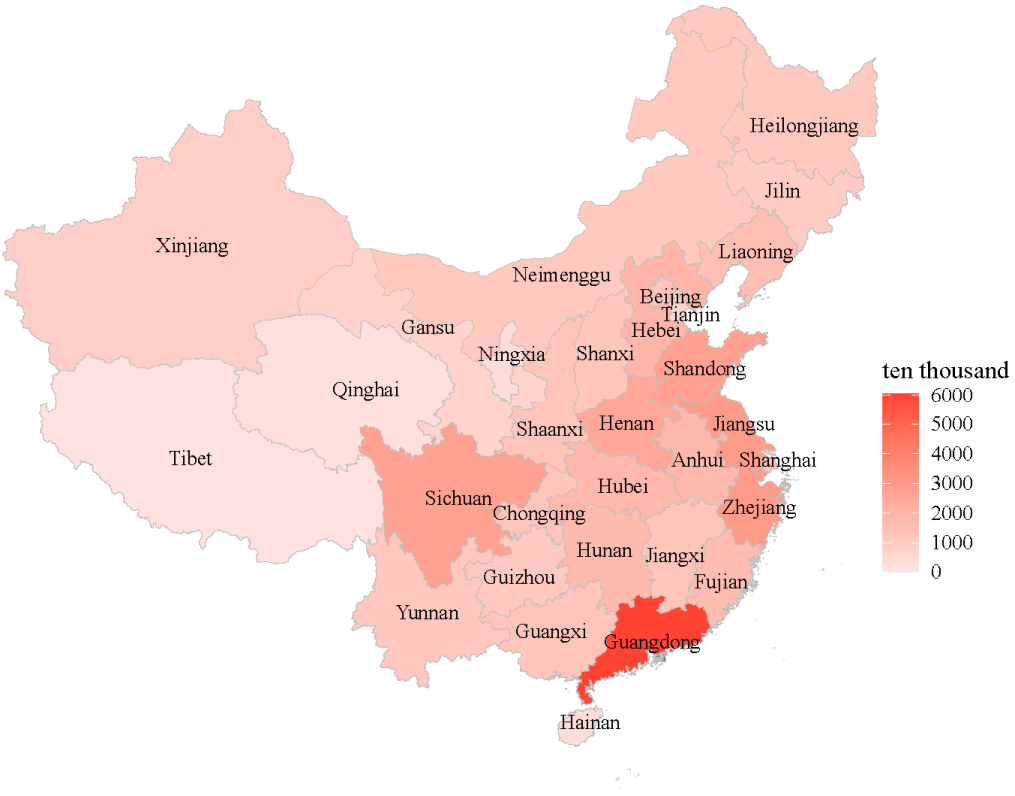



**Figure 2.** The geographic distribution of immigrants in China. Source: China Statistical Yearbook.

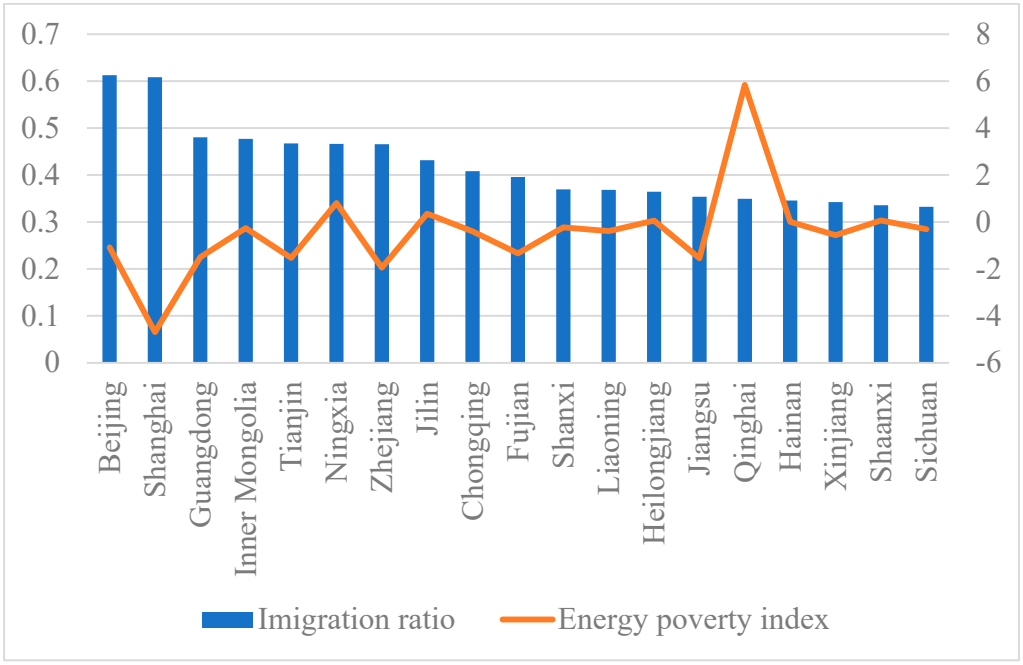



**Figure 3.** Top 20 regions with highest immigration rates and related energy poverty index. Source: immigration ratio is from the China Statistical Yearbook, 2020; energy poverty index 2020 is calculated by the authors.

## 2. Literature Review

The influence of energy poverty on social factors has been widely studied in many different aspects, such as economic performance [7] and social stability [8]. Since energy poverty will have impacts at both the micro- and macro-levels, we pay special attention to the micro-level because migration decisions are made by a person. Among these studies, the impacts on health and environmental equality are the most relevant to immigration.

Regarding the impacts of energy poverty on personal health conditions, many related studies have been published in recent years. For example, Yun et al. [9] proved that energy poverty negatively influences residents' health. Indoor combustion emissions can increase household air pollution of PM 2.5. Due to the low accessibility to clean energy, the risk of residents' illnesses and death is increased. This situation is more problematic in Chinese rural areas than in urban areas. Therefore, clean fuel should be widely promoted to mitigate the negative impact on health conditions. Zhang, Li, and Han [3] further proposed a multidimensional measurement to prove that energy poverty is a serious problem in China. Households that fall into the energy poverty trap would have trouble obtaining convenient forms of energy, such as heating for warming in winter or air conditioners for cooling in summer. They would usually choose to burn solid fuel for indoor cooking and warming, which causes worse health conditions. Thus, it is urgent to improve the construction of energy infrastructure to alleviate energy poverty. In addition, there are also some studies showing the consequences of energy poverty on mental health. Tod and Thomson [10] mentioned that mental disease is common among all age groups that fall into energy poverty, especially for residents who have trouble solving the heating problem in winter. Living in cold housing increases the probability of contracting colds and flu recurrently. Under the torture of disease, residents will easily fall into depression. Hence, it is vital to improve residents' health by reducing energy poverty.

Energy poverty has been seen as an effective indicator of environmental equality. Households with a lower income have a lower ability to afford sustainable energy and are compelled to use much cheaper and high-polluting fuels. In particular, during the long period of the pandemic, the situation was much more serious [11]. Thus, households with severe energy poverty have a higher probability of becoming entrepreneurs to expand their ways of obtaining a higher income due to challenge-based theory [12]. Nguyen and Su [13] further explained that energy poverty matters for gender environmental inequality resulting from the large gender income gap. Particularly impacted by traditional opinions, women have fewer opportunities to find higher-salary jobs. Thus, energy poverty is much more acute among women. It is noted that the pursuit of better health conditions and higher income levels is always thought to be the reason why residents migrate [14,15]. Unfortunately, the studies on energy poverty and migration are separate. Therefore, this research attempts to fill the gap between energy poverty and internal immigration.

## 3. Theoretical Development and Hypothesis

This section investigates the mechanism by which energy poverty affects internal immigration. We argue that energy poverty can influence migration decisions through three important channels, which are green macroeconomic growth, job market opportunities, and personal health. The justification of these three channels is presented below.

For the channel of green macroeconomic growth, energy poverty is negatively related to local green economic development. This justifies the notion that green macroeconomic growth relates to internal migration. There is a prominent disparity in green economic inequality and electricity accessibility across different provinces in China. In particular, provinces with a lower economic level (e.g., Guizhou, Sichuan, and Yunnan) have relatively lower energy accessibility. Meanwhile, provinces with a higher green economic growth rate (e.g., Beijing, Shanghai, and Guangdong) have a relatively higher energy accessibility [16]. The deepening green economic gap among regions in turn reflects the construction capacity of energy infrastructure. Therefore, regions with outstanding economic performance could easily support residents' demand for energy and achieve "green development" [17]. It

is noted that areas with a higher green economic growth also have higher immigration rates [18]. Combining the potential relationship between green economic growth and energy poverty, areas with lower energy poverty will be more attractive to immigrants.

For the channel of job market opportunities, areas with high energy poverty often provide scarce vacancies. This justifies the notion that job market opportunities strongly affect internal migration. Moreover, energy poverty will also lead to a high level of income inequality [19]. In view of energy accessibility, households with lower incomes have a lower capacity to obtain energy, while in view of energy consumption, a higher share of energy expenditure is also a common phenomenon among low-income households [20]. Specifically, poverty experience can motivate a person's grasp of entrepreneurship, which is consistent with the theory of underdog entrepreneurship proposed by Miller and Le Breton-Miller [21]. Thus, residents have incentives to migrate to regions with higher incomes and more job opportunities to avoid energy poverty.

For the channel of health conditions, energy poverty is proven to be harmful to residents' health [22]. This justifies the notion that health conditions influence internal migration. For regions with a lower ability to access clean energy, residents mainly depend on traditional energy, which emits harmful gas resulting in air pollution exacerbation. In addition, rising mental health problems have a significantly positive relationship with poverty experience [23]. Being energy-poor can even hurt a person's self-esteem as a result of systematic dependence on social welfare [24]. Thus, there is no doubt that residents are more willing to live in areas with lower energy poverty. Therefore, we posit the first hypothesis as follows:

**H1.** *Energy poverty has a negative effect on internal immigration.*

Energy poverty shows great disparities among different areas in China. Non-coastal areas have a more serious growing problem of energy poverty than coastal areas. This phenomenon is related to the disparities in economic patterns among areas [25]. Since resource-type economies play an important role in non-coastal areas, non-coastal areas have a higher sensitivity to energy changes. Coastal areas have entered a new type of urbanization, which depends on the internet service sector. This service sector has a strong promoting effect on absorbing migrant labor. Thus, coastal areas have less dependency on energy change and have a higher accessibility to energy due to higher income levels [26]. Michieka et al. [27] further showed that, due to coal being limited in time and location, resource-type economies are not sustainable. In the long run of the energy transition, workers in labor-intensive industries will obtain lower wages or even lose their jobs due to the weakening competitiveness of the traditional energy industry. Thus, laborers have a stronger willingness to migrate to overcome the limitations of energy constraints, which is much more obvious in non-coastal areas.

In addition, energy poverty is related to subjective well-being. Zhang et al. [28] found that energy poverty decreases the level of residents' life satisfaction. The usage of solid fuels causes indoor air quality to worsen. It has a negative impact on people's health conditions. Thus, people who live in energy poverty have a lower life satisfaction. They also desperately hope to migrate for a higher life quality. According to the survey of China's Happiest City in the year 2022, there are only four cities from non-coastal areas in the top ten happiest cities by provincial capitals. Thus, the energy poverty effects on internal immigration should be much greater in non-coastal regions. The second hypothesis is proposed as follows:

**H2.** *The effects of energy poverty on internal immigration only exist in non-coastal regions and do not exist in coastal regions.*

## 4. Methodology

### *4.1. Panel Threshold Model*

In the empirical study, the panel threshold model is employed due to two reasons. First, the panel threshold model has excellent performance in capturing nonlinearity (e.g., the relationship between internal migration and energy poverty). It specifies that samples can be distributed into classes based on the value of an observed factor. By introducing the threshold value of energy poverty, the model allows for a more flexible and accurate representation of internal migration relationships than a linear model. Second, the panel threshold model provides interpretable insights by identifying and estimating threshold values of energy poverty. It can help us to identify critical points in the sample that provide a much clearer understanding of the relationship. Whether there exist threshold effects of energy poverty on internal immigration in China is our main question. Following Hansen [29], a panel threshold model is employed. The single threshold model is written as

$$IM_{it+1} = \theta_1 POV_{it} + \theta_2 Z_{it} + \beta_1 GDP_{it} I(POV_{it} \leq \gamma) + \beta_2 GDP_{it} (POV_{it} > \gamma) + \mu_i + e_{it}$$

The subscript $i$ represents province, and the subscript $t$ represents time. The dependent variable is the total number of provincial internal immigrants ($IM_{it+1}$) at time $t+1$. One year forward is taken to alleviate the endogenous problem. $\mu_i$ represents individual unobserved effects. The within transformation is used to remove the individual unobserved effects, where * is used to denote such a transformation. The main independent variable is provincial energy poverty ($POV_{it}$). $Z_{it}$ includes a series of control variables, such as the unemployment rate ($UNE_{it}$), the old-age dependency ratio ($OLD_{it}$), the air pollution ($AIR_{it}$), and the total domestic water consumption ($WAT_{it}$). $I(\cdot)$ is the indicator function, while the observations are divided into two parts depending on whether threshold variable $POV_{it}$ is smaller or larger than threshold $\gamma$. The specification of the model includes one slope coefficient on GDP, because economic development is the key variable of interest that plays a central role in attracting immigration. Specifically, the influence of energy poverty on immigration could show high disparities among different levels of economy. Hence, GDP is used to as a critical value to differentiate energy poverty. Finally, $e_{it}$ is an error term with mean zero and constant variance.

Ordinary Least Squares (OLS) is always used to estimate the slope coefficient $\beta$ for any set $\gamma$ as follows:

$$\hat{\beta}(\gamma) = (POV^*(\gamma)' POV^*(\gamma))^{-1} POV^*(\gamma)' IM^*$$

The regression residual vector is

$$\hat{e}^*(\gamma) = IM^* - POV^*(\gamma)\hat{\beta}(\gamma)$$

The summation of squared errors $S_1(\gamma)$ is

$$S_1(\gamma) = \hat{e}^*(\gamma)'\hat{e}^*(\gamma) = IM^{*\prime}(\mathbf{1} - POV^*(\gamma)'(POV^*(\gamma)\prime POV^*(\gamma))^{-1} POV^*(\gamma)\prime) IM^*$$

where **1** is the identity matrix. The estimation of $\gamma$ is achieved by minimizing the above equation, which could be seen as

$$\hat{\gamma} = \underset{\gamma}{argmin} S_1(\gamma)$$

After obtaining $\hat{\gamma}$, the slope estimator can be solved as $\hat{\beta} = \hat{\beta}(\hat{\gamma})$. $\hat{e}^* = \hat{e}^*(\hat{\gamma})$ is the solution of the residual vector, while the residual variance is

$$\hat{\sigma}^2 = \frac{1}{n(T-1)} S_1(\hat{\gamma})$$

where $n$ represents the number of cross-sections, and $T$ represents the time.

The major concern here is whether the threshold effects are statistically significant. The null hypothesis is $\beta_1 = \beta_2$. If the null hypothesis is rejected, the model has threshold effects. The model under the null hypothesis is described as

$$IM_{it+1} = \theta_1 POV_{it} + \theta_2 Z_{it} + \beta_1 GDP_{it} + \mu_i + e_{it}$$

And considering the transformation, the model becomes

$$IM^*_{it+1} = \theta_1 POV^*_{it} + \theta_2 Z^*_{it} + \beta_1 GDP^*_{it} + e^*_{it}$$

The statistical test used is the F-test, which is calculated as

$$F_1 = (S_0 - S_1(\hat{\gamma}))/\hat{\sigma}^2$$

where $S_0 = \tilde{e}^{*\prime} \tilde{e}^*$, and $\tilde{e}^*$ is estimated using OLS.

Additionally, the possibility that there may be multiple thresholds cannot be ruled out directly, so the number of thresholds needs to be determined. The double-threshold model is assumed to be

$$\begin{aligned} IM_{it+1} = \theta_1 POV_{it} + \theta_2 Z_{it} + \beta_1 GDP_{it} I(POV_{it} \le \gamma_1) \\ + \beta_2 GDP_{it} I(\gamma_1 < POV_{it} \le \gamma_2) \\ + \beta_3 GDP_{it} I(\gamma_2 < POV_{it}) + u_i + e_{it} \end{aligned}$$

When fixing $\hat{\gamma}_1$, the criterion for $\hat{\gamma}_2$ is

$$S_2{}^r(\gamma_2) = \begin{cases} S(\hat{\gamma}_1, \gamma_2), \ \hat{\gamma}_1 < \gamma_2 \\ S(\gamma_2, \hat{\gamma}_1), \ \gamma_2 < \hat{\gamma}_1 \end{cases}$$

Thus, the estimation for $\hat{\gamma}_2{}^r = \underset{\gamma_2}{argmin} S_2{}^r(\gamma_2)$.

However, Bai [30] proved that $\hat{\gamma}_2{}^r$ is stable but $\hat{\gamma}_1$ is not. Thus, the criterion of $\hat{\gamma}_1$ is refined while fixing $\hat{\gamma}_2{}^r$:

$$S_1{}^r(\gamma_1) = \begin{cases} S(\gamma_1, \hat{\gamma}_2{}^r), \ \gamma_1 < \hat{\gamma}_2{}^r \\ S(\hat{\gamma}_2{}^r, \gamma_1), \ \hat{\gamma}_2{}^r < \gamma_1 \end{cases}$$

Thus, the estimation for $\hat{\gamma}_1{}^r = \underset{\gamma_1}{argmin} S_1{}^r(\gamma_1)$. The test value of whether to use two thresholds is based on the statistic

$$F_2 = \frac{S_1(\hat{\gamma}_1) - S_2{}^r(\hat{\gamma}_2{}^r)}{\hat{\sigma}^2}$$

where $\hat{\sigma}^2 = \frac{S_2{}^r(\hat{\gamma}_2^r)}{n(T-1)}$. If the test value is larger than the critical value, the two-threshold model is accepted. Then, we continue to test three thresholds using the same logic. If the two-threshold model is rejected, the one-threshold model is accepted.

### *4.2. The Kink Model*

Following Seo and Shin [31], we adopt the specification of the kink effect. There are two advantages of the kink model. First, it is similar to the panel threshold model, which captures threshold effects where the relationship between variables changes abruptly at a particular threshold. However, it further tests the situation of a kink (not a jump). Second, it has outstanding and flexible performance in explaining the impact of an intervention, which provides valuable information for our policy implications.

The panel threshold model can be written as

$$IM_{it+1} = \beta x_{it} + (1, x_{it})\delta\{POV_{it} > \gamma\} + u_i + \varepsilon_{it}$$

where $x_{it}$ includes exogenous variables or control variables; $POV_{it}$ is the threshold variable; $\delta$ is the parameter; $\gamma$ is the threshold; $u_i$ is the individual unobserved effects; and $\varepsilon_{it}$ is the error term. To avoid bias from $u_i$, the model is estimated via the first difference transformation using the Generalized Method of Moments (GMM). Thus, $u_i$ is removed. However, one of the $x_{it}$ variables may have a linear relationship with the threshold variable that causes a kink. The kink effect can be described as

$$(1, x_{it})\delta = K(POV_{it} - \gamma)$$

where $K$ is the kink slope. Under this specification, we establish the kink threshold model as

$$IM_{it+1} = \beta x_{it} + K(POV_{it} - \gamma)\delta\{POV_{it} > \gamma\} + u_i + \varepsilon_{it}$$

which is estimated through GMM [32].

### *4.3. Measurements of the Energy Poverty Index*

The concept of energy poverty is vast and often ambiguous. We adopt the most relevant conceptual interpretation in the existing literature that, for developing countries, energy poverty represents household hardship in accessing modern energy products. The lower the coverage of modern energy, the worse the energy poverty situation [33].

Practically, an energy poverty index is constructed to measure the provincial level of energy poverty in China, which is similar to Ren, Jiang, Narayan, Ma, and Yang [5]. The key to popularizing modern energy is promoting the usage of electricity and clean cooking fuels. Thus, multiple influencing factors are required to construct an energy poverty index. For example, these energy-indicating factors include (1) domestic power consumption per capita; (2) liquefied gas consumption per capita; (3) natural gas consumption per capita; (4) the coverage of solar water heaters per capita; (5) the coverage of solar houses per capita; (6) the popularity of ventilators per hundred households; and (7) the popularity of clean cookers per hundred households. The lower the use rate of each factor, the worse the energy poverty. The PCA method has been widely applied in energy studies (e.g., [34]). Considering that a principal component analysis has outstanding performance in obtaining necessary information and lowering the dimension of factors [35], the PCA method is used to establish an energy poverty index. The principal components acquired from the method are not dependent on each other and are obtained by weighting all factors. The first principal components listed have the largest contributions to establishing the index. To avoid the biased effects from the different units of energy poverty factors, these factors are all standardized, and the first component is finally used based on the rule of conventional cumulative proportion. The larger the index value, the worse the energy poverty. Table 1 presents the results of the PCA method, where the score of each factor is listed.

**Table 1.** Principal components from the PCA method of energy poverty.

| Variable | Comp1 | Comp2 | Comp3 |
|---|---|---|---|
| Domestic power consumption | −0.372 | 0.513 | 0.167 |
| Liquefied gas consumption | −0.02 | −0.2 | −0.177 |
| Natural gas consumption | 0.369 | 0.335 | −0.208 |
| Coverage of solar water heaters | 0.038 | 0.473 | −0.602 |
| Coverage of solar houses | 0.404 | 0.172 | 0.688 |
| The popularity of ventilators | −0.424 | 0.493 | 0.247 |
| The popularity of clean cookers | 0.618 | 0.299 | −0.024 |

### *4.4. The Control Predictors*

Immigration is a complicated problem that involves a series of theories, and a wide range of factors have been examined to determine their relationships with immigration. These factors can be generally divided into three parts, economic factors (GDP and UNE), demographic factors (OLD), and environmental factors (AIR and WAT).

GDP is a vital economic factor to reflect sustainable development. Kwilinski et al. [36] stressed that the immigration rate increases with a higher GDP per capita. Kwan et al. [37] stated that the scale of surplus labor in agriculture is still large, while GDP is promoted significantly with the industrial sector absorbing surplus labor. Hence, we include GDP to represent sustainable development in attracting internal immigration.

The unemployment rate is one of the most popular economic factors in analyzing immigration. According to the China Rural Development Survey, off-farm employment is accelerated, while labor flows mainly from rural to urban areas [38]. Specifically, off-farm employment and part-time employment are more sought after by migrants, which promotes farmland abandonment [39]. Thus, the unemployment rate (UNE) is used to measure the unemployment situation.

Age structure has always been a popular demographic factor in analyzing migration patterns [40]. In recent decades, rural–urban migrants have increased the labor supply in urban areas and stimulated the local economy [41]. Influenced by the birth control policy, China has entered an aging society [42], which will surely change migration patterns in the future. The surplus of agricultural laborers in China has been gradually diminishing [43]. The Lewis turning point refers to the special period of labor from the surplus stage to the shortage stage. This implies that China has passed the Lewis turning point and faces the challenge of labor shortages. Ren et al. [44] further proved that the aging problem has a huge impact on food security and agricultural sustainability. Farmers in the elderly age group have a relatively lower uptake rate of leading agricultural technology and weak physical strength in farming work. The negative effect of the aging problem on farming is prominent when labor productivity becomes much lower, and the income of elderly farmers decreases rapidly. Thus, elderly residents may reconsider migrating to a new place to improve their quality of life. Meanwhile, Gu, Jie, and Lao [14] found that there exists a significant inverted U pattern in elderly migration. Specifically, the eastern region had the highest absorption of older adults before 2005, while the attraction has been gradually decreasing since 2005. Considering that the age structure has changed and that the number of potential migrants is depleting, we include the old-age dependency ratio (OLD), which is measured by the population aged 65+ divided by the population aged 16–64 to reflect the age structure.

In recent years, some scholars have gradually paid attention to how environmental changes explain migration patterns globally [45]. Air pollution is one of the most important indicators affecting migration. With accelerating urbanization, air pollution has become a thorny problem that negatively influences residents' living quality and labor productivity [46]. Li et al. [47] proved that cities with serious air pollution lower the settlement willingness and house-buying intention of migrants. Moreover, air pollution has a significant negative effect on migrants' income levels. Considering that sulfur dioxide is a common factor of atmospheric pollutants, we use the emission of sulfur dioxide to evaluate air quality (AIR).

Besides climate change, water stress is one of the most detrimental risks influencing the development of the economy. It is estimated that increasing water scarcity will generate less hydropower, which can cause an economic loss of at least USD 3 trillion [48]. Specifically, the current global water consumption is huge, and many developing countries are facing serious water shortages. In China, the expanded urbanization and growing population have worsened water pollution, especially in coastal areas [49]. Du et al. [50] proved that the increasing number of migrants in coastal areas stimulated a higher need for water and exacerbated the water scarcity situation and water pollution patterns. Water stress will

reduce the living quality of migrants and lower their migration willingness. Based on this, this paper includes total domestic water consumption (WAT) to measure water stress.

## 5. Data

This research collects data from 2001 to 2020 for each province in China to explore the influence of energy poverty on internal immigration, and they were obtained from the China Statistical Yearbook, China Rural Statistical Yearbook, and China Provincial Statistical Yearbook. In addition, to eliminate the biasedness caused by the statistical system, the data exclude Hong Kong, Macau, and Taiwan. Detailed information on the variables, such as units, measurements, and sources, is listed in Table 2.

**Table 2.** Data description.

| Variable | Unit | Measurement | Source |
| --- | --- | --- | --- |
| Internal immigration (IM) | Person | The log of the number of internal immigrants. | China Statistical Yearbook |
| Energy poverty (POV) | Index | Index using principal component analysis (PCA) of the following factors: (1) domestic power consumption per capita; (2) liquefied gas consumption per capita; (3) natural gas consumption per capita; (4) coverage of solar water heaters per capita; (5) coverage of solar houses per capita; (6) popularity of ventilators per hundred households; and (7) popularity of clean cookers per hundred households. | Calculated by authors from China Statistical Yearbook; China Rural; Statistical Yearbook |
| Gross Domestic Product (GDP) | RMB per person | The log of the total real GDP divided by its total population. | China Statistical Yearbook |
| Unemployment rate (UNE) | Ratio | The unemployment rates. | China Statistical Yearbook |
| Age structure (AGE) | Ratio | The population aged 65+ divided by the population aged 16–64. | China Statistical Yearbook |
| Air pollution (AIR) | Ten thousand tons | The log of the sulfur dioxide emissions. | China Statistical Yearbook |
| Water consumption (WAT) | Billion tons | The log of the total domestic water consumption. | China Statistical Yearbook |

Table 3 shows the summary statistics of the variables. The second column shows the sample observations, and the third and fourth columns show the mean and standard deviation. The last two columns show the minimum and maximum values. For example, the standard deviation of the energy poverty index (POV) is 1.283. The minimum level is −4.689, and the maximum level is 11.663, which implies that energy is unevenly distributed in China.

**Table 3.** Summary statistics.

| Variables | Observations | Mean | SD | Min | Max |
| --- | --- | --- | --- | --- | --- |
| IM | 620 | 2,208,187.987 | 5,099,602.553 | 101.833 | 60,635,086.000 |
| POV | 620 | 0.000 | 1.282 | −4.689 | 11.663 |
| GDP | 620 | 35,705.631 | 27,609.334 | 3000.000 | 164,158.000 |
| UNE | 620 | 3.515 | 0.712 | 1.200 | 6.500 |
| OLD | 620 | 0.131 | 0.034 | 0.063 | 0.255 |
| AIR | 620 | 56.007 | 45.093 | 0.073 | 200.200 |
| WAT | 620 | 8.355 | 8.037 | 0.200 | 54.030 |

A pairwise correlation of the variables is shown in Table 4. For instance, the correlation between the energy poverty index (POV) and internal immigration (IM) is −0.201 and significant at the level of 0.01. The pairwise correlation analysis shows that multicollinearity can be negligible.

**Table 4.** Pairwise correlations.

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| (1) IM | 1 | | | | | | |
| (2) POV | −0.201 *** | 1 | | | | | |
| (3) GDP | 0.292 *** | −0.404 *** | 1 | | | | |
| (4) UNE | −0.132 *** | 0.039 | −0.429 *** | 1 | | | |
| (5) OLD | 0.289 *** | −0.408 *** | 0.501 *** | −0.025 | 1 | | |
| (6) AIR | −0.069 * | −0.107 *** | −0.365 *** | 0.227 *** | −0.118 *** | 1 | |
| (7) WAT | 0.400 *** | −0.450 *** | 0.424 *** | −0.246 *** | 0.292 *** | 0.126 *** | 1 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## 6. Empirical Results

### 6.1. Panel Threshold Model

The number of thresholds in a model should be identified first, which is shown in Table 5. They are estimated using OLS taking into account (sequentially) one, two, and three thresholds. The table includes two parts: the test statistics $F_1$, $F_2$, and $F_3$, along with their bootstrap $p$-values, while the default bootstrap number of 300 is adopted. It is found that the test for a single threshold $F_1$ is highly significant with a bootstrap $p$-value of 0.010. But the tests for double and triple thresholds ($F_2$ and $F_3$) are not statistically significant, with bootstrap $p$-values of 0.722 and 0.962, respectively. Therefore, the remainder of the analysis is based on the single-threshold model.

**Table 5.** Threshold effects test result.

| Threshold Effects Test | F Test | $p$-Value | Crit10 | Crit5 | Crit1 |
|---|---|---|---|---|---|
| Single threshold | $F_1 = 14.981$ *** | 0.010 | 11.286 | 12.648 | 14.763 |
| Double threshold | $F_2 = 5.942$ | 0.722 | 12.063 | 13.250 | 17.881 |
| Triple threshold | $F_3 = 6.093$ | 0.962 | 28.349 | 30.273 | 33.656 |

Notes: bootstrap repeats 300 times; Crit10, Crit5, and Crit1 represent the critical values in 10%, 5% and 1%, respectively; *** $p < 0.01$; ** $p < 0.05$, * $p < 0.1$.

The point estimate of the single threshold and the asymptotic 95% interval are reported in Table 6. The estimated numerical value of the threshold is 0.930, and the two classes of provinces indicated by the point estimates are those with "relative low energy poverty" ($\gamma \leq 0.930$) and "relative high energy poverty" ($\gamma > 0.930$). The confidence interval using likelihood ratio statistics is plotted in Figure 4. The value of $\gamma$, where the likelihood ratio intersects with the zero axis, is the point estimate. The 95% confidence interval for only one threshold is presented from the LR values by the values of $\gamma$, where the dotted line is above the likelihood ratio.

**Table 6.** Threshold value estimation.

| Model | Threshold Value | 95% Confidence Interval | |
|---|---|---|---|
| | | Lower | Upper |
| One threshold | 0.930 | 0.621 | 0.948 |

Table 7 shows the number of provinces that fall into the two classes in each year. It is an interesting result that the number of regions with a relatively higher energy poverty index rises rapidly from 2 to 5. There has been an upward trend in the number of relatively severe energy poverty regions since 2010.

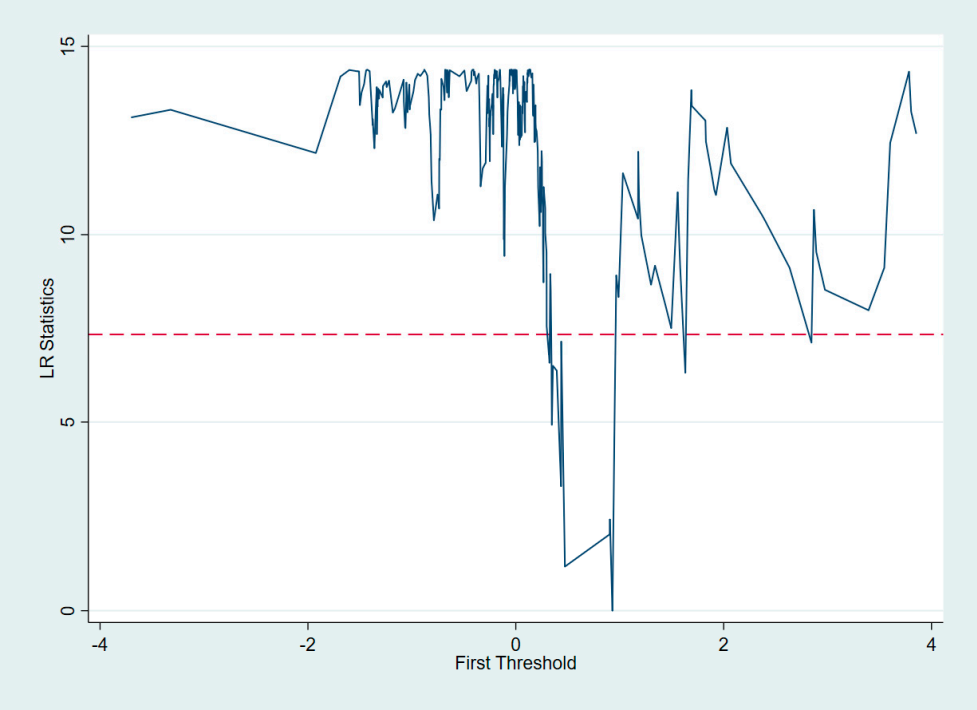



**Figure 4.** Confidence interval construction for a single-threshold model. Note: the confidence interval is 95%.

**Table 7.** Number of provinces in each class by year.

| Year | GDP (POV $\leq$ 0.930) | GDP (POV > 0.930) |
|---|---|---|
| 2001 | 29 | 2 |
| 2002 | 29 | 2 |
| 2003 | 26 | 5 |
| 2004 | 26 | 5 |
| 2005 | 27 | 4 |
| 2006 | 28 | 3 |
| 2007 | 28 | 3 |
| 2008 | 28 | 3 |
| 2009 | 28 | 3 |
| 2010 | 28 | 3 |
| 2011 | 27 | 4 |
| 2012 | 27 | 4 |
| 2013 | 27 | 4 |
| 2014 | 27 | 4 |
| 2015 | 27 | 4 |
| 2016 | 27 | 4 |
| 2017 | 27 | 4 |
| 2018 | 27 | 4 |
| 2019 | 27 | 4 |

Table 8 reports the panel threshold model results. Model (1) only includes the energy poverty index (POV) and the threshold effect item. Models (2)–(5) show the results when each control variable is added. Model (6) is the full model, which shows that energy poverty has significantly negative effects on internal immigration at the 0.01 level. Hypothesis 1 is supported. The point estimates suggest that internal immigration is positively related to GDP, with "relatively low energy poverty" provinces having a lower coefficient of 0.332 than the "relatively high energy poverty" provinces of 0.607. The results further support the notion that energy poverty has a threshold effect on internal immigration.

**Table 8.** Panel threshold model results.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | **IM** | **IM** | **IM** | **IM** | **IM** | **IM** |
| POV | −0.166 * | −0.190 ** | −0.141 | −0.072 | −0.167 * | −0.158 * |
| | (−1.904) | (−2.201) | (−1.588) | (−0.795) | (−1.960) | (−1.813) |
| UNE | | −0.489 *** | | | | −0.492 *** |
| | | (−3.897) | | | | (−3.879) |
| AGE | | | 0.042 | | | 0.016 |
| | | | (1.532) | | | (0.563) |
| AIR | | | | −0.271 *** | | −0.115 |
| | | | | (−3.610) | | (−1.398) |
| WAT | | | | | 1.486 *** | 1.385 *** |
| | | | | | (4.971) | (4.525) |
| GDP (POV ≤ 0.930) | 1.123 *** | 0.891 *** | 1.018 *** | 0.990 *** | 0.643 *** | 0.332 ** |
| | (13.285) | (8.678) | (9.355) | (10.827) | (5.056) | (2.191) |
| GDP (POV > 0.930) | 1.476 *** | 1.204 *** | 1.363 *** | 1.327 *** | 0.940 *** | 0.607 *** |
| | (13.101) | (9.173) | (10.144) | (11.172) | (6.101) | (3.474) |
| Constant | 7.043 *** | 10.027 *** | 7.066 *** | 8.712 *** | 7.080 *** | 10.860 *** |
| | (15.688) | (11.333) | (15.749) | (13.589) | (16.102) | (11.965) |
| AIC | 1747.070 | 1733.141 | 1746.581 | 1735.372 | 1723.372 | 1703.758 |
| R-sqrt | 0.275 | 0.295 | 0.279 | 0.292 | 0.306 | 0.336 |
| F-test | 70.321 | 57.886 | 53.455 | 57.143 | 61.170 | 39.809 |
| Observations | 589.000 | 589.000 | 589.000 | 589.000 | 589.000 | 589.000 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

### *6.2. Robustness Analysis*

Table 9 reports the result of the kink threshold model through GMM. Model (1) includes the energy poverty index (POV) and the kink item. Model (2) to Model (7) present the results when each control variable is added. It is noted that the POV is significant in all models, which further justifies the notion that the energy poverty negatively influences internal immigration. The kink slope is also significant in all models, which offers concrete support for the existence of a kink.

**Table 9.** Kink threshold model through GMM.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | **IM** | **IM** | **IM** | **IM** | **IM** | **IM** | **IM** |
| POV | −16.682 *** | 5.869 *** | −5.476 *** | −8.005 *** | 7.000 *** | 9.002 *** | −16.853 *** |
| | (−20.066) | (15.186) | (−10.509) | (−24.604) | (18.266) | (11.631) | (−7.616) |
| Kink slope | 16.971 *** | −4.485 *** | 1.273 * | 8.321 *** | 1.616 *** | −6.900 *** | 9.257 *** |
| | (20.592) | (−10.488) | (1.721) | (31.419) | (3.093) | (−8.825) | (3.670) |
| GDP | | 3.246 *** | | | | | 1.352 *** |
| | | (81.496) | | | | | (2.649) |
| UNE | | | −6.909 *** | | | | −3.837 *** |
| | | | (−48.891) | | | | (−8.129) |
| AGE | | | | 0.259 *** | | | −1.077 *** |
| | | | | (25.185) | | | (−9.588) |
| AIR | | | | | −2.801 *** | | 1.285 *** |
| | | | | | (−46.740) | | (9.100) |
| WAT | | | | | | 13.874 *** | 6.161 *** |
| | | | | | | (37.070) | (10.845) |
| Constant | −0.546 *** | −0.148 ** | −0.546 | 0.206 *** | −0.051 | −0.669 *** | −0.554 ** |
| | (−25.068) | (−2.516) | (−1.129) | (5.711) | (−0.293) | (−11.185) | (−2.499) |
| No. of province | 31.000 | 31.000 | 31.000 | 31.000 | 31.000 | 31.000 | 31.000 |
| No. of year | 19.000 | 19.000 | 19.000 | 19.000 | 19.000 | 19.000 | 19.000 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

### *6.3. Heterogeneity Analysis*

The internal immigration patterns in different regions are presented in Tables 10–13. To perform a regional heterogeneity analysis, the regions are divided into two groups, which are non-coastal areas and coastal areas based on the geographic location. Table 10 shows the panel threshold model results of non-coastal regions, and Table 11 shows the panel threshold model results of coastal regions. Model (6) in Table 10 shows that energy poverty significantly negatively influences internal immigration at the 0.01 level. Specifically, there exists a significant threshold effect of energy poverty through GDP on internal immigration. However, Model (6) in Table 11 indicates that, for coastal regions, there is no significant relationship between energy poverty and internal immigration, and even the threshold effect is not significant in coastal regions. The results imply that the influence of energy poverty is much more sensitive in non-coastal regions. Table 12 displays the kink threshold model through the GMM of non-coastal regions, while Table 13 reveals the coastal regions' GMM results. Model (7) in Table 12 is the full model of non-coastal regions, which shows that there exist negative influences of energy poverty on internal immigration. The kink slope is also significant in all models, which offers concrete support for the existence of a kink in non-coastal regions. However, in Table 13, there is still no significant effect of energy poverty on internal immigration and no kink effect in coastal regions. The results are consistent with Hypothesis 2.

**Table 10.** Panel threshold model results in non-coastal regions.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | **IM** | **IM** | **IM** | **IM** | **IM** | **IM** |
| POV | 0.160 ** | −0.193 * | −0.048 | −0.051 | 0.101 | −0.199 * |
| | (2.026) | (−1.960) | (−0.443) | (−0.493) | (1.285) | (−1.952) |
| UNE | | −0.901 *** | | | | −0.877 *** |
| | | (−5.201) | | | | (−4.931) |
| AGE | | | 0.063 | | | 0.009 |
| | | | (1.437) | | | (0.197) |
| AIR | | | | −0.266 *** | | −0.062 |
| | | | | (−2.749) | | (−0.573) |
| WAT | | | | | 1.476 *** | 1.336 *** |
| | | | | | (4.212) | (3.767) |
| GDP (POV $\leq$ 0.930) | 1.454 *** | 0.736 *** | 0.948 *** | 1.019 *** | 1.000 *** | 0.300 |
| | (11.381) | (6.035) | (5.975) | (9.387) | (6.068) | (1.593) |
| GDP (POV > 0.930) | 1.057 *** | 1.016 *** | 1.245 *** | 1.341 *** | 0.616 *** | 0.544 ** |
| | (10.168) | (6.971) | (6.642) | (9.773) | (4.227) | (2.534) |
| Constant | 7.267 *** | 12.160 *** | 7.004 *** | 8.317 *** | 7.462 *** | 12.552 *** |
| | (13.780) | (10.894) | (13.127) | (11.288) | (14.420) | (11.162) |
| AIC | 1147.163 | 1124.224 | 1152.328 | 1146.545 | 1130.682 | 1112.149 |
| R-sqrt | 0.302 | 0.346 | 0.296 | 0.306 | 0.335 | 0.376 |
| F-test | 51.397 | 47.084 | 37.383 | 39.321 | 44.791 | 30.435 |
| Observations | 380.000 | 380.000 | 380.000 | 380.000 | 380.000 | 380.000 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 11.** Panel threshold model results in coastal regions.

| | (1) IM | (2) IM | (3) IM | (4) IM | (5) IM | (6) IM |
|---|---|---|---|---|---|---|
| POV | −0.444 ** | −0.445 ** | −0.433 ** | −0.242 | −0.401 ** | −0.298 |
| | (−2.425) | (−2.425) | (−2.354) | (−1.097) | (−2.226) | (−1.348) |
| UNE | | −0.068 | | | | −0.151 |
| | | (−0.381) | | | | (−0.827) |
| AGE | | | 0.021 | | | −0.006 |
| | | | (0.616) | | | (−0.159) |
| AIR | | | | −0.221 | | −0.119 |
| | | | | (−1.621) | | (−0.798) |
| WAT | | | | | 1.724 *** | 1.715 *** |
| | | | | | (2.918) | (2.705) |
| GDP (POV ≤ 0.930) | 1.005 *** | 0.963 *** | 0.966 *** | 0.889 *** | 0.362 | 0.218 |
| | (6.169) | (4.855) | (5.509) | (5.010) | (1.327) | (0.685) |
| GDP (POV > 0.930) | 0.803 *** | 0.756 *** | 0.774 *** | 0.716 *** | 0.196 | 0.056 |
| | (3.976) | (3.192) | (3.727) | (3.441) | (0.681) | (0.166) |
| Constant | 8.000 *** | 8.479 *** | 7.926 *** | 9.568 *** | 7.748 *** | 9.681 *** |
| | (9.015) | (5.501) | (8.838) | (7.303) | (8.854) | (5.509) |
| AIC | 594.032 | 595.876 | 595.624 | 593.219 | 587.052 | 591.282 |
| R-sqrt | 0.261 | 0.261 | 0.262 | 0.270 | 0.292 | 0.298 |
| F-test | 22.896 | 17.133 | 17.212 | 17.973 | 19.963 | 11.559 |
| Observations | 209.000 | 209.000 | 209.000 | 209.000 | 209.000 | 209.000 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 12.** Kink threshold model through GMM in non-coastal regions.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | IM | IM | IM | IM | IM | IM | IM |
| POV | −52.729 *** | −17.660 *** | −8.918 *** | −17.444 *** | −31.950 *** | −18.957 *** | −28.750 *** |
| | (−13.606) | (−15.126) | (−11.023) | (−9.054) | (−11.685) | (−15.108) | (−12.546) |
| Kink slope | 51.985 *** | 17.693 *** | 10.755 *** | 14.694 *** | 33.807 *** | 21.933 *** | 28.793 *** |
| | (13.412) | (15.008) | (13.515) | (7.134) | (12.184) | (15.615) | (11.909) |
| GDP | | 0.243 * | | | | | −0.717 * |
| | | (1.860) | | | | | (−1.650) |
| UNE | | | 2.209 *** | | | | −5.230 *** |
| | | | (13.514) | | | | (−5.706) |
| AGE | | | | 0.132 *** | | | −0.694 *** |
| | | | | (7.002) | | | (−4.678) |
| AIR | | | | | 1.147 *** | | 1.872 *** |
| | | | | | (12.461) | | (8.178) |
| WAT | | | | | | 13.313 *** | 9.175 *** |
| | | | | | | (31.086) | (10.111) |
| Constant | −0.192 *** | 0.398 *** | −0.049 *** | −0.074 *** | 0.342 *** | 0.423 *** | 0.423 *** |
| | (−130.769) | (18.662) | (−2.941) | (−5.222) | (9.182) | (5.779) | (5.788) |
| No. of province | 20.000 | 20.000 | 20.000 | 20.000 | 20.000 | 20.000 | 20.000 |
| No. of year | 19.000 | 19.000 | 19.000 | 19.000 | 19.000 | 19.000 | 19.000 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 13.** Kink threshold model through GMM in coastal regions.

| | (1) IM | (2) IM | (3) IM | (4) IM | (5) IM | (6) IM | (7) IM |
|---|---|---|---|---|---|---|---|
| POV | −17.328 *** | −3.246 *** | −26.398 *** | −6.120 *** | −12.431 *** | −5.594 *** | −93.573 |
| | (−6.167) | (−3.681) | (−4.169) | (−6.274) | (−3.153) | (−6.261) | (−1.312) |
| Kink slope | 54.031 *** | 18.300 *** | 59.006 *** | 28.834 ** | 28.418 *** | 8.484 *** | 191.362 |
| | (6.341) | (4.934) | (3.960) | (2.292) | (3.050) | (4.361) | (1.447) |
| GDP | | −0.317 | | | | | 26.811 |
| | | (−0.642) | | | | | (0.386) |
| UNE | | | 0.437 | | | | 13.135 |
| | | | (0.363) | | | | (0.576) |
| AGE | | | | 0.169 ** | | | −0.126 |
| | | | | (2.384) | | | (−0.030) |
| AIR | | | | | −0.347 | | −1.405 |
| | | | | | (−0.889) | | (−0.408) |
| WAT | | | | | | 4.502 *** | −21.769 |
| | | | | | | (18.747) | (−0.320) |
| Constant | −0.591 *** | −0.493 *** | −1.059 *** | −0.160 ** | −1.047 *** | −0.665 *** | −1.244 *** |
| | (−34.913) | (−12.732) | (−37.515) | (−2.351) | (−39.339) | (−6.284) | (−33.492) |
| No. of province | 11.000 | 11.000 | 11.000 | 11.000 | 11.000 | 11.000 | 11.000 |
| No. of year | 19.000 | 19.000 | 19.000 | 19.000 | 19.000 | 19.000 | 19.000 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## 7. Conclusions

At present, energy poverty is regarded as a vital factor for sustainable development. This study utilizes an energy poverty index and attempts to investigate the effects of energy poverty on internal immigration. It is found that areas with a lower level of energy poverty attract more migrants. In particular, energy poverty also has a significant threshold effect through GDP on internal immigration. The results remain robust under the specification of the kink threshold model estimated using GMM. Energy poverty is still widespread in most places in China. And there is still a long way to go to continuously affect the social and economic perspectives, such as migration. Based on our findings, the policy implications are presented below.

First, central and local governments should support the construction of energy infrastructure and encourage residents to use clean energy to raise their life quality [51]. It is obvious that migrants from traditional sectors to modern sectors have a positive contribution to the sustainable development of economic growth in China [52], and this can be accelerated by the development of clean energy. Thus, the government and communities should also create opportunities for migrants to use clean energy conveniently. Consequently, they will have better conditions to increase their income and contribute to local economic development. Second, policymakers should pay attention to the specific energy needs of different kinds of migrants according to their personal characteristics, which should be more inclusive. For example, due to China having entered an aging society, governments face multiple social problems with older migrants [52]. There exist large difficulties for them in obtaining and using clean energy [53]. Thus, policymakers can strengthen their efforts to promote the awareness of clean energy by enhancing energy services and providing energy subsidies to reduce the living burden for the elderly.

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