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Convergence of carbon emissions at the household level in China: A distribution dynamics approach

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ABSTRACT

Since household carbon emissions (HCEs) have become a new growing source and a significant contributor to global emissions, the reduction of HCEs is crucial. To formulate targeted and effective emission mitigation policies, we need to fully understand the characteristics of the distribution and evolution of per capita HCEs and their urban-rural and regional heterogeneity. This paper explores the transitional dynamics of per capita HCEs in China by employing the distribution dynamics approach with panel data compiled at the household level. We find that the overall per capita HCEs are unimodal distribution in the long run and the distribution dynamics of the per capita HCEs between the urban and rural areas or among the regional subgroups are quite different. However, the speed of convergence has accelerated over time. Moreover, our findings indicate that the per capita HCEs in the urban areas will achieve convergence to an emission level much higher than that of the rural areas. Meantime the per capita HCEs in Northeast China will converge to an emission level much higher than those of the other three regions. These findings provide valuable insights for policymakers in implementing differentiated environmental policies for different regions and between urban and rural households in China.

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1. Introduction

Since household carbon emissions (HCEs) have become a new growing source and a significant contributor to global emissions, the reduction of HCEs is crucial. Currently, most emission mitigation efforts have been focused on the production side, such as emission trading schemes and the advancement of low-carbon energy technologies. Many studies, however, have shown that a large proportion of total carbon emissions come from the household sector, for example, in developed countries, more than 80% for the U.S. (Bin and Dowlatabadi, 2005), 61% for Japan (Nansai et al., 2012), and 52% for Korea (Park and Heo, 2007). In developing countries, the share is relatively small, but it is proliferating (Su and Ang, 2017). Therefore, to cut carbon emissions effectively, more considerable attention should be paid to the substantial reduction of household carbon emissions (HCEs).

As the largest emitter in the world, mitigation of HCEs is increasingly important but faces a unique challenge from various disparities. In China's case, HCEs have also become an important source of the total national emissions in recent years (Li et al., 2019a; Zhang et al., 2019a). Though HCEs only account for approximately 34% of the national total (Mi et al., 2020), they are expected to continue rising over the next few decades due to rapid urbanization and fast economic growth.[1] The Chinese government has put forward a series of policies to cut emissions and transit into a low-carbon economy, among which the transformation of households towards green, low-carbon consumption and lifestyles has become an important issue in this transition (Li et al., 2019b). However, the significant disparities in per capita HCEs between urban and rural areas and among regions have made it difficult to cut CO_2 emissions effectively.

A better understanding of the spatial distribution and evolution of HCEs in the economy helps predict future carbon emissions and design appropriate carbon mitigation policies. For instance, evidence of emission divergence across households may suggest non-sustainable lifestyles and consumption patterns, as well as substantial costs of implementing and monitoring environmental policies (Sauter et al., 2016). Even in the possible presence of emission convergence,

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[1] According to the CO_2 emissions factors provided by the IPCC (2006) and data from China Energy Statistics Yearbooks, we calculated the annual growth rate of direct household carbon emissions in China to be 6.3% from 2006 to 2016, while the annual growth rate of the total CO_2 emissions was 3.3% over the same period.

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mitigation policy must also consider whether households tend to converge to a high or low level of HCEs. For instance, if the distribution of HCEs is not the same for all households, then high-emission groups and the associated causes must be identified so that targeted carbon reduction measures can be taken.[2] However, most of the existing studies in the literature are based on aggregated data at the national, sub-national, or sectoral level and thus ignore individual/household disparities in carbon emissions. See Pettersson et al. (2014) for a comprehensive review of the earlier literature. Besides, most literature investigates the evolution of carbon emissions mainly with the traditional measures of convergence (beta, sigma, and stochastic convergence) and conventional parametric approaches (cross-sectional, panel data regressions, and unit root tests), which are based on strong assumptions (Wu et al., 2016). As a result, little information is provided on the entire shape of the spatial distribution as well as the dynamics of CO_2 emissions among China's households. Finally, the empirical results from the literature have overall been mixed and sensitive to the approach adopted and data set used (Pettersson et al., 2014). Therefore more in-depth research is still needed in order to advance our understanding of the convergence phenomenon and its possible consequences concerning the design of mitigation policies.

This study aims to augment the existing literature on the convergence of CO_2 emissions by adding HCEs per capita at the household level in China to the convergence debates. To make better use of the nationwide, large-scale survey data, we apply a continuous distribution dynamics approach to perform this empirical analysis. It makes several contributions to the current literature. First, we construct a data set of CO_2 emissions at the household level, and conduct the empirical analysis from the perspective of households. The household-level data set of CO_2 emissions include 11,425 households spanning the period from 2012 to 2016 and therefore provides much information than aggregated data used in the literature. Second, we apply a continuous distribution dynamics approach to investigate the dynamics of carbon emissions at the household level. The spatial distributions of HCEs are typically highly skewed to the right and suggest the presence of significant disparities in HCEs, which is usually overshadowed by aggregated data and may have an unexpected impact on convergence measures. The advantage of the distribution dynamics approach is that it is completely data-driven and can provide the dynamics of the entire shape of the distribution. Third, we explore the dynamics of HCEs in China not only with the full sample, but also across different subgroups, namely various periods, urban-rural groups, and geographical groups. This is especially useful in the identification of HCEs convergence for different subgroups as well as the design of targeted mitigation measures. Finally, in addition to the commonly used three-dimensional plot or contour map, we also apply net mobility probability plot and ergodic distribution plot to show explicitly the shape and level of HCEs convergence, which can significantly improve the traditional distribution dynamics analysis and present a comparison of the transitional dynamics of HCEs among various groups, and thereby provide more realistic and meaningful insights for policymakers.

The rest of the paper is organized as follows. Section 2 briefly reviews the relevant literature. Section 3 presents the methodology and data. Section 4 reports the empirical results. Section 5 provides further discussion. Section 6 concludes.

2. Literature review

Since the pioneering work by Strazicich and List (2003), a relatively rich empirical literature exploring the convergence of CO_2 emissions has emerged, such as Presno et al. (2018), Erdogan and Acaravci (2019) and Awaworyi Churchill et al. (2020). Strazicich and List (2003) performed both panel unit root tests and cross-sectional regressions to investigate the convergence of CO_2 emissions in 21 industrialized countries for the 1960–1997 period. In recent years the research on the convergence of emissions has investigated mainly three different convergence concepts (beta, sigma, and stochastic convergence) with various econometric approaches (cross-sectional or panel data regressions, unit root tests, and distributional analysis) as well as different types of samples and datasets (among countries, across regions or sectors in one single country) (Wu et al., 2016; Cheong et al., 2019). As Pettersson et al. (2014) have presented a detailed literature review of the previous research, we only discuss the papers on the subject matter that published after 2013. Overall, the recent research on the convergence of carbon emissions can be broadly grouped into two main strands according to the samples and datasets used.

The first strand focuses on CO_2 convergence among countries and is relatively rich. This research has typically investigated carbon convergence either at the global level or in the context of a smaller sample of 20–30 industrialized countries (see Table 1) and focused on per capita carbon emissions. As for the empirical results, one might say that no consensus has been reached on the validity of the convergence hypothesis. Some studies indicated the existence of convergence of per capita CO_2 emissions as a whole (Runar et al., 2017; Awaworyi Churchill et al., 2018; Presno et al., 2018). Meantime, some studies found that the convergence of CO_2 emissions depends on different countries and econometric methodology (Herrerias, 2013; Li and Lin, 2013; Yavuz and Yilanci, 2013; Robalino-López et al., 2016; Ahmed et al., 2017; Cai et al., 2018; Fernández-Amador et al., 2018; Cai and Wu, 2019; Erdogan and Acaravci, 2019; Haider and Akram, 2019; Awaworyi Churchill et al., 2020). However, other studies showed no evidence of convergence of per capita carbon emissions in the full sample (Li and Lin, 2013; Evans and Kim, 2016; Kounetas, 2018; Erdogan and Acaravci, 2019). Besides, considering that many existing studies using production-based emissions may ignore the environmental impacts of consumption, few studies examined the convergence of CO_2 emissions by households. Karakaya et al. (2019) investigated the convergence patterns in production-based and consumption-based emissions in 35 Annex B countries for the period between 1990 and 2015. The results provided evidence for convergence of production-based emissions as well as divergence of consumption-based emissions in the Annex B countries. Solarin (2019) tested the convergence of both CO_2 emissions and carbon footprints in 27 OECD countries and showed that comprehensive convergence is not valid.

The second strand of studies centers on single countries and uses sub-national data to examine the convergence hypothesis of CO_2 emissions (see Table 2). Partly due to data availability, this category has a strong emphasis on China and the USA. Many studies support the convergence of carbon emissions for regions or sectors as a whole (Baldwin and Wing, 2013; Huang and Meng, 2013; Wang and Zhang, 2014; Wu et al., 2016; Yang et al., 2016; Acar and Yeldan, 2018; Tong and Tariq, 2020). On the contrary, some studies could not find evidence for the carbon convergence at the country level (Baldwin and Wing, 2013; Wang et al., 2014). Besides, some studies suggest that carbon convergence exists in some of the regions or sectors (Li et al., 2014; Wang et al., 2014; Burnett, 2016; Apergis and Payne, 2017; Oliveira and Bourscheidt, 2017).To sum up, all these studies mainly investigated the convergence of CO_2 emissions on the production side except Mi et al. (2020), which evaluated the convergence of carbon footprints across households for 12 different income groups of China's 30 regions. The results showed that the convergence of carbon footprints exist in China.

In general, we can see that existing studies are more likely to work on the convergence of CO_2 emissions with different samples and datasets as well as various econometric methods. As a result, conflicting results were reported as some studies show that per capita emissions are convergent while others indicate that they are divergent. Thus

[2] The disparities in the distribution of HCEs stem from many factors that affect consumption of energy and goods and services, such as socio-economic factors, household characteristics and geographic factors, etc. A more detailed literature review on this issue can be found in Zhang et al. (2015).

Table 1
Summary of recent studies on convergence of CO_2 emissions among countries.

Study	Sample	Methodology	Empirical findings
Herrerias (2013)	162 countries	Panel unit root tests	Divergence in all types of energy sources and club convergence in most countries
Li and Lin (2013)	110 countries	System GMM	Convergence in sub-samples Divergence in the full sample
Yavuz and Yilanci (2013)	G7 countries	TAR panel unit root tests	Partial convergence in the first regime and divergence in the second regime
Evans and Kim (2016)	11 Asian countries	Distribution dynamics approach	Divergence of relative CO_2 emissions
Robalino-López et al. (2016)	10 South Africa countries	Phillips and Sul approach	Club convergence
Ahmed et al. (2017)	162 countries	Wavelet-based unit root tests	Convergence among 38 countries out of 162
Runar et al. (2017)	124 countries	Parametric and nonparametric panel data methods	Convergence in global and sub-samples
Awaworyi Churchill et al. (2018)	44 countries	LM and RALS-LM unit root tests	Convergence
Cai et al. (2018)	21 OECD countries	Quantile unit root test with Fourier function	Convergence in 9 countries as a whole and divergence in the rest of the countries
Fernández-Amador et al. (2018)	66 countries and 12 composite regions	Bayesian structural model	Existence of country-specific conditional convergence
Kounetas (2018)	23 EU countries	Distribution dynamics analysis	Divergence
Presno et al. (2018)	28 OECD countries	Nonlinear stationarity	Convergence
Rios and Gianmoena (2018)	141 countries	Spatial panel data	Convergence
Cai and Wu (2019)	21 OECD countries and 19 emerging market economies	Panel unit root tests	Convergence in 11 OECD countries and 10 emerging market economies
Erdogan and Acaravci (2019)	28 OECD countries	Panel data methods	Stationary at the country-specific level and non-stationary at the panel level
Haider and Akram (2019)	53 countries	Phillips and Sul approach	Club convergence
Karakaya et al. (2019)	35 Annex B countries	Cross-sectional regression	Convergence in production emissions and divergence in consumption emissions
Solarin (2019)	27 OECD countries	RALS-LM unit root tests	Convergence of CO_2 emissions (or carbon footprints) in 12 (or 15) out of the 27 countries
Awaworyi Churchill et al. (2020)	17 emerging market economies	LM and RALS-LM unit root-tests	Convergence in 11 out of the 17 countries

further and extensive works are still required on the subject matter. Moreover, it is important to note that most existing studies have used aggregated data to evaluate the convergence of per capita carbon emissions from the perspective of production. As consumption-based emissions have accounted for a larger proportion of the total emissions, detailed studies on per capita CO_2 emissions from the perspective of consumption are needed. To provide sufficient insights for policymakers to formulate appropriate mitigation policies, it is critical to conduct a detailed analysis of carbon convergence at the household level. However, to the best of our knowledge, no research has examined the convergence hypothesis with datasets on HCEs at the household level so far.

In this paper, we aim to fill this gap by investigating the carbon convergence from a consumption perspective as well as use data on CO_2 emissions in China at the household level. Besides, taking the typical

Table 2
Summary of recent studies on convergence of CO_2 emissions in one single country.

Study	Sample	Methodology	Empirical findings
Baldwin and Wing (2013)	50 US states and DC	Index number decomposition technique	Divergence at the national level and convergence at the regional level
Huang and Meng (2013)	Urban areas in 30 provinces of China	Spatial panel data	Convergence
Li et al. (2014)	50 states of the USA	Sequential panel selection method	Convergence in 12 states
Wang and Zhang (2014)	6 sectors across 28 provinces in China	Panel regression and unit root-tests	Convergence
Wang et al. (2014)	29 provinces of China	Log t test method	Divergence at the country level and club convergence at the province level
Burnett (2016)	48 states of USA	Phillips-Sul algorithm and panel data analysis	Convergence in 26 states and divergence in the others
Wu et al. (2016)	286 cities of China	Continuous distribution dynamics approach	Convergence Club convergence
Yang et al. (2016)	30 Chinese provinces	System GMM	Convergence
Apergis and Payne (2017)	Aggregate, by sector, and by fossil fuel type of 50 states of USA and DC	Phillips-Sul club Convergence approach	Multiple convergence clubs
Oliveira and Bourscheidt (2017)	33 sectors among 39 countries	Panel data analysis	Convergence in 4 sectors.
Acar and Yeldan (2018)	22 sectors in Turkey	Panel unit root tests and regression	Conditional convergence
Mi et al. (2020)	30 provinces in China	Cross-sectional regression	Convergence of carbon footprints
Tong and Tariq (2020)	30 Chinese provinces	Panel regression	Beta convergence

characteristics of the datasets used into account, we choose to apply a distribution dynamics approach to conduct the relevant analysis, which is particularly suitable for the current datasets.

3. Methodology

3.1. The distribution dynamics approach

The early distribution dynamics approach suggested by Quah (1993) is applied to investigate the dynamics of economic growth in the first place. However, the discretization to construct the transition probability matrix is crude and ad hoc, and the empirical results are sensitive to the discretization process. To address these issues, Quah (1997) adopted a stochastic kernel in place of the transition probability matrix to obtain relatively reliable estimation results, and it has been widely used in many studies on the convergence of economic growth (Li and Cheong, 2016), energy use (Cheong et al., 2019; Shi et al., 2020) and energy intensity (Wu et al., 2018) since then. For the reliability of the results, we use the continuous distribution dynamics approach to explore the dynamics of per capita carbon emissions in China at the household level.

Suppose that x and y are the relative per capita HCEs in period t and $t+\tau$ with $\tau>0$. Let $f_t(x)$ and $f_{t+\tau}(y)$ represent the density function of x and y in period t and $t+\tau$, respectively. If we assume that the evolution of the distribution of variable x and y is time-invariant, then $f_{t,t+\tau}(y,x)$, the joint density function for τ, can be expressed as follows:

$$f_{t,t+\tau}(y,x)=\frac{1}{nh_xh_y}\sum_{i=1}^{n}K\left(\frac{x-x_i}{h_x},\frac{y-y_i}{h_y}\right) \tag{1}$$

where x_i and y_i are the values of the relative per capita HCEs in period t and $t+\tau$, h_x and h_y are the bandwidths of variable x and y, respectively. The optimal values of the bandwidth can be obtained with the procedure proposed by Silverman (2018), K(·) is the Epanechnikov kernel function, and n is the number of observations.[3]

The conditional probability density function $g_\tau(y|x)$ can be calculated through $f_t(x)$ and $f_{t,t+\tau}(y,x)$,

$$g_\tau(y|x)=\frac{f_{t,t+\tau}(y,x)}{f_t(x)} \tag{2}$$

From Eq. (2), we notice that the future per capita HCEs in period $t+\tau$ depend only on their specific values in period t. Thus, the future distribution of the per capita HCEs can be predicted through the relationship between the distribution of x at time t and y in period $t+\tau$,

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

where $g_\tau(y|x)$, the stochastic kernel, can be iterated to generate the following long-run ergodic distribution (Johnson, 2000):

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

By doing this, we can have the information about the transition process and long-run distribution of the per capita HCEs from the transitional dynamics and the ergodic distribution. The ergodic distribution is the steady-state equilibrium distribution in the long run. Many significant findings can be derived from observing the shape of the ergodic distribution. The height of the distribution (values in the vertical axis) represents the proportion of households, while the values of the per capita HCEs can be observed from the horizontal axis. The peak of the ergodic distribution implies that a large portion of the households will congregate around the value of per capita HCEs of the peak; therefore, it can provide information on the convergence level of the data.

Furthermore, based on Wu et al. (2016), we can derive the Mobility Probability Plot (MPP) which is the net upward mobility probability for moving upward within the distribution. MPP is estimated as follow:

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

A positive value of MPP implies that the household has a higher tendency of increasing the per capita HCEs in the future, while a negative value of MPP means that the household has a higher probability of decreasing the per capita HCEs. By observing the MPP, one can understand the movement of the entities within the distribution, thereby gaining an understanding of the shape of the distributions and the underlying trend behind the changes in the shape of the distribution.

In order to observe the convergence patterns of the four regions, the full dataset was separated into four regional datasets to provide a comparison of the shapes of the distributions. By comparing the ergodic distributions and the MPPs of the four regions, one can know more about the disparity among the four regions in detail regarding the dispersion, shape, and movement of the entities within the distribution in detail.

3.2. Method to calculate HCEs

The total CO_2 emissions for an individual household k in our sample consisted of two parts: direct CO_2 emissions C_{direct_k}, and indirect CO_2 emissions $C_{indirect\_k}$. The direct CO_2 emissions for household k are the emissions from the household's final consumption of fossil fuels, i.e., coal, oil, and gas (Zhang et al., 2015). We can calculate the direct CO_2 emissions for household k with the emissions coefficient method (IPCC, 2006), which are widely used in the literature (Qu et al., 2013; Wiedenhofer et al., 2017). The direct CO_2 emissions for household k are:

$$C_{direct\_k}=\sum_i f_i Energy_{ik} \tag{6}$$

where f_i is the CO_2 emissions factor of energy source i, and $Energy_{ik}$ is the quantities of energy sources i consumed by household k.

The indirect CO_2 emissions for household k are estimated with the Input-Output Modeling (IOM) approach, which is widely used by researchers (Golley and Meng, 2012; Wiedenhofer et al., 2017). The calculation of the indirect CO_2 emissions for household k is as follows:

$$C_{indirect\_k}=D(I-A)^{-1}Expend_k \tag{7}$$

where D is the row vector of direct emission intensities in each sector, and A is the inter-sector matrix of direct input coefficients, thus $(I-A)^{-1}$ is the Leontief inverse matrix. $Expend_k$ is the column vector of the expenditures on goods and services consumed by household k.

3.3. Data

We apply three datasets to calculate the total CO_2 emissions for each household in our sample: (i) Samples of Chinese households for the latest available years (2012, 2014 and 2016) from China Family Panel Studies (CFPS)[4]; (ii) China's Input-Output Table (IOT) from the World Input-Output Database (WIOD, Timmer et al., 2015); and (iii) Carbon emissions for China's 35 sectors in 2007 from WIOD.[5]

CFPS is a national representative longitudinal survey of Chinese households, which was launched in 2010 and implemented every two years thereafter by the Institute of Social Science Survey of Peking University (ISSS). The sample covers almost 15 thousand households for every year and spreads over 25 provinces in 2010 and all 31 provinces in 2016. In this paper, we obtained all the information on consumption expenditures and demographics of each household from CFPS for 2012, 2014, and 2016.

[3] The stochastic kernel is estimated based on per capita HCEs of all the households. As the sample size becomes large enough, the estimation results will be more reliable.

CFPS collects 26 consumption expenditure items, most of which have corresponding items in the Chinese National Bureau of Statistics (NBS), and there are three expenditure items related to the energy source that households consume directly.[6] We converted the expenditures on energy consumption into physical quantities according to the national average price of the specific energy source in the same year and then calculated the direct HCEs of each household according to Eq. (6).

When calculating the indirect HCEs, we firstly adjusted the prices of expenditure items from CFPS for the three years to constant prices in 2007 according to the CPI sub-indices for both urban and rural areas provided by NBS. Then we obtained the Leontief inverse matrix from IOT and per-Yuan CO_2 emissions intensities coefficients for all 35 sectors from WIOD.[7] By combining the detailed household expenditure items on the consumption side with the Leontief inverse matrix and the CO_2 emissions intensities coefficients,[8] we can estimate the indirect CO_2 emissions for every surveyed household over the three years according to Eq. (7).

To reduce bias caused by outliers, we dropped 1% of households with the highest and lowest emissions and incomes. Thus, we obtained consolidated datum with Chinese households' total CO_2 emissions for each household spread across the three interview years. To calculate the distribution dynamics of per capita HCEs, panel data is needed. Though a unique ID in different years should represent the same household in CFPS, household demographics may change due to marriage, migration, education, or other reasons, which may lead to significant changes in HCEs. To enhance the accuracy of results, we take the household as the same for two consecutive years according to the following four variables, household ID, family size, urban or rural location, and province. Finally, we have two panel data sets, there are 5717 households in 2012 and 2014 and 5708 households in 2014 and 2016. The data that we employed in this study are the latest ones. It is worth noting that for distribution dynamics analysis, if the number of yearly data is large enough, it is better to rely on the latest data rather than the old data. It is because the obsolete data may contain information on history that is associated with policies that are no longer in place; therefore, if one incorporates these obsolete data in the analysis, it may create an error in the forecast. For distribution dynamics analysis, it is thus better to have a short span of data with the latest information, rather than a long time series of obsolete data. Given that the number of data in each year is more than 5700, which is large enough for the computation, therefore, we can conduct the analysis and provide a better forecast by relying on the latest data.

4. Results

Similar to the empirical work with the distribution dynamics approach, we use the relative per capita HCEs, which is each household's per capita carbon emissions divided by its yearly average as the main variable to be analyzed. We studied both the full sample and several sub-sample groups.

4.1. Transitional dynamics of the overall relative per capita HCEs

Fig. 1a and b illustrate the transitional dynamics of the overall relative per capita HCEs for the two periods. The three-dimensional distribution plot of the overall relative per capita HCEs (Fig. 1a) describes the likelihood of a household transiting from a fixed value of relative per capita HCEs in period t to particular values of relative per capita HCEs in period $t+1$. Thus, high values along the diagonal indicate a tendency to remain. From Fig. 1a, we may find that the concentration of probability mass is not situated along the diagonal, which means low persistence in relative position changes among households. In other words, most of the households with a certain value of relative per capita HCEs in period t tend to move to other positions in the coming period. The contour map (Fig. 1b), a top-down view of the three-dimensional plot, presents the features more clearly.

As the three-dimensional distribution plot of the transition probability and contour map are not enough to show clearly the transitional dynamics of the relative per capita HCEs, we employ the distribution of net transition probability plot and the ergodic distribution plot to present more insights into the future movement of the household for a certain value of the relative per capita HCEs, as shown in Fig. 1c and d.

In Fig. 1c, it is apparent that households with different initial values of relative per capita HCEs have a different net probability of upward or downward transition. However, a monotonous downward trend is evident here, and it intersects with the horizontal axis when the value of the relative per capita HCEs is about 0.65. Specifically, households whose initial values of the relative per capita HCEs smaller than 0.65 have a net upward transition probability, which signals a tendency of increase in their relative per capita HCEs in the future. On the other hand, households whose initial values of the relative per capita HCEs over 0.65 have a net downward transition probability, and their relative per capita HCEs tend to decline in the future. Considering that the economy will continue developing steadily in China and most Chinese households will experience emission increases with income growth in the future, the convergence of HCEs can be seen as a positive signal for emissions control.

From the ergodic distribution plot in Fig. 1d, an evident unimodal convergence of the relative per capita HCEs in China can be achieved in the long run if the distribution dynamics don't change. And the relative per capita HCEs may converge to about 0.4, which is far below the average value (the relative per capita HCEs $= 1$). This is a good sign as it suggests that the emission levels of a majority of the households are below the average HCEs of the whole country in the future.

4.2. Transitional dynamics of the relative per capita HCEs over different periods

Fig. 1 has shown that the relative per capita HCEs in China show the unimodal distribution in the long run and the overall relative per HCEs value is below the average value. It is natural to know whether the convergence process of HCEs is alike over different periods. To this end, the full sample is divided into two parts, namely 2012–2014 and 2014–2016, and stochastic kernel analyses, as well as the transitional dynamics of the relative per capita HCEs, are conducted for each period. To save space, the three-dimensional distribution plots of the transition probability and the contour plots are not presented here.

Fig. 2 presents the distribution dynamics of the relative per capita HCEs in different periods. It can be seen that though the net transition probability of the relative per capita HCEs is alike in the two periods, the values of emissions convergence are quite different. Firstly, Fig. 2a shows that both the net transition probability plots are monotonously downward, however, households with their relative per capita HCEs below 0.7 in 2012–2014 are more likely to emit more CO_2 emissions in the next period, while the corresponding cut-off point is 0.6 in 2014–2016. Secondly, when the relative per capita HCEs are smaller

[4] Before doing the study, we made a comprehensive comparison of the main household survey datasets in China and found that either the respondents in some surveys are inconsistent with the topic, or the time span, availability or expenditure items in some other surveys cannot meet the requirement of this paper. Therefore, we think CFPS is the more appropriate dataset at the moment.

[5] The classification of sectors in IOT and WIOD are the same greatly reduces the bias arising from the processing of data matching. Meanwhile, carbon emissions of each sector can be obtained directly from WIOD, which are much helpful in calculating the carbon emissions for each household.

[6] These are expenditures on fuel (including coal, firewood, charcoal, liquefied gas and so on), local transportation and heating.

[7] In RMB according to the exchange rate in 2007.

[8] The National Economic Industry Classification (GB/T 4754–2011) and China's IOT for 135 sectors in 2007 by NBS are important references in the process of aggregating. The detailed process of data matching can be found in the Appendix to Zhang et al. (2020).

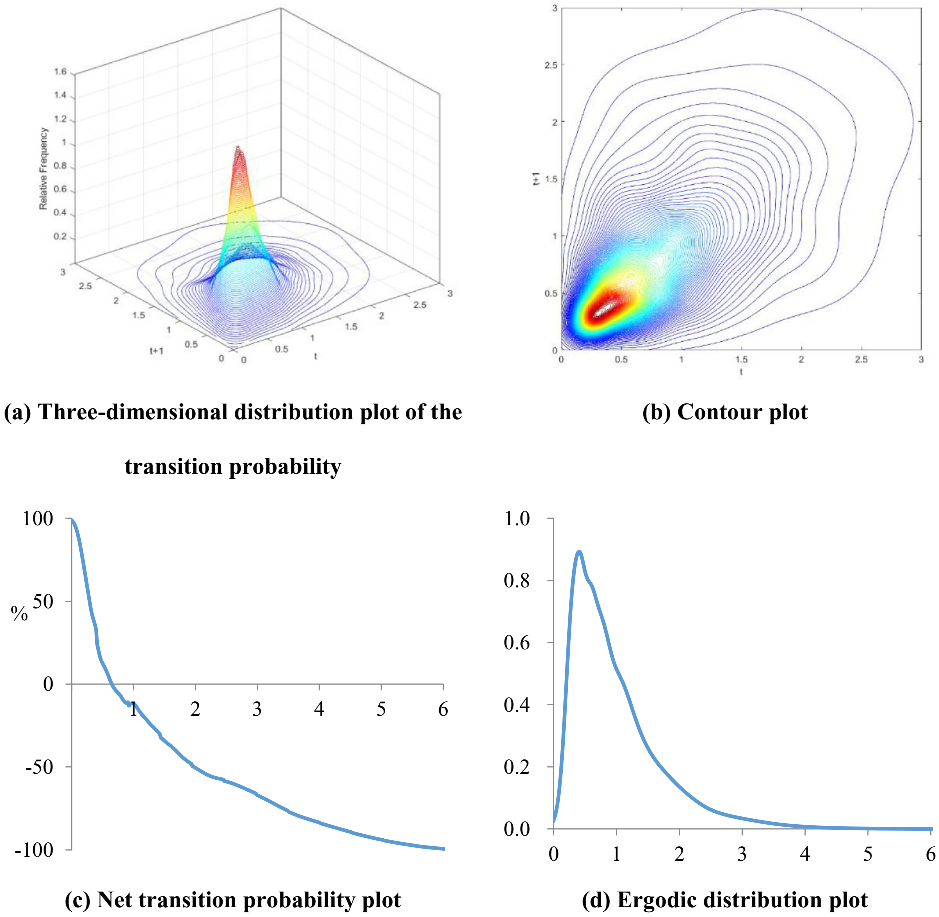

Fig. 1. Relative per capita HCEs dynamics across all the households. Note: In Fig. 1a, a line projected from a fixed value on the *Period t* axis traces out a probability density over the kernel, describing the relative likelihood of transiting into particular values in *Period* $t+1$. The emerging unimodality is evident here. Fig. 1b is just the view from the above of Fig. 1a, where contours have been drawn at the indicated levels and projected onto the base of the graph.

than 2.5, households in 2012–2014 are more likely to increase their CO_2 emissions than in 2014–2016, and the situation is reversed when the relative per capita HCEs are larger than 2.5.

Moreover, Fig. 2b shows that though both the distribution of the relative per capita HCEs in the two periods show unimodality, the distribution of the relative per capita HCEs in 2012–2014 is more dispersed than in 2014–2016. The relative per capita HCEs will converge to 0.8 in the long run in 2012–2014, while the value of emissions convergence is 0.4 in 2014–2016. This is also a positive signal that households in China tend to have a lower emission level in the future.

4.3. Transitional dynamics of the relative per capita HCEs between urban and rural areas

Due to significant differences in socio-economic development and government policies between the urban and rural areas in China

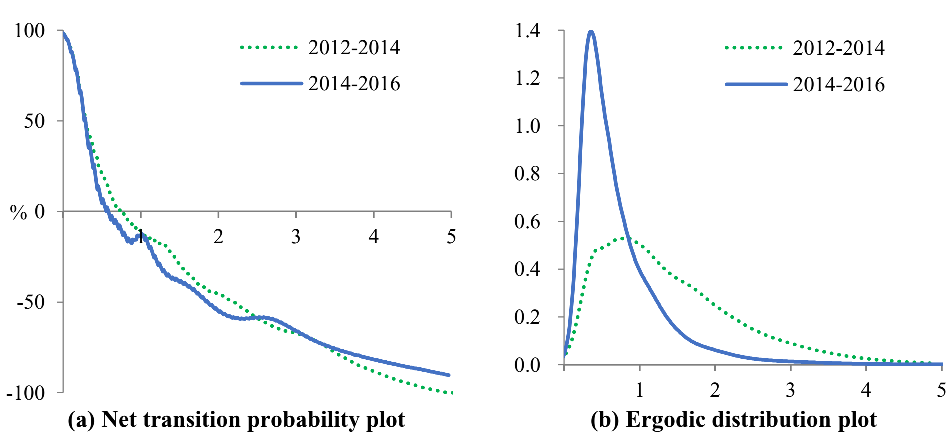

Fig. 2. Relative per capita HCEs dynamics across households over different periods.

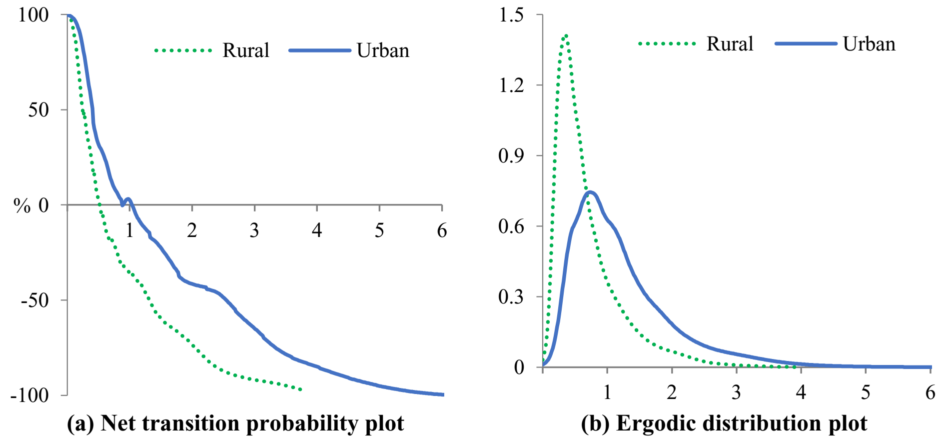

Fig. 3. Relative per capita HCEs dynamics across urban and rural areas.

(Wang and Zhang, 2016; Wiedenhofer et al., 2017), large disparities exist in per capita HCEs between urban and rural households. And it is necessary to make a detailed comparison of the transitional dynamics of the relative per capita HCEs between the urban and rural households in China. Relevant results are shown in Fig. 3.

It is clear that though the net transition probability of the relative per capita HCEs is alike for households in urban or rural areas, the values of emissions convergence are quite different. Fig. 3a shows clearly that the rural households with the relative per capita HCEs smaller than 0.5 have a positive net transition probability, while the relative per capita HCEs of urban households may decrease when their relative per capita HCEs are larger than 1 (above the average value).

As shown in the ergodic distribution plot (Fig. 3b), the per capita HCEs in urban and rural areas tend to converge in the long run, however, the relative per capita HCEs of rural households tend to converge to a lower emission level of 0.35, while the relative per capita HCEs of urban households tend to converge to a much higher emission level of 0.7.

4.4. Transitional dynamics of the relative per capita HCEs across regions

China is a large country with considerable differences in many aspects among regions, such as factor endowments, weather conditions, and environmental policies. To better understand the distribution dynamics of HCEs in different regions, we divide China into four regions according to physical and geographical characteristics: East, Middle, West, and Northeast. The relevant results are presented in Fig. 4. We may notice that the distribution dynamics of the four regions are not the same, thereby suggesting that region-specific policies should be designed rather than a universal policy for the whole country.

From Fig. 4a, we can see that the net transition probabilities of all the four regions decrease monotonically, which indicates a strong tendency of convergence of the relative per capita HCEs among households in the four regions. In the meantime, the cut-off points of the relative per capita HCEs for the East, Middle, West, and Northeast are about 0.75, 0.55, 0.55 and 0.9, respectively. All of them are smaller than 1. Take the East as an example, if the relative per capita HCEs of the households in the East are larger than 0.75, there exists a tendency of carbon emission reductions. Similar results can be drawn for the other three regions.

Moreover, by comparing the ergodic distributions of the relative per capita HCEs in the four regions, we can find out that households in the East, Middle, and West will reach the convergence to almost the same value of the relative per capita HCEs (around 0.4). However, the distribution of the relative per capita HCEs of the Middle is the most concentrated, followed by the West, East, and Northeast. Besides, the relative per capita HCEs in the Northeast will converge to a value when the per capita HCEs is about 0.9 times of the average, which is quite close to the average value. Moreover, the Northeast has the highest level of

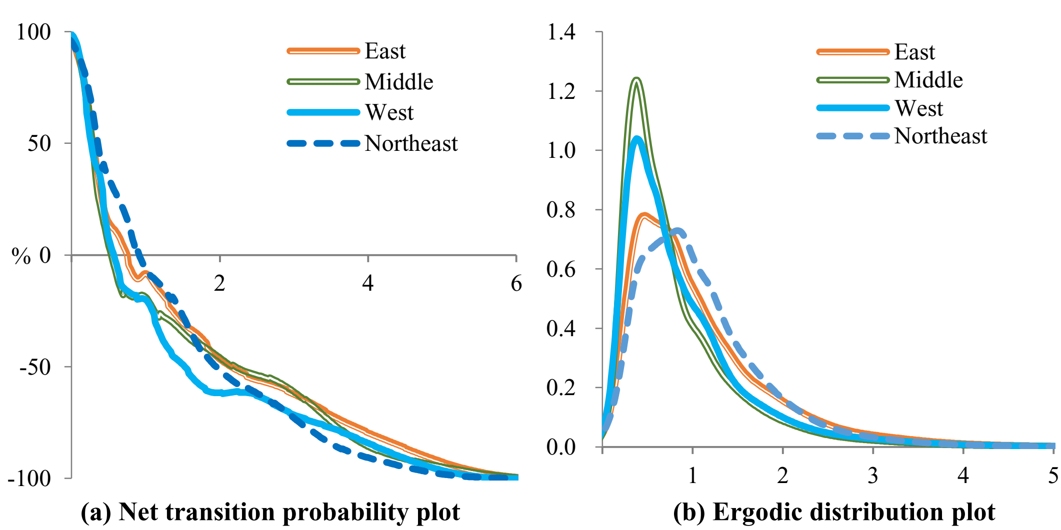

Fig. 4. Relative per capita HCEs dynamics across different regions.

emissions convergence, followed by the West, East, and Middle, from which we may conclude that the performance of carbon emission control is the best in the Middle and the worst in the Northeast.

5. Discussion

We have introduced the nonparametric continuous distribution dynamics approach to studying the behavior of the entire distribution of the variable of interest and analyzing the convergence of the per capita HCEs in China using household-level survey data. Our results suggest that the convergence of the overall per capita HCEs may be achieved in China, which is consistent with Mi et al. (2020) and is a positive signal for emission reductions in the future.[9] Both Mi et al. (2020) and this study evaluated the convergence of CO_2 emissions from the consumption side and reached the same conclusion of HCEs convergence in China, however, there exist three main differences: (i) Mi et al. (2020) estimated HCEs for 12 different income groups of China's 30 provinces with data obtained from the provincial statistical yearbooks, while this study quantified HCEs with survey data at the household level; (ii) the research time period was not the same, which was 2007–2012 in Mi et al. (2020) and 2012–2016 in this study; and (iii) compared to the traditional conditional convergence approach used in Mi et al. (2020), we applied the distribution dynamic approach according to the typical characteristics of the survey data. Moreover, we also find that the levels of HCEs convergence under various classifications of households are quite different in the long run, especially between the urban and rural areas or among the four main regions in China, which are very helpful to policymakers.

Firstly, the existence of HCEs convergence does not mean that mitigation policies are of little importance. Considering that the realization of HCEs convergence may take a very long time, suitable environmental policies are still needed to promote emissions reduction. As we have demonstrated, almost all the ergodic distributions are unimodal and positive skew, which means that the mean of HCEs is larger than the median and the mode in the long run, and thus a substantial share of CO_2 emissions can be released by a few high-emission households. From the perspective of equity, mitigation policies should be adaptively deployed according to households' levels of CO_2 emissions and their driving factors. Considering that income is the most important influencing factor of HCEs (Wiedenhofer et al., 2017), and households with lower relative per capita HCEs usually are low-income groups, we should not regard low-income households as the main targets for more stringent environmental regulations though they have net upward transition probabilities. Instead, providing funds to low-income residents to promote the formation of energy-saving and emission-reduction behaviors has been proved effective in decreasing HCEs (Yi, 2015). Meantime, to achieve the required carbon emission reduction targets, appropriate policies for households with high emissions should be put forward to accelerate the process of HCEs convergence in China.

Secondly, while continue implementing environmental policies directed at the production-side is efficient in cutting CO_2 emissions, the absence of consumption-based emission reductions from local government's mitigation strategies appears to be a significant global issue (Millward-Hopkins et al., 2017). Since emission reductions achieved by policies directed at the production-side are overshadowed by emissions associated with household consumption, it is critical to undertake effective and efficient measures promoting green consumption pattern and low-carbon lifestyles of households, for the increase of household's willingness to reduce emissions is still the primary challenging task (Li et al., 2019a). Relevant measures, such as the application of energy efficiency label (Shi, 2014; Liu et al., 2016), the introduction of the carbon taxes, and the progressive electricity tax, are required to transform the behaviors of consumers and motivate them to adopt greener and low-carbon lifestyles.

Thirdly, targeted mitigation policies should be deployed according to the typical characteristics of urban and rural households. The transition dynamics analyses for urban and rural areas suggest that cutting CO_2 emissions from urban households is the key point of the carbon mitigation policy. However, it should be noted that although the income gap between the urban and rural households is still significant, the annual growth rate of income, as well as consumption of the rural households, has exceeded that of the urban counterparts in recent years, which is the main reason behind the fast increase of rural HCEs. Furthermore, China is experiencing rapid urbanization and socio-economic transition, and thus households will change their lifestyles and consumption patterns in the future. It is thus important to formulate policies in adapting to the changes in lifestyles of rural households due to urbanization and socio-economic development (Li et al., 2019a). Given that the rapid urbanization process is set to continue in China, it is essential to improve city planning and build more low-carbon housing and transportation system so as to provide the necessary infrastructure for green and low-carbon urban lifestyles.

Lastly, through policy guidance and education, the government should encourage the formulation of green and low-carbon lifestyles for households as well as promote high efficiency of energy use in the East and Northeast regions. The regional distribution dynamics analyses show significant disparities in HCEs among the four regions in China. As we grouped provinces in China according to their geographic proximity or systemic significance, it is expected that HCEs of the four regions will converge to their levels of CO_2 emissions. More specifically, the levels of emission convergence of the East and Northeast will be much higher than those of the Middle and West. Hence cutting the HCEs of the East and Northeast regions is very crucial for the realization of the overall HCEs reductions in China. However, while the high HCEs in the Northeast region are likely correlated to the high levels of income (Lyons et al., 2012),[10] it could also be partly because of the harsh climate conditions in the winter. Zheng et al. (2011) also discovered that there is a strong negative correlation between HCEs and the average January temperature in the Northeast. When it comes to the Northeast regions, besides the above policies, the diversification of energy use and the reduction of dependence on the coal combustion in heating are the top priority to cutting HCEs. Furthermore, the Northeast should improve building energy efficiency so as to decrease demand for heating in winter as there are significant cost-effective potentials of emission reductions (Song et al., 2018).

6. Conclusions

The convergence of per capita CO_2 emissions has played an important role in projecting future emission pathways and designing environmental policies. In contrast to most previous work focusing on the convergence of emissions from the production side, this paper explores the transitional dynamics of per capita HCEs in China by employing a distribution dynamics approach with panel data compiled at the household level. There are three important conclusions. Firstly, per capita HCEs are found to converge in China over the research time period 2012–2016, and the speed of convergence has accelerated over time. For the full sample, a monotonous downward trend can be seen from the net transition probability plot, which means that households with low initial relative per capita HCEs tend to have higher levels of emissions in the future while those higher emitters have a

[9] Mi et al. (2020) is the most related research to our study. Moreover, as previously mentioned, many studies mainly examined the convergence of CO_2 emissions from the production side with various approaches and drew mixed results. As the influencing factors of the convergence of production-based CO_2 emissions (i.e., production technology, economic structure, and regulation policy, etc.) are not the same as those of the convergence of consumption-based CO_2 emissions (i.e., income, demographics, lifestyle and consumption pattern, etc.), we choose to leave the detailed comparisons of these two types of convergence results to further studies.

[10] In 2016, the per capita disposable incomes in the East, Middle, West and Northeast are ¥ 15,498, ¥ 11,794, ¥ 9918 and ¥ 12,275 separately.

higher probability to reduce their emissions. The achievement of convergence of per capita HCEs can be attributed to the government's considerable efforts to promote energy conservation and emission reductions. For example, the Chinese government has targeted reductions in energy intensity and carbon intensity of 16% and 17% respectively during the 12th five-year period (2011–2015) (Li and Wang, 2012), and there have also been similar emission reduction targets and mitigation measures in recent years. As China will continue to take measures to combat climate change as well as promote sustainable development, especially the transition of lifestyles and consumption patterns towards low-carbon products and services, it is reasonable to believe that the convergence of per capita HCEs can be achieved in China in the long run.

Secondly, the distribution dynamics of per capita HCEs between urban and rural areas are quite different, especially in the emission levels of convergence. There is a visible urban-rural divide in China, and it is still one of the most significant challenges for China's sustainable development. Though the results suggest that convergence exists in urban and rural areas in the case of per capita HCEs, our findings also indicate that the relative per capita HCEs in urban areas will achieve convergence to an emission level (0.7) much higher than that of the rural areas (0.35). Compared with rural households, urban households have much higher levels of income and more modern lifestyles, and thus resulting in higher CO_2 emissions.

Thirdly, the convergence of the relative per capita HCEs varies significantly across China's regions. In general, there exist marked regional disparities in income and notable regional differences in the fuel mix, weather conditions, lifestyles, and consumption patterns, resulting in different distribution dynamics of per capita HCEs. In all four regions, the relative per capita HCEs converge during the research time period 2012–2016. Moreover, households in the East, Middle, and West will converge to almost the same level of the relative per capita HCEs (0.4), while households in Northeast China will converge to an emission level (0.9) much higher than those of the other three regions.

According to our research, the convergence of the overall per capita HCEs which can be achieved in China is a positive signal for emission reductions, but it does not mean that policymakers need to do nothing to tackle HCEs. In fact, the mitigation of HCEs is very important to the reduction of total carbon emissions for the achievement of emission-reduction targets and sustainable development in China. Thus appropriate policies are needed to encourage green consumption and low-carbon lifestyles of households so as to save large quantities of energy and CO_2 emissions in China. Whilst the result that the levels of HCEs convergence under various classifications of households are quite different in the long run, especially between the urban and rural areas or among the four main regions in China, are also very helpful to policymakers. Specifically, in formulating mitigation policies, policymakers should pay more attention to the possible gaps in emissions by households between urban and areas or among different regions and the relevant driving factors. Though China has taken into account regional equality in the distribution of mitigation responsibilities, equality at the household or individual level is seldom considered (Zhang et al., 2019b; Mi et al., 2020). Thus mitigation actions need to be formulated according to the typical characteristics of various households and induce changes in consumption patterns with carbon taxes, carbon literacy, and other policy tools. For example, the government should encourage the formulation of green and low-carbon lifestyles for households as well as promote high efficiency of energy use in the East and Northeast regions.

It is worth noting that distribution dynamics analysis can only reveal the differences among different groups but cannot directly associate the differences with the environmental policies. Therefore, one potential research direction in the future is to evaluate the impacts of different environmental policies on the convergence of carbon emissions and present theoretical explanations for those disparities. Besides, with the expansion of the time period and samples in the future, a re-examination of the dynamics of HCEs with various econometric methods can be done to shed more light on the convergence of CO_2 emissions as well as provide significant insights for policymakers.

Acknowledgments

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