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Convergence and distribution dynamics of energy consumption among China's households

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Abstract

Whether there will be a long-run equilibrium (steady state) in energy demand per capita is a critical question for energy and environmental policy makers. While many studies have been done on energy production and energy consumption, little attention has been paid to whether disparities in relative household energy consumption (RHEC) converge, and how the use of aggregated data has serious limitations. This paper is the first study to investigate the convergence and dynamics of household energy consumption in China. The results are helpful to Chinese policy makers when trying to identify the key groups for priority interventions. The study finds that variability in the RHEC is very high and that many households will likely change their energy consumption patterns in the coming years. Overall, Chinese households have two convergence clubs. The current dynamics will probably lead to lower energy consumption for most households. The study suggests that policy makers should pay particular attention to households that have too low or too high RHEC level, mainly in rural areas and in the western region.

Keywords: household energy consumption; convergence clubs; transitional dynamics; regional disparity; China;

JEL classification: C29; Q41; R29

1 Introduction

Whether there will be a long-run equilibrium (steady state) in energy demand per capita is a critical question for energy and environmental policy makers (Cheong et al., 2019). There are active debates in the energy economics literature on whether cross-sectional differences or convergence in energy-related measures across countries is equally applicable to households. While there are many studies devoted to energy production and energy consumption, little attention has been paid to whether disparities in relative household energy consumption (RHEC) diminish over time and whether urbanization and regional characteristics affect the RHEC in the long-run equilibrium (Chen et al., 2016; Cheng et al., 2019).

This question is particularly important for China because it has experienced a dramatic increase in energy consumption alongside its remarkable economic growth. China's energy use per capita increased from 0.77 tons of oil equivalent (toe) in 1990 to 2.3 toe in 2015, despite the energy intensity decreasing from 21 Mega Joule (MJ)/$2011 PPP GDP to 6.7 MJ/$2011 PPP GDP over the same time period (World Bank, 2018). Due to the continued dominance of coal in the energy mix over the next couple of decades (Hao et al., 2015; Shi et al., 2020; Y. Zhang et al., 2019), the expected growth in China's energy consumption, and the concomitant growth in emissions and local pollution, is of great concern globally (Wang et al., 2019; Zhang et al., 2020).

The dynamics of China's energy consumption are an important issue because China is the world's largest energy user and CO_2 emitter. China emitted about 27.6% of the world's GHG emissions in 2017 (BP, 2018). International emission commitments and energy security concerns force China to prioritize the management of energy consumption. The first mandatory target for reducing the country's energy intensity was set at 20% in the 11th Five-Year-Plan (FYP, 2006–2010) in 2005 (P. Zhang et al., 2019). Later, the State Council incorporated mandatory energy targets into the annual performance evaluations of local officials (Li et al., 2016). Energy caps were also introduced by the Chinese government, and these have been continuously revised in recent decades, reflecting the challenges and further need to better understand China's energy consumption dynamics (Liu et al., 2018).

Understanding the impacts of regional groups and urbanization on the convergence and dynamics of household energy consumption can help in the projection of future energy consumption and the design of specific energy policies. There are two challenges regarding residential energy consumption (Herrerias et al., 2017). First, the shift towards a new, domestically- oriented growth model will incentivize urbanization and household consumption (Zhang et al., 2020). However, it will create a need to find a balance between urbanization and the achievement of a low carbon economy. Second, the existing policies to reduce and decarbonize residential energy consumption are challenged by disparities in regional growth paths. While the industrial sector has still been dominating China's energy consumption, residential energy consumption has emerged to become an important phenomenon due to the rapid industrialization and urbanization (Zhang et al., 2020). Herrerias et al. (2017) used a cluster analysis to test for convergence in China's residential consumption of coal, gas and electricity, in both rural and urban areas and across regions.

There are several gaps in the literature. First, the existing studies on the convergence of energy consumption or energy intensity, even recent ones, such as Cheong and Wu (2018); Herrerias et al. (2017) and Kim (2015) still use aggregate data at the city level or even provincial level. Neither reveal the energy consumption at the household level. Second, regression models were employed in many previous studies which analyze the impacts of different independent variables on the RHEC (Jareemit and Limmeechokchai, 2019; Niu et al., 2019; Wu et al., 2019). However, a major shortcoming is that such regression models cannot include many independent variables due to the problems of multicollinearity. Therefore, regression methods can only be used for examining the effects of a few explanatory variables; and the impacts of other relevant factors are neglected. Another shortcoming is that the output of regression models is the forecasted value of the dependent variable. This cannot be used to forecast the evolution of a distribution, which is a two-dimensional entity. Third, regression models also fail to provide any information on convergence, such as the value of the convergence and the number of convergence clubs in the distribution. In fact, the single value estimation of regression models cannot reveal the heterogeneity across households. However, this information is crucial for policy-making. Moreover, the parametric methods that are frequently used in the literature can produce misleading results due to ignorance about the information relating to multimodal distribution (Quah, 1993, 1997). Indeed, they cannot depict the entire shape and dynamics of the distribution (Quah, 1993).

Our work contributes to the existing literature by examining the convergence patterns and dynamics of household energy consumption in China. This is the first study that investigates the convergence and dynamics of household energy consumption in China with household survey data. Herrerias et al. (2017) is the first paper using provincial data of China to investigate the convergence patterns of residential energy consumption in China. The major advantage of household-level data is to provide more heterogeneity than the provincial or prefecture-level data (Yu et al., 2019). With the consideration of heterogeneity in household energy consumption per capita, Chinese policy makers can identify the key groups for priority interventions and formulate more effective policy to reduce the energy consumption inequality. In addition, the distribution dynamics method is used to forecast the shape of the distribution of household energy consumption at per capita levels in the long run. The results of this study also enhance the knowledge of intra-distribution mobility for the RHEC based on the mobility probability plots (MPPs), a new methodology developed by (Cheong and Wu, 2013) that has emerged in recent years .

The rest of this paper is arranged as follows: Section 2 presents a literature review; Section 3 introduces the data preparation process; Section 4 discusses the methodology and presents a new representation framework for distribution dynamics analysis; Section 5 gives the empirical results; and Section 6 provides conclusions and implications.

2 Literature review: household energy consumption and convergence

In recent decades, convergence in energy consumption (including various energy carriers), using per capita energy consumption data or energy intensity, has become a hot topic in the energy economic literature. Convergence analysis has been extended from its traditional territory of economic growth literature[1] to the energy economics fields, such as energy intensity convergence (Ezcurra, 2007; Le Pen and Sévi, 2010; Liddle, 2009), carbon emission convergence (Wu et al., 2016), energy (electricity) consumption per capita convergence (Fallahi and Voia, 2015; Payne et al., 2017a), and energy price convergence across markets (Sheng and Shi, 2013). Both Fallahi and Voia (2015) and Meng et al. (2013) investigated the convergence in energy use per capita among OECD countries. Examining convergence in energy consumption per capita from 1970 to 2013, Mohammadi and Ram (2017) found no convergence across the United States. They explained it as variations in structural factors. Through their investigation of the convergence of renewable energy consumption per capita across the United States, Payne et al. (2017a) found that both β- and σ-convergence existed and that stochastic convergence exited for a majority of the States once allowance was made for structural breaks. Payne et al. (2017b) also found the presence of stochastic convergence in relative fossil fuel consumption per capita in the United States. An examination of emission convergence in the United States, Apergis and Payne (2017) revealed multiple convergence clubs in the aggregate by sector, and for two of the three fossil fuel sources (natural gas and coal). Liddle (2009) found that the growth of energy consumption per capita has been slowed down due to shifts from raw coal to electricity and thus improved energy efficiency.

Many studies have linked energy consumption to economic convergence, such as energy market integration and economic growth convergence across countries (Sheng and Shi, 2013). Another study examined convergence in economic growth and energy intensity (Wesley Burnett and Madariaga, 2017). Electricity use per capita, is a better indicator for standard of living than income (Kim, 2015) and particularly popular in the

[1] A detailed description of the different concepts of economic convergence and various testing methods can be found in (Islam, 2003).

energy convergence literature. Many studies have investigated the convergence of electricity consumption and electricity consumption per capita, such as Borozan (2017); Cheong et al. (2019); Herrerias and Liu, (2013); and Kim (2015).[1]

The limited studies in the literature on energy or energy-intensity convergence in China have focused mainly on the provincial or prefecture level. Their findings have not been consistent: while some claimed a declining trend in convergence (Ma and Stern, 2008; Zhang, 2003), others had the opposite results (Zhao et al., 2010). (Herrerias et al. (2017) claimed to be the first study on the convergence patterns related to residential energy consumption per capita in urban and rural areas and across China's regions. Different steady-states of residential energy consumption between rural and urban residents were documented by Herrerias et al. (2017). The aggregate data used in the previous studies on China's energy consumption convergence could not estimate the impacts of individual characteristics on energy consumption. In a study of the stochastic electricity-intensity convergence across provinces, Herrerias and Liu (2013) found multiple convergence clubs.

Whether energy consumption converges across households and reaches steady states can inform the projection of future energy demand. However, this is rarely studied due to the complicated information pertaining to technological progress, economic growth and population growth. There is huge uncertainty when predicting energy demand. The traditional energy outlooks, such as IEA (2017), consider economic growth, population growth and technological progress as drivers. However, the relationship between the driving factors and energy consumption is more complicated than the outlook models often assume. For example, the large body of empirical research on the relationship between energy consumption and income has produced conflicting results on the direction of the causality. Moreover, the explicit assumption that countries and regions converge at the same path is also questionable (Herrerias et al., 2017). T. Zhang et al. (2019) further demonstrated that most of the existing studies that used pre-assumptions about the influencing factors in the case of access to

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[1] A summary list of studies on electricity consumption convergence can be found in (Cheong et al., 2019).

electricity were biased or even wrong. However, some of the uncertainties in projecting energy demand could be removed from the projections, which are done on the demand side and in unit terms (such as household).

Another major issue in the empirical literature on convergence analyses in energy economics is methodology. The majority of existing convergence methods require a strong assumption about the underlying distribution. σ-convergence and β-convergence are two popular technologies used in the economic growth literature (Barro and Sala-i-Martin, 1995) but not been extended to energy economics field (Payne et al., 2017a; Sheng and Shi, 2013). Many other approaches have been used more recently, such as LM and RALS-LM unit root tests with endogenously-determined structural breaks to test for stochastic convergence (Payne et al., 2017a, 2017b) and the Phillips-Sul club convergence approach (Apergis and Payne, 2017). Previous studies have shown that the conclusions from these parametric studies are often misleading due to wrong assumptions about the distribution (Quah, 1993).

The distribution dynamics approach avoids this problem by making no assumptions about the underlying distribution of the population. Most applications of distribution dynamics have focused on carbon emission convergences, such as Nguyen Van (2005) for the global case and Evans and Kim (2016) for 11 Asian countries. Worldwide energy intensity convergence has also been studied, such as (Ezcurra, 2007; Herrerias, 2012). For China, Wang (2011) examined the source of each province's energy productivity growth in their distribution dynamics. Applying distribution dynamics with mobility probability plots (MPPs), Wu et al. (2016) investigated carbon emission convergence among Chinese cities. Cheong et al. (2019) investigated electricity consumption per capita convergence across China's provinces. Among the small number of distributed dynamics studies, there has been no use of such an approach on household level data.

In summary, the existing literature has often used aggregated and parametric methods and there has been no application of household data. It is demonstrated below that a distribution dynamics approach which does not assume the underlying distribution of the population has some advantages over the parametric methods.

3 Household energy consumption in China: the data

This paper used the annual China Family Panel Studies (CFPS) survey data. Launched in 2010 by the Institute of Social Science Survey of Peking University in China, it is a nationally representative, annual longitudinal survey of Chinese communities, families, and individuals which collects individual-, family-, and community-level longitudinal data (Xie and Hu, 2014). The CFPS baseline survey has interviewed 14,960 households in 25 mainland provinces (excluding Inner Mongolia, Xinjiang, Tibet, Hainan, Ningxia, Qinghai, Hong Kong, Macau, and Taiwan), representing about 95% of the Chinese population (Zhang et al., 2014). As the CFPS started to comprehensively calculate the energy consumption of households only recently in 2014, this paper used the CFPS data of 2014 and 2016 to conduct research. Since distribution dynamics analysis requires observations of households for at least two consecutive years, the observations existing only in 2014 or 2016 were excluded. Therefore, the micro database used in this study was made up of those households that exist both in 2014 and 2016. Our analytical sample of the CFPS included 6,222 households, 56.17% of which were in rural areas and 43.83% in urban areas.

The core variable of this paper was the RHEC, which is expressed by dividing the actual energy consumption per capita of each household by the mean of the actual energy consumption per capita at the national level. The specific process is as follows: first, HEC expenditure is equal to the sum of fuel consumption and electricity consumption. For the CFPS, household fuel consumption includes gas, liquefied natural gas, coal, firewood and charcoal. Second, each HEC expenditure was divided by the total number of family members to obtain the HEC per capita. Then, the nominal consumption per capita was converted into real consumption by using the fixed-base price index of water, electricity and fuel in urban and rural areas within 25 Chinese provinces in 2014 and 2016, which is 100 in 2011, respectively. This information obtained from China's Statistics Agency. The unit of energy consumption per capita was RMB yuan.

Finally, this paper used the average of real energy consumption per capita for all households in 2014 and 2016 to represent the national mean for 2014 and 2016, respectively. On this basis, each household's annual real energy consumption per capita was divided by the annual national mean to obtain the relative household energy consumption per capita in 2014 and 2016. A ratio equal to 1 indicated that the real energy consumption per capita of the households was equal to the national mean. If this ratio was greater than 1, the real energy consumption per capita of the households was greater than the national mean. Conversely, if the ratio was less than 1, the real energy consumption per capita of households was lower than the national mean.

$$RHEC = \frac{household's\ energy\ consumption\ per\ capita}{the\ national\ mean} \tag{1}$$

For this paper, China was divided into four subregions: the eastern region, central region, western region and northeastern region, according to the degree and phase of economic development. The provinces included in this study were: 1) Eastern region: Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, and Guangdong; 2) Central region: Shanxi, Henan, Hubei, Hunan, Anhui, and Jiangxi; 3) Western region: Chongqing, Guangxi, Shaanxi, Sichuan, Guizhou, Yunnan, and Gansu; and 4) Northeastern region: Liaoning, Jilin, and Heilongjiang.

Table 1 presents the statistics of the RHEC in China. Four main conclusions can be drawn from it. First, for the 6,222 households that existed in both 2014 and 2016, the mean of their energy consumption was equal to 1. The reason for this result is that the RHEC was based on the ratio of annual energy consumption of the households divided by the national mean. Thus, the mean must be equal to 1. Second, the RHEC of the urban households was significantly higher than the national mean (e.g., the mean of the urban households is 1.155), while the RHEC of the rural household was significantly below the national mean(e.g., the mean of the rural households is only 0.879). The results revealed that energy consumption in China's urban and rural households had obvious characteristics of inequality: the urban households accounted for more than half of the nation's total consumption of fuel, electricity and other resources. Third, in terms of different regions, the mean value of the RHEC in the eastern region was 1.128. In the northeast is was 1.073, and in the central and western regions it was less than 1.

A key finding was that the RHEC in the eastern and northeastern regions of China was higher than the national mean, while that in the central and western regions was lower than the national mean. Further analysis showed that obvious consumption inequality among China's different regions in terms of the RHEC. This was reflected in the large RHEC in the eastern and northeastern regions, and the small RHEC in the central and western regions.

[Insert Table 1 Here]

4 Methodology

The distribution dynamics approach was first proposed by (Quah, 1993). It has been developed for unveiling important information which is not readily available from the traditional analyses such as the sigma-convergence analysis and the beta-convergence analysis. It is worth noting that for the former approach, the same value of inequality measurement may derive from two entirely different distributions, therefore, it is difficult to reach the conclusion that convergence can be achieved by merely observing the trend of the inequality measurement. For the latter approach, Quah has shown that it has the issue of Galton's Fallacy, and so it is not appropriate to claim convergence by relying on this approach alone. On the contrary, distribution dynamics approach provides a lot of important information to the readers, such as the current shape and the evolving trend of the distribution. Moreover, the probability of the movement of the entities within the distribution can also be derived. Finally, one can also prepare the forecast of the equilibrium distribution in the long-run.

It can be broadly divided into the traditional Markov transition matrix analysis and the stochastic kernel approach. A major problem of the former is the demarcation of the state associated with the selection of grid values. This is an arbitrary process and the results largely depend on the means of demarcation. The stochastic kernel approach is better as it can circumvent this issue, hence its use in this study.

The bivariate kernel estimator is defined as:

$$\hat{f}(x,y) = \frac{1}{nh_1h_2}\sum_{i=1}^{n} K(\frac{x-X_{i,t}}{h_1},\frac{y-X_{i,t+1}}{h_2}) \quad (2)$$

where n is the number of observations, h_1 and h_2 are the bandwidths which are calculated on the basis of the approach proposed by (Silverman, 2018), K is the normal density function, x is a variable representing the RHEC of a household at time t, y is a variable representing the RHEC of that household at time t+1, $X_{i,t}$ is an observed value of the RHEC at time t, and $X_{i,t+1}$ is the observed value of RHEC at time t+1.

An adaptive kernel approach with flexible bandwidth was employed to take the sparseness of the data into consideration (Silverman, 2018). Assuming that the process is time-invariant and first order, and the distribution at time $t+\tau$ depends on t only and not on any previous distributions, then the relationship between the distributions at time t and time $t+\tau$ can be represented by:

$$f_{t+\tau}(z) = \int_0^{\infty} g_{\tau}(z|x)f_t(x)dx \quad (3)$$

where $f_{t+\tau}(z)$ is the τ-period-ahead density function of z conditional on x, $g_{\tau}(z|x)$ is the transition probability kernel which maps the distribution from time t to $t+\tau$, and $f_t(x)$ is the kernel density function of the RHEC distribution at time t.

The ergodic density function, given that it exists, can be computed by:

$$f_{\infty}(z) = \int_0^{\infty} g_{\tau}(z|x)f_{\infty}(x)dx \quad (4)$$

where $f_{\infty}(z)$ is the ergodic density function when τ is infinite. This analysis can provide pertinent information on future development of the RHEC distribution.

(Cheong and Wu, 2013) developed the mobility probability plot (MPP) for interpreting mobility probability. The MPP has been employed to analyze transitional dynamics in various research areas, such as industrial output (Cheong and Wu, 2018), rural household income (Li and Cheong, 2016), electricity (Cheong et al., 2019) and even carbon dioxide emissions (Cheong and Wu, 2018; Wu et al., 2016).

The MPP can be constructed by computing $p(x)$ which is defined as the net upward mobility probability:

$$p(x) = \int_x^{\infty} g_\tau (z|x)dz - \int_0^x g_\tau (z|x)dz \tag{5}$$

The MPP shows the net upward mobility probability against the RHEC. It is worth noting that a positive value implies that the household has a net probability of moving upwards; whereas a negative value of net upward mobility probability implies that the household has a net probability of moving downwards in the distribution. Interested readers can refer to (Cheong and Wu, 2013).

5 Results and discussion

The transitional dynamics of China's RHEC is shown in Figure 1 as a three-dimensional plot, and in Figure 2 as a contour map. The contour map is basically an overhead view of the three-dimensional plot. These two types of display tools are employed widely in the stochastic kernel analysis literature.

5.1 Overall transitional dynamics

In Figure 1, it is notable that the higher the relative frequency, the more the data in the region. It can be observed that the RHEC is higher between 1 and 1.5, and much lower between 0 and 0.5. This result shows that the RHEC of most households in China was between 1 and 1.5, but for only a few households it was 0.5 or below.

[Insert Figure 1 Here]

On the one hand, for those households that will convergence to RHEC of less than 0.5, poverty alleviation measures need to be implemented to provide these households with basic living conditions. On the other hand, the government should not overlook those households with an RHEC greater than one as the high variability in the figure suggests that a small number of these households are at risk of increasing their RHEC to more than two, leading to a sharp increase in energy consumption.

Figure 2 presents the ergodic distribution for the RHEC with annual transitions. The ergodic distribution shows the steady-state distribution of China's household energy consumption per capita in the future if the distribution dynamics remain unchanged. Figure 2 portrays multiple convergence clubs. The highest peak in the RHEC is 0.56, indicating that many Chinese households' relative energy consumption level would converge to a value of 0.56. However, there is another obvious peak in the RHEC around 0.7. This indicates that the RHEC of many Chinese households will eventually converge to around 0.56, while some other households will converge to around 0.7, thereby indicating the emergence of convergence clubs.

[Insert Figure 2 Here]

Figure 3 presents the mobility probability plot for China's RHEC. The horizontal axis of the figure represents the RHEC while the vertical axis represents the net probability of an increasing RHEC. The upper half of the vertical axis represents the probability that the RHEC will increase, whereas the lower half represents the probability that the RHEC will decrease. As can be seen from Figure 3, if a household's RHEC is close to 0, then it has a probability of almost 100% to move up in the next period. In contrast, if a household's RHEC is close to 6, then the net probability is -84%, indicating that the relative consumption of this household will drop in the future. It is observed that the MPP intersects the horizontal axis at 0.63, indicating that the probability of Chinese household energy consumption per capita rising or falling is equal when the value is at 0.63. On the left-hand side of 0.63, there is a higher probability of moving up. On the right-hand side of 0.63, there is a higher probability of moving down. As the intersection point is lower than 1, the inequality in the RHEC in China is quite significant. The energy consumption of a few wealthy households is much higher than the national mean, while for most other households, the RHEC is lower than the national mean. This can also be verified from the statistics shown in Table 1. In Table 1, the mean of the RHEC is 1, but the median of the RHEC is only 0.67. As the findings suggest that when the value of the RHEC is around 0.63 or above, the households are under the threat of a decline in energy consumption. Furthermore, this paper finds that there are some obvious peaks around 0.25 and 0.5, meaning that the RHEC of these households is more likely to move upwards compared to the others. In addition, when the RHEC is around 0.35, the net probability of an increase in the RHEC will drop rapidly.

[Insert Figure 3 Here]

5.2 Urban and rural heterogeneity

Figure 4 shows the ergodic distribution of the RHEC for the urban and rural households. As can be seen from Figure 4(a), the highest peak of the RHEC in the urban households was 0.48, indicating that many Chinese urban households' relative energy consumption will converge to a value of around 0.48. In addition to the highest peak of 0.48, there was also another obvious peak in the RHEC around 0.63. This reflects the emergence of convergence clubs in energy consumption for the urban households.

From Figure 4(b), it is observed that many Chinese rural households' RHEC will converge to around 0.57. However, there is also another obvious peak of RHEC around 0.31. This implies that the RHEC of many rural households will eventually converge to a value around 0.57, but that many of these will converge to the values of around 0.31. This also reflects the issue of convergence clubs in the relative energy consumption for the rural households.

When comparing Figures 4(a) and 4(b), it can be seen that the highest value in the vertical axis of Figure 4(a) is 0.83, while for Figure 4(b) it is 0.65, thereby indicating that the convergence in the RHEC among the urban households is more significant than for the rural households. In other words, the inequality in rural households is more serious than in the urban households. However, the value of the primary convergence among the urban households (0.48) was much lower than for the rural households (0.57). Given the overall lower income among the rural households compared to the urban households, rural households face higher pressure in energy costs than do their urban counterparts.

[Insert Figure 4 Here]

Figure 5 presents the mobility probability plot for the RHEC of the urban and rural households. It shows that the MPP of the urban households intersects the horizontal axis at 0.73. Some small peaks occur at around 0.28 and 0.65, meaning that the urban households in this range of RHEC are more likely to move upwards compared to the others. Meanwhile, the MPP of the rural households intersects the horizontal axis at 0.69. Some obvious peaks occur at 0.35 and 0.63, meaning that the rural households within this range of RHEC are more likely to move upwards than the others.

Three important results emerge from the comparison of the MPP between the rural households and urban households in Figure 5. First, there are many intersection points between the MPPs of the urban households and rural households. This means that the dynamics of the RHEC in urban households are not significantly different from those of the rural households. Second, the intersection point of the MPP and horizontal axis for urban households (0.73) is larger than for rural households (0.69). When the RHEC is greater than 0.69 and smaller than 0.73, urban households are more likely to move up than rural households. Third, when the RHCE is greater than 1.32, the MPP of urban households is higher than that of rural households. In this case, the RHEC of rural households is significantly more likely to decline than for urban households. This result has important policy implications, namely, that when the RHCE is greater than 1.32, it is difficult for the rural households to maintain a high level of energy consumption (above the national mean) but it is easier for the urban households.

[Insert Figure 5 Here]

5.3 Regional disparity

Figure 6 presents the ergodic distribution for the RHEC of all the households in the different regions. Three important findings can be derived from Figure 6(a)-(d): first, from the peak point of view, the highest peak value of the central region (0.63) was the greatest amongst all the regions, and the highest peak values of the RHEC in the central and northeastern regions were significantly greater than those in the eastern and western regions. Second, there were more than two peaks in the RHEC in each of China's four regions. There were two peaks in the eastern region, of which the highest was 0.51 and the other was 0.78. In the central region, there were also two peaks in the RHEC. The highest was 0.63 and the other was 1.65. There were two peaks in the western region, at 0.46 and 0.51 respectively. However, in the northeastern region, there were three peaks. The highest was 0.56, the next was 0.7 and the other was 1.5. Convergence clubs were found in each of the four regions, but were more obvious in the northeastern region. Third, the peak in the northeastern region had a vertical height of 0.85. This was the highest among the regions. Therefore, the convergence of the RHEC in the other three regions was not as obvious as in the northeastern regions. In other words, the distributions were more dispersed in the other three regions of China.

The value of convergence in the central region was the greatest, followed by that in the northeastern region and then the eastern region, while the western region came last. These results indicate that the RHEC convergence of many households in the central region was at a higher level, but for many households in the western region it was at a much lower level than for the central region. This demonstrates that China's regional development is seriously imbalanced. Ideally, the Chinese government should pay more attention to these regional differences.

[Insert Figure 6 Here]

Figure 7 shows the mobility probability plot for the RHEC in China's regions. Some important conclusions can be drawn from Figure 7: first, the intersection points between the horizontal axis and the MPP of the households in the eastern, central and the northeastern regions were 0.79, 0.72 and 0.82, respectively, higher than those in the western region, whose intersection point was only 0.54. This finding corroborates the results derived from Figure 6. Second, in the eastern region, the MPP had no obvious jump points on the left side of the intersection point. The steep shape of the MPP indicates a sharp drop in the MPP. Only when the RHCE was greater than 1 would the MPP have obvious jump points. In the central region, the MPP would show a less obvious jump point near the intersection point. When the RHEC was less than 0.35, the MPP dropped sharply. Moreover, when the RHEC was greater than 0.35 and less than 0.72, the decline of MPP was very flat. In the western region, when RHEC was equal to 0.35, the MPP would show a very obvious jump point. To the left of the point, the MPP had a slight rebound, while to the right, the MPP dropped sharply. By contrast in the northeastern region, there would be a very obvious jump point in the MPP when the RHEC was equal to 0.69. Before the line on the right side of the jump point intersects the horizontal axis (i.e. RHEC is greater than 0.69 and less than 0.82), the MPP showed the characteristics of rapid decline.

According to Figures 6 and 7, the western region had the lowest value of convergence, and the intersection point between the MPP of this region and the horizontal axis was also the smallest among the four regions. This result has important policy implications: the western region may be at a significant disadvantage in terms of access to energy consumption. In order to eliminate the inequalities in household consumption among the different regions, the Chinese government must carry out targeted poverty alleviation in the western region and increase the support for households in the western region so that they can have greater access to electricity and thereby benefit from the many opportunities which would accompany it. The various levels of government need to strengthen the investment and construction of energy infrastructure in the western region.

[Insert Figure 7 Here]

6 Conclusions and implications

Whether there will be a long-run equilibrium (steady state) in energy demand per capita is a critical question for energy and environmental policy makers (Cheong et al., 2019). While many studies have investigated energy production and energy consumption, little attention has been paid to whether disparities in the relative household energy consumption (RHEC) diminish over time and whether urbanization and regional characteristics will affect the RHEC in the long-run equilibrium. Most of the previous studies on convergence of energy consumption or energy intensity used aggregated data at the city (prefecture) or provincial level and thus could not reveal many policy insights.

Using household survey data, this paper examined the convergence patterns and dynamics of residential energy consumption in China. It is the first study to investigate the convergence and dynamics of household energy consumption in China. With the consideration of heterogeneity in household energy consumption per capita, the results are useful to Chinese policy makers in identifying the key groups for priority interventions.

It was found that the variability in the RHEC was very high and that many households will change their energy consumption status in the next period. Some households with an RHEC greater than one may jump to an RHEC of more than two. However, the RHEC was stable for the households with an RHEC of 0.5 and below. This suggests that households with an RHEC that is too low to meet basic moderate modern living standards is undesirable.

Overall, Chinese households have two convergence clubs. The main club had the highest RHEC peak at 0.56, and the second convergence club had a peak level of around 0.7. These results suggest that the current dynamics will lead to lower energy consumption for most households are thus quite desirable.

The inequalities in energy consumption among Chinese households were significant as most households will remain at an RHEC level of 0.63. The inequality was obvious between urban and rural households. The former converged to an RHEC of between 0.48 and 0.63 while the later converged to only an RHEC of between 0.51 and 0.31. The significant difference in the RHEC levels between the two convergence clubs in the rural households also suggests that the inequalities among rural households were more serious than for the urban households.

The rural-urban analysis suggests that rural households will converge to a lower level of energy consumption than urban households, but that the rural households were subject to higher financial pressures than their urban counterparts because the urban households have higher per capita incomes. The regional analysis shows that China's regional development is seriously unbalanced: the western region may be at a significant disadvantage in terms of access to energy consumption.

Based on the findings, the following policy implications can be drawn: First, policy makers need to pay attention to the households that have an RHEC level below basic living standards. For those households that will convergence to RHEC of less than 0.5, Poverty alleviation measures need to be implemented to provide these households with basic living conditions. A good example is China''s PV poverty alleviation programs (Xu et al., 2019), which increase access to clean energy and alleviates poverty at the same time. On the other hand, households with an RHEC of more than 1 and may possibly jump to higher levels and should be monitored and encouraged to scale down their energy consumption. Second, governments need to pay more attention to the rural households than to the urban households for at least two reasons: firstly, to reduce inequalities among rural households, and secondly, to mitigate the financial pressures (measured as the share of energy costs in total household income) of some rural households. Last, the Chinese government needs to support households in the western region. In order to eliminate the inequalities in household consumption among regions, the Chinese government must increase the support for households in the western region by helping them gain access to affordable and quality energy. While China has achieved universal access to electricity, access to clean coking fuels are still a major challenge, which is particularly serious in the western region where households have lower rate of access to natural gas for cooking than other regions (Liao et al., 2016).

References

Apergis, N., Payne, J.E., 2017. Per capita carbon dioxide emissions across U.S. states by sector and fossil fuel source: Evidence from club convergence tests. Energy Econ. 63, 365–372.

Barro, R.J., Sala-i-Martin, X.X., 1995. Economic Growth. MIT Press, Cambridge.

Borozan, D., 2017. Testing for convergence in electricity consumption across Croatian regions at the consumer's sectoral level. Energy Policy 102, 145–153.

BP, 2018. Statistical Review of World Energy 2018. British Petroleum, London.

Chen, Y., Yu, J., Kelly, P., 2016. Does the China factor matter: What drives the surge of world crude oil prices? Soc. Sci. J. 53, 122–133.

Cheng, D., Shi, X., Yu, J., Zhang, D., 2019. How does the Chinese economy react to uncertainty in international crude oil prices? Int. Rev. Econ. Financ. 64, 147–164.

Cheong, T.S., Li, V.J., Shi, X., 2019. Regional disparity and convergence of electricity consumption in China: A distribution dynamics approach. China Econ. Rev. 58, 101154. https://doi.org/10.1016/j.chieco.2018.02.003

Cheong, T.S., Wu, Y., 2018. Convergence and transitional dynamics of China's industrial output: A county-level study using a new framework of distribution dynamics analysis. China Econ. Rev. 48, 125–138.

Cheong, T.S., Wu, Y., 2013. Regional disparity, transitional dynamics and convergence in China. J. Asian Econ. 29, 1–14.

Evans, P., Kim, J.U., 2016. Convergence analysis as spatial dynamic panel regression and distribution dynamics of CO2 emissions in Asian countries. Empir. Econ. 50, 729–751.

Ezcurra, R., 2007. Distribution dynamics of energy intensities: A cross-country analysis. Energy Policy 35, 5254–5259.

Fallahi, F., Voia, M.C., 2015. Convergence and persistence in per capita energy use among OECD countries: Revisited using confidence intervals. Energy Econ. 52, 246–253.

Hao, Y., Zhang, Z.Y., Liao, H., Wei, Y.M., 2015. China's farewell to coal: A forecast of coal consumption through 2020. Energy Policy 86, 444–455.

Herrerias, M.J., 2012. World energy intensity convergence revisited: A weighted distribution dynamics approach. Energy Policy 49, 383–399.

Herrerias, M.J., Aller, C., Ordóñez, J., 2017. Residential energy consumption: A convergence analysis across Chinese regions. Energy Econ. 62, 371–381.

Herrerias, M.J., Liu, G., 2013. Electricity intensity across Chinese provinces: New evidence on convergence and threshold effects. Energy Econ. 36, 268–276.

IEA, 2017. World Energy Outlook 2017. OECD Publishing, Paris.

Islam, N., 2003. What have we learnt from the convergence debate? J. Econ. Surv. 17, 309–362.

Jareemit, D., Limmeechokchai, B., 2019. Impact of homeowner's behaviours on residential energy consumption in Bangkok, Thailand. J. Build. Eng. 21, 328–335.

Kim, Y.S., 2015. Electricity consumption and economic development: Are countries converging to a common trend? Energy Econ. 49, 192–202.

Le Pen, Y., Sévi, B., 2010. On the non-convergence of energy intensities: Evidence from a pair-wise econometric approach. Ecol. Econ. 69, 641–650.

Li, H., Zhao, X., Yu, Y., Wu, T., Qi, Y., 2016. China's numerical management system for reducing national energy intensity. Energy Policy 94, 64–76.

Li, S., Cheong, T.S., 2016. Convergence and mobility of rural household income in China: new evidence from a transitional dynamics approach. China Agric. Econ. Rev. 8, 383–398.

Liao, H., Tang, X., Wei, Y.M., 2016. Solid fuel use in rural China and its health effects. Renew. Sustain. Energy Rev. 60, 900–908.

Liddle, B., 2009. Electricity intensity convergence in IEA/OECD countries: Aggregate and sectoral analysis. Energy Policy 37, 1470–1478.

Liu, Q., Lei, Q., Xu, H., Yuan, J., 2018. China's energy revolution strategy into 2030. Resour. Conserv. Recycl. 128, 78–89.

Ma, C., Stern, D.I., 2008. China's changing energy intensity trend: A decomposition analysis. Energy Econ. 30, 1037–1053. https://doi.org/http://dx.doi.org/10.1016/j.eneco.2007.05.005

Meng, M., Payne, J.E., Lee, J., 2013. Convergence in per capita energy use among OECD countries. Energy Econ. 36, 536–545.

https://doi.org/http://dx.doi.org/10.1016/j.eneco.2012.11.002

Mohammadi, H., Ram, R., 2017. Convergence in energy consumption per capita across the US states, 1970–2013: An exploration through selected parametric and non-parametric methods. Energy Econ. 62, 404–410. https://doi.org/http://dx.doi.org/10.1016/j.eneco.2016.07.002

Nguyen Van, P., 2005. Distribution Dynamics of CO2 Emissions. Environ. Resour. Econ. 32, 495–508. https://doi.org/10.1007/s10640-005-7687-6

Niu, S., Li, Z., Qiu, X., Dai, R., Wang, X., Qiang, W., Hong, Z., 2019. Measurement of effective energy consumption in China ' s rural household sector and policy implication. Energy Policy 128, 553–564. https://doi.org/10.1016/j.enpol.2019.01.016

Payne, J.E., Vizek, M., Lee, J., 2017a. Is there convergence in per capita renewable energy consumption across U.S. States? Evidence from LM and RALS-LM unit root tests with breaks. Renew. Sustain. Energy Rev. 70, 715–728. https://doi.org/http://dx.doi.org/10.1016/j.rser.2016.11.252

Payne, J.E., Vizek, M., Lee, J., 2017b. Stochastic convergence in per capita fossil fuel consumption in U.S. states. Energy Econ. 62, 382–395. https://doi.org/http://dx.doi.org/10.1016/j.eneco.2016.03.023

Quah, D., 1993. Empirical Cross-Section Dynamics in Economic Growth. Eur. Econ. Rev. 37, 426–434.

Quah, D.T., 1997. Empirics for Growth and Distribution: Stratification, Polarization, and Convergence Clubs. J. Econ. Growth. https://doi.org/10.1023/A:1009781613339

Sheng, Y., Shi, X., 2013. Energy market integration and equitable growth across countries. Appl. Energy 104, 319–325. https://doi.org/10.1016/j.apenergy.2012.10.043

Shi, X., Wang, K., Shen, Y., Sheng, Y., Zhang, Y., 2020. A permit trading scheme for facilitating energy transition: A case study of coal capacity control in China. J. Clean. Prod. 256, 120472. https://doi.org/10.1016/j.jclepro.2020.120472

Silverman, B.W., 2018. Density estimation: For statistics and data analysis, Density Estimation: For Statistics and Data Analysis. https://doi.org/10.1201/9781315140919

Wang, C., 2011. Sources of energy productivity growth and its distribution dynamics in China. Resour. Energy Econ. 33, 279–292. https://doi.org/http://dx.doi.org/10.1016/j.reseneeco.2010.06.005

Wang, K., Wu, M., Sun, Y., Shi, X., Sun, A., Zhang, P., 2019. Resource abundance, industrial structure, and regional carbon emissions efficiency in China. Resour. Policy 60, 203–214. https://doi.org/10.1016/j.resourpol.2019.01.001

Wesley Burnett, J., Madariaga, J., 2017. The convergence of U.S. state-level energy intensity. Energy Econ. 62, 357–370. https://doi.org/http://dx.doi.org/10.1016/j.eneco.2016.03.029

World Bank, 2018. World Development Indicators. The World Bank, Washingtong, D.C.

Wu, J., Wu, Y., Guo, X., Cheong, T.S., 2016. Convergence of Carbon Dioxide Emissions in Chinese Cities: A Continuous Dynamic Distribution Approach. Energy Policy 91, 207–219.

Wu, S., Zheng, X., You, C., Wei, C., 2019. Household energy consumption in rural China: Historical development, present pattern and policy implication. J. Clean. Prod. 211, 981–991. https://doi.org/10.1016/j.jclepro.2018.11.265

Xie, Y., Hu, J., 2014. An Introduction to the China Family Panel Studies (CFPS). Chin. Sociol. Rev. 47, 3–29.

Xu, L., Zhang, Q., Shi, X., 2019. Stakeholders strategies in poverty alleviation and clean energy access: A case study of China's PV poverty alleviation program. Energy Policy 135. https://doi.org/10.1016/j.enpol.2019.111011

Yu, J., Shi, X., Laurenceson, J., 2019. Will the Chinese economy be more volatile in the future? Insights from urban household survey data. Int. J. Emerg. Mark. https://doi.org/10.1108/IJOEM-04-2019-0290

Zhang, C., Xu, Q., Zhou, X., Zhang, X., Xie, Y., 2014. Are poverty rates underestimated in China? New evidence from four recent surveys. China Econ. Rev. 31, 410–425.

Zhang, H., Shi, X., Wang, K., Xue, J., Song, L., Sun, Y., 2020. Intertemporal lifestyle changes and carbon emissions: Evidence from a China household survey. Energy Econ. 86, 104655. https://doi.org/10.1016/j.eneco.2019.104655

Zhang, P., Shi, X.P., Sun, Y.P., Cui, J., Shao, S., 2019. Have China's provinces achieved their targets of energy intensity reduction? Reassessment based on nighttime lighting data. Energy Policy 128, 276–283. https://doi.org/10.1016/j.enpol.2019.01.014

Zhang, T., Shi, X., Zhang, D., Xiao, J., 2019. Socio-economic development and electricity access in developing economies : A long-run model averaging approach. Energy Policy 132, 223–231.

Zhang, Y., Rui, N., Shi, X., Wang, K., Qian, X., 2019. Can energy-price regulations smooth price fluctuations? Evidence from China's coal sector. Energy Policy 128, 125–135. https://doi.org/https://doi.org/10.1016/j.enpol.2018.12.051

Zhang, Z., 2003. Why did the energy intensity fall in China's industrial sector in the 1990s? The relative importance of structural change and intensity change. Energy Econ. 25, 625–638. https://doi.org/http://dx.doi.org/10.1016/S0140-9883(03)00042-2

Zhao, X., Ma, C., Hong, D., 2010. Why did China's energy intensity increase during 1998–2006: Decomposition and policy analysis. Energy Policy 38, 1379–1388. https://doi.org/http://dx.doi.org/10.1016/j.enpol.2009.11.019

Figures

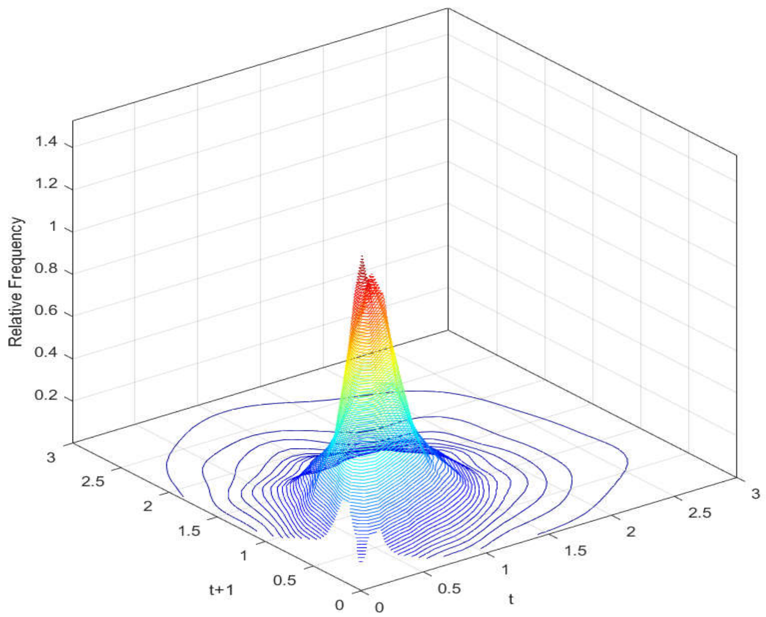


Figure 1. Three-dimensional plot of transition probability kernel for the RHEC in China with annual transitions.

Source: authors' calculation.

Note: The vertical axis is relative frequency, while the two horizontal axes are the

RHEC values at t and t+1.

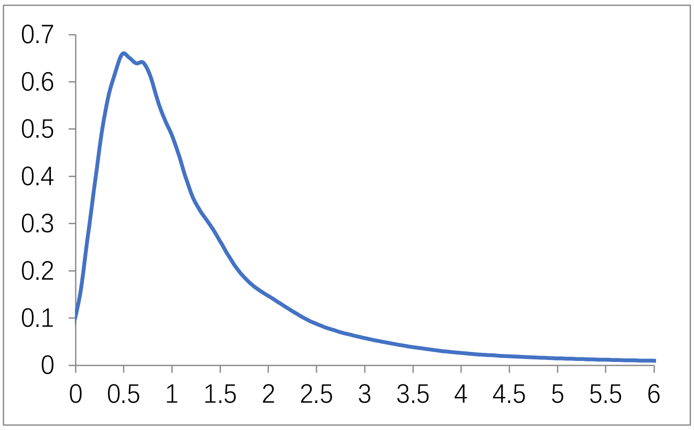


Figure 2. Ergodic distribution for the RHEC in China with annual transitions.

Source: authors' calculation.

Note: The vertical axis is the proportion, while the horizontal axis is the RHEC value.

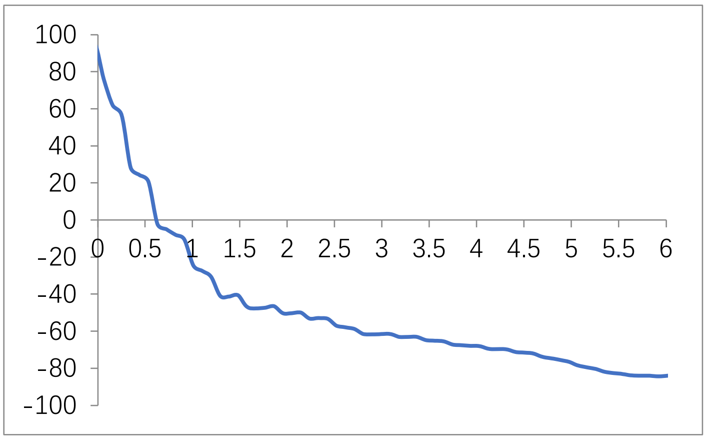
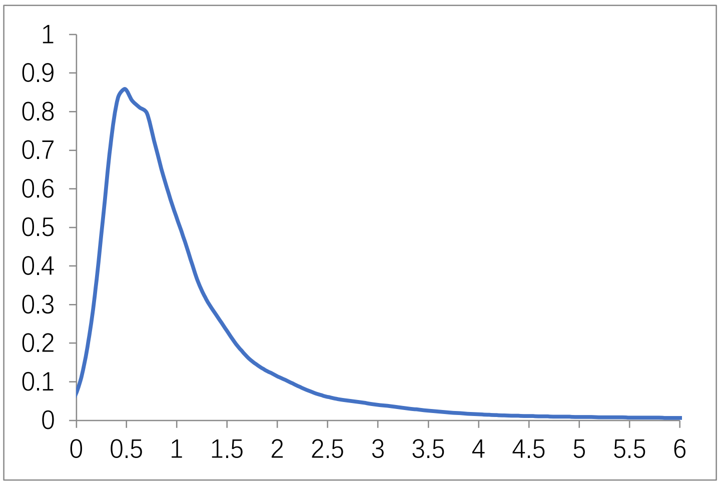


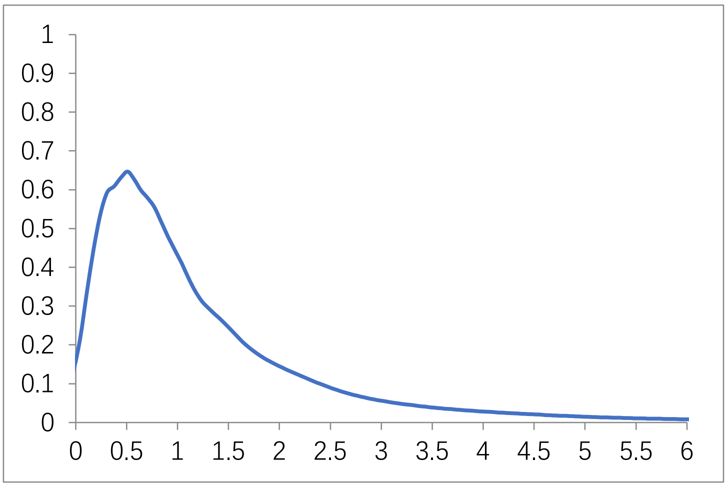
Figure 3. Mobility probability plot (MPP) for RHEC in China with annual transitions.

Source: authors' calculation.

Note: The vertical axis is the net probability of moving upward, while the horizontal axis is the RHEC value.



(a) the urban households



(b) the rural households

Figure 4. Ergodic distribution for RHEC of the urban and rural households in China.

Source: authors' calculation

Note: The vertical axis is the proportion, while the horizontal axis is the RHEC value.

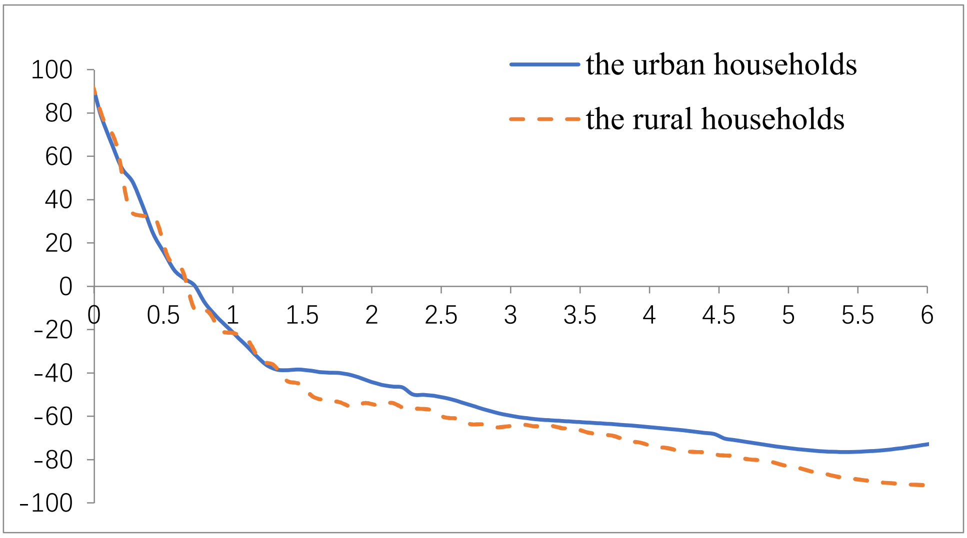
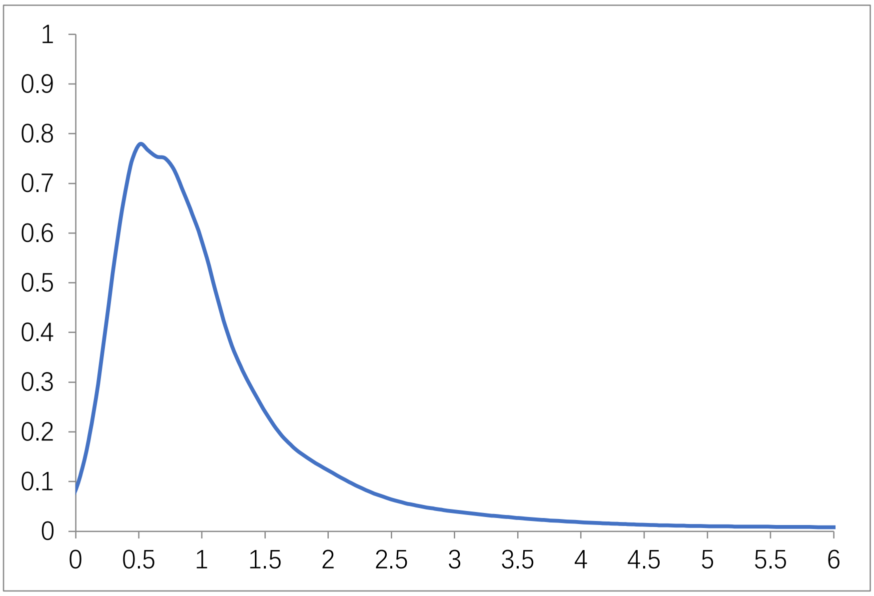


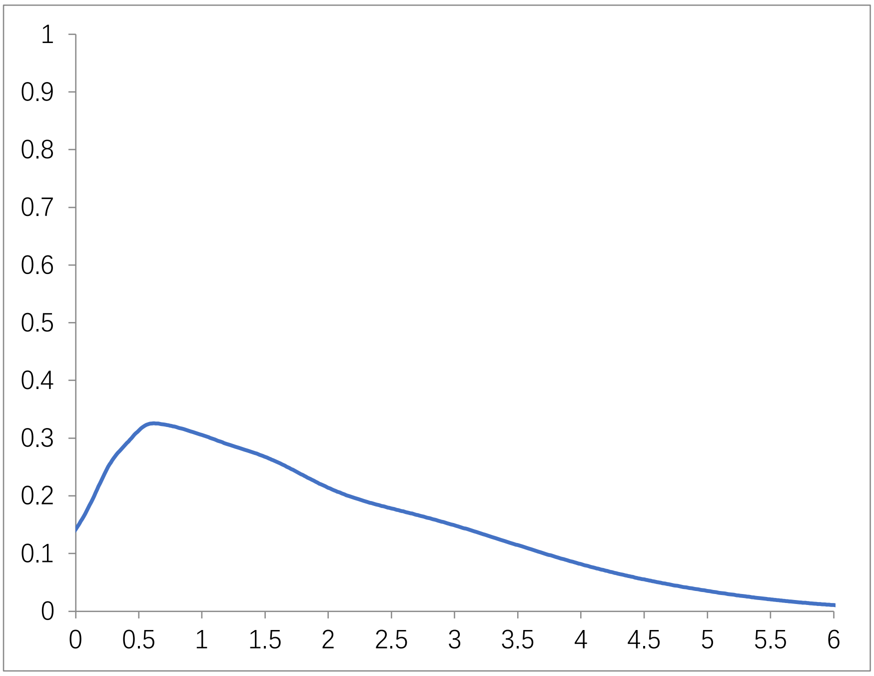
Figure 5. Mobility probability plot (MPP) for RHEC of the urban and rural households in China.

Source: authors' calculation

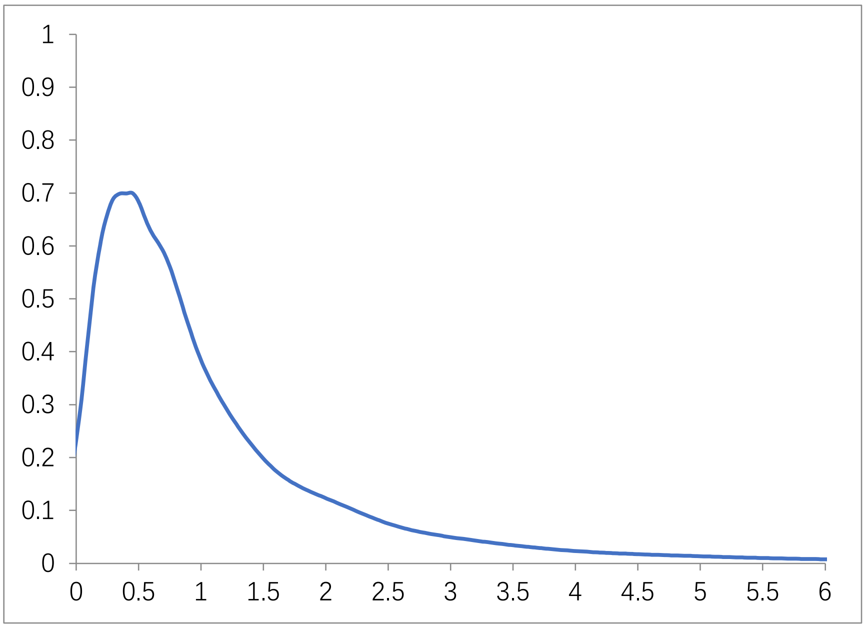
Note: The vertical axis is the net probability of moving upward, while the horizontal axis is the RHEC value.



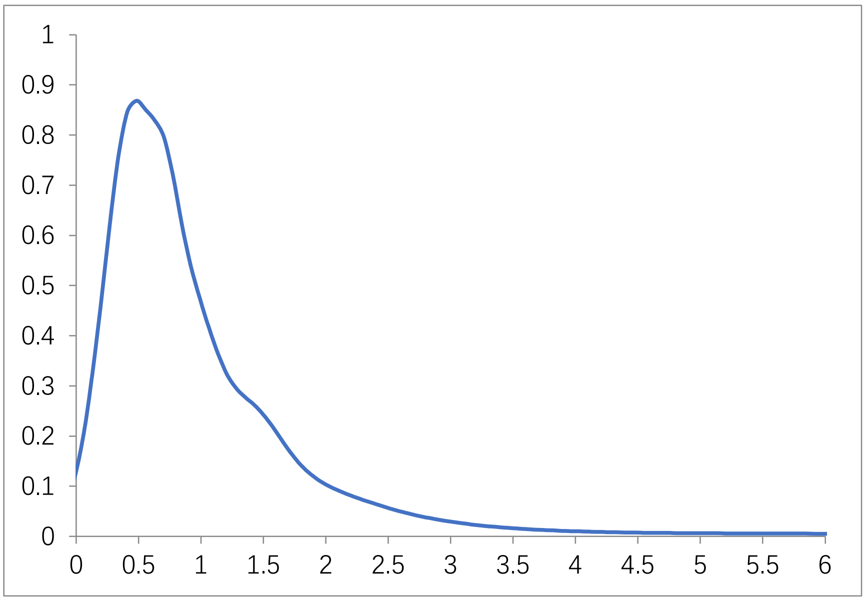
(a) the eastern region



(b) the central region



(c) the western region



(d) the northeastern region

Figure 6. Ergodic distribution for RHEC in China within different regions.

Source: authors' calculation.

Note: The vertical axis is the proportion, while the horizontal axis is the RHEC value.

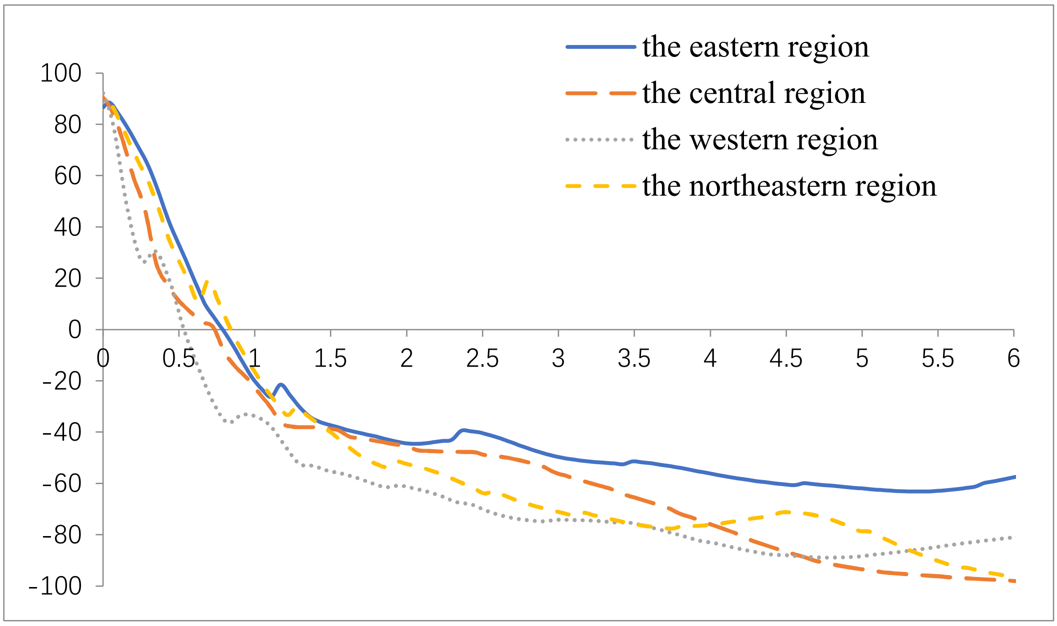


Figure 7. Mobility probability plot for RHEC in China within different regions.

Source: authors' calculation.

Note: The vertical axis is the net probability of moving upward, while the horizontal axis is the RHEC value.

Tables

Table 1. Summary statistics of the RHEC in China

Variables	Observations	Mean	Median	Standard deviation
All the households	6222	1.000	0.670	1.401
The urban households	2727	1.155	0.818	1.401
The rural households	3495	0.879	0.539	1.389
Households in the eastern region	1919	1.128	0.842	1.199
Households in the central region	1603	0.850	0.572	1.132
Households in the western region	1653	0.950	0.506	1.802
Households in the northeastern region	1047	1.073	0.739	1.367