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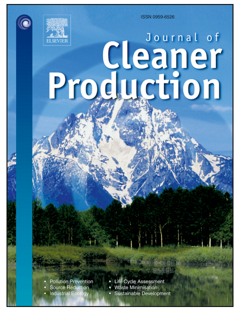

Urbanisation, agriculture and convergence of carbon emissions nexus: Global distribution dynamics analysis

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Abstract:

Urbanisation and agriculture have been commonly used in the studies of carbon emissions. However, the issue of convergence of carbon emissions and intensity across countries with different urbanisation and agrarian structures has been under-researched. Unlike previous studies, we examine whether the urbanisation level and the agrarian orientation determine the tendency for countries' relative carbon intensity (REPC) and relative per capita carbon emissions (REPGDP) to converge over time. We employ the display tools of the distribution dynamics approach and a panel of 217 countries from 2000 to 2016. The main findings are as follows. First, with one exception, two to four convergence clubs will emerge across all groups of countries in the long run. Second, most of the clubs occur at values far from (below and above) the global average emissions level. Third, we construct the '*policy priority list'* consisting of the above-average carbon emitters with a high tendency to diverge further from the global average in the coming years. Accordingly, we identify the least urbanised (most agrarian-oriented) countries with a REPC value of around 2.2 (1.9) to have a 65% (80%) probability of further divergence. Fourth, the results based on the REPC vis-à-vis the REPGDP variable are largely different. The study extends the existing knowledge about the urbanisation, agriculture and carbon emissions nexus and offers policy recommendations.

Keywords: CO2 emission; Urbanisation; Agriculture; Distribution dynamics; Convergence

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1. Introduction

An ongoing global climate change is largely caused by greenhouse gases (hereafter GHG) emitted by the burning of fossil fuels (IPCC, 2021; Wei et al., 2022). Carbon dioxide accounts for 77% of all GHG and is the main culprit of the greenhouse effect (Huang et al., 2022), whilst high levels of CO2 emissions will have a huge and irreversible impact on the Earth's climate and devastating effects on animals, humans, and ecosystems (e.g., Logan, 2010; Tang et al., 2018; Yang et al., 2021). Therefore, it is necessary to reduce greenhouse gas emissions.

The urban areas and the agriculture sector are two major sources of total global carbon emissions accounting for around 70% and 14%, respectively (IPCC, 2015; Fais et al., 2016). Furthermore, the urban population is expected to double, whilst the global production of food necessary to feed a growing population will have to grow by 70% by 2050 (World Bank, 2021, 2022). Moreover, expanding urban areas are increasingly more exposed to climate change-driven natural disasters (e.g., floods) and agricultural production is by default extremely vulnerable to climate change (Wu et al., 2019; Shan et al., 2020). Against such a backdrop, a growing body of empirical research has examined the relationships between urbanisation, agriculture, and carbon emissions. However, the results of the extant literature are controversial with mixed empirical findings on the nexus between urbanisation and CO2 emissions (e.g., Martínez-Zarzoso and Maruotti, 2011; Sadorsky, 2014; Liu and Bae, 2018; Yao et al., 2018). In addition, only a few studies take temporal and spatial perspectives to explore the cross-country convergence of CO2 emissions in the dropback of urbanisation (e.g., Bhattacharya et al., 2020; Wang et al., 2022). Furthermore, most of the studies use either absolute or per capita carbon convergence, whereas they neglect the carbon intensity which is an important monitoring and target indicator of CO2 emissions abatement (e.g., Wu et al., 2016; Apergis and Payne, 2017; Acar et al., 2018; Wei et al., 2020; Shi et al., 2021a).

The above-mentioned gaps in the environmental economics research are puzzling given that in international negotiations on climate change, two popular allocation schemes used to determine countries' share in the global carbon mitigation burden are (1) per capita carbon emissions and (2) carbon intensity [1] (Frankel, 2007; Mattoo and Subramanian, 2012; Bhattacharya et al., 2020). Additionally, carbon intensity and per capita carbon emissions even within the same country or region can follow the opposite paths (Parker and Bhatti, 2020). Scholars argue that the convergence of carbon intensity and per capita carbon emissions could result in a fairer climate framework by making high-emitting countries more likely to accept a greater role in climate commitments, thereby positively influencing future multilateral climate negotiations and agreements (e.g., Aldy, 2006; Apergis et al., 2020). Accordingly, the convergence of both measures is important from the perspective of energy management and formulation of efficient climate measures and policies.

Against such a backdrop, the objective of this study is to explore the urbanisation, agriculture and convergence of CO2 emissions nexus in international settings. We deliver three

[1] E.g., China and India both state their emissions reduction goals in terms of carbon intensity.

distinct contributions to the existing body of knowledge. Firstly, to the best of our knowledge, this study is the first to use the visual tools of Quah's (1997) distribution dynamics approach to test whether CO2 emissions converge or diverge across countries grouped along agricultural and urbanisation thresholds. Therefore, this research can augment previous studies mostly based on econometric analysis. The former focuses on the study of the shape of the distribution across time, so it can provide insights and forecasts for the future shape of a distribution which is a two-dimensional entity. Although the conventional econometrics techniques are quite powerful, they cannot offer a two-dimensional forecast because the econometrics technique can only provide a forecasted value of the dependent variable rather than the shape of a distribution. Therefore, employing the distribution dynamics analysis in this study not only can fill an important gap in the literature for this research area but can also supplement the findings of existing studies by offering new information on the change in the shape of global distributions of CO2 emissions across time. Furthermore, Although the strand of parametric method-based literature provides a summary of the statistic of interest, it neglects the important information on multimodal distribution, which may contaminate data and lead to misleading results (Quah, 1990, 1997; Wei et al., 2020). Here we divide the data into several sub-categories according to different thresholds of urbanisation and agrarian orientation. This, in turn, enables detailed information about the impacts of these two factors on the shape of carbon emissions' long-run steady-state distribution.

Secondly, this study employs a novel display tool of distribution dynamics introduced by Cheong and Wu (2018), namely, the Mobility Probability Plot (hereafter MPP). This tool offers detailed and precise visual information regarding the probability of movement of the countries within the distribution. The MPP enables us to construct a '*policy priority list*', consisting of the above-average carbon emitters with the highest probability to diverge further above the global average emissions in the coming years. In a policy context of the global emphasis on energy conservation and emissions reduction, early identification of priority countries with different urbanisation and agrarian structures can be conducive to the formulation of timely, bespoke, and proactive climate policies[2] taking into consideration the specific profiles of the countries to avoid potential negative socioeconomic side effects.

Thirdly, To the best of our knowledge, this is the most comprehensive study ever performed to explore the evolution and trend of global CO2 emissions by using distribution dynamics analysis. Specifically, this study examines the cross-country convergence-divergence patterns and long-run evolution of per capita CO2 emissions and CO2 intensity across 217 countries grouped according to their urban and agrarian structure. Stochastic kernel analyses are performed based on the global sample to draw a complete picture of the evolution and convergence of CO2 emissions around the world.

[2] MPP provides detailed information about the direction and probability of movement of countries' carbon emissions in years to come. As such it can be seen as a powerful leading indicator, useful in formulating proactive climate policies. On the other hand, simply ranking and comparing countries' emissions levels or growth rates (lagging indicators) as a basis of climate decisions, would yield a reactive set of policies. We would like to thank the anonymous reviewer for pointing out this important aspect.

The paper proceeds as follows. The next section briefly reviews the literature. Section 3 describes the data and methodology, followed by results and discussions in Section 4. Based on the research findings, a series of policy recommendations are prescribed in the last section, together with the conclusion.

2. Literature Review

The three most prominent theories explaining the urbanisation–environment nexus: ecological modernisation, urban environmental transition (and compact city) theories make a case for both positive and negative (positive) impacts of urbanisation (Sadorsky, 2014). While many scholars have tested these theories empirically, the results remain mixed and inconclusive.

Concerning individual countries, particularly reach empirical research exists on China as the largest carbon emitter and developing country in the world which has been undergoing rapid urbanisation. For example, Zhang and Lin (2012) and Liu and Bae (2018) find that urbanisation increases CO2 emissions in China from 1995 to 2010 and from 1970 to 2015, respectively. On the contrary, Yao et al. (2018) employ the panel threshold regression (hereafter PTR) model to show the negative effect of Chinese urbanisation on per capita carbon emissions and carbon intensity between 2001 and 2014. In a recent study, Zhang et al. (2020) report results suggesting that urbanisation can be a driving force behind non-fossil energy development leading to the future low-carbon transition of the Chinese economy. However, Zhao et al. (2020) document a U-shaped relationship, whereas according to Liu et al. (2023) urbanisation has a very small impact on carbon emissions. The above studies highlight that even concerning the same country, the results are mixed.

As for cross-country literature, numerous studies estimate the effect of urbanisation on CO2 emissions using the STIRPAT [3] framework. E.g., Martínez-Zarzoso and Maruotti (2011) examine 88 developing countries and find evidence of an inverted-U relationship between urbanisation and emissions from 1975 to 2003. However, according to Sadorsky (2014), urbanisation does not have a significant association with carbon emissions in 15 emerging countries. Lin et al. (2017) document a small positive effect of urbanisation only in 31 upper-middle-income countries (out of 53 developing countries) during the 1991-2013 period. On the contrary, in a panel of 55 developing countries between 1992 and 2012, Lv and Xu (2019) find more (less) significant decreasing impact of urbanisation on per capita CO2 emissions in the short (long) run.

Many studies employ the PTR model to examine the association between urbanisation and emissions across countries with different income levels. For example, Li and Lin (2015) study a sample of 73 countries during the 1971-2010 period and show that in the low, lower-middle and high (upper-middle) income countries, urbanisation positively (negatively) affects carbon emissions. However, in a panel of 137 countries from 2002 to 2012, Wang and Wang (2021)

[3] STIRPAT stands for Stochastic Impacts by Regression on Population, Affluence and Technology.

document an inverted *"U"* shaped (positive nonlinear) correlation in the high-income (low, lower-middle, and upper-middle-income) countries.

Many other cross-country studies use various parametric and nonparametric research methods to investigate linear, nonlinear, static, dynamic, short- and long-run relationships between urbanisation and carbon emissions. However, to the best of our knowledge, only two studies examine the urbanisation-CO2 emissions convergence nexus. Bhattacharya et al. (2020) employ Phillips and Sul's (2007) convergence-club approach to study the convergence of carbon emissions intensities in 70 countries and document two and three convergence clubs in consumption-based and territory-based CO2 intensity, respectively. Furthermore, they use logit models and include urbanisation as one of the determinants of convergence club membership. Specifically, Bhattacharya et al. (2020) argue that as urbanisation raises, so does the likelihood of a country's membership in a low-carbon intensity club. Most recently, Wang et al. (2022) employ the dynamic PTR model and treat urbanisation as a threshold variable in a sample of 59 developing economies. The authors find evidence of two convergence clubs in absolute carbon emissions and argue that "The conditional convergence level of carbon emission growth in low-urbanization areas is much greater than that in high-urbanization areas." (p.166).

While the relationship between urbanisation and carbon emissions has been thoroughly examined in international settings, there is much smaller literature on the cross-country agriculture-CO2 emissions nexus, with more studies examining individual, mainly developing countries (e.g., Waheed et al., 2018; Phiri et al., 2021). Among scholars who conduct transnational research, Ben and Ben (2017) employ a panel cointegration framework and report a decreasing long-run effect of the agriculture sector's contribution (as a % of GDP) on CO2 emissions in a panel of five African countries between 1980 and 2011. A similar negative relationship is found by Rafiq et al. (2016) in the study based on the STIRPAT model and a sample of 53 countries. However, the opposite positive effect is documented by Liu et al. (2017) in a panel of BRICS countries from 1992 to 2013. More recently, Dar and Asif (2020) and Cai et al. (2022) examine a similar set of five South Asian economies using a fully modified ordinary least squares model and show that the agriculture sector's contribution has a reducing impact on CO2 emissions.

Summing up, large (some) empirical literature uses various models and yields mixed findings on the relationships between urbanisation levels (agriculture sector's contribution) and carbon emissions. Nevertheless, a careful examination of relevant literature highlights that only two recent studies (Bhattacharya et al., 2020; Wang et al., 2022) examine the cross-country convergence of CO_2 emissions in the context of urbanisation. Likewise, the majority of studies employ either absolute or per capita CO2 emissions in their analyses. Furthermore, to the best of our knowledge, there is no research using the distribution dynamics approach and the MPP tool to examine international convergence-divergence patterns of CO2 emissions with countries grouped according to their urbanisation levels and agrarian orientation. To fill these gaps in the existing literature, this study examines the long-term cross-country evolution of global carbon emissions (and intensities) with urbanisation and agrarian orientation as grouping tools (threshold variables). Specifically, three visual presentation tools of the distribution dynamics approach are employed.

3. Data and Methodology

The data employed in this study are compiled from the World Development Indicators database of the World Bank. Two variables are used to evaluate the impacts on CO2 emissions, namely, relative carbon intensity (REPGDP), and relative per capita carbon emissions (REPC). REPGDP is measured as CO2 emissions (kg) per 2010 USD of GDP in each country divided by the world average in a year, while REPC is measured as CO2 emissions (metric tons) per capita in each country divided by the world average in this year. It is worth noting that relative values are better for the analysis since the disparity amongst the countries can be observed directly. For instance, if a country has a REPC value of 1, it means that this country's level of emissions is equal to the world average, while a value smaller (higher) than 1 indicates the level of emissions below (above) the world average. The data employed in this study are from 2000 to 2016 because the data from 2017 onwards have not been available for many countries at the time of conducting the analyses.

The distribution dynamics approach was developed by Quah (1997) and can be classified into two major groups, namely, the traditional Markov transition matrix analysis and the stochastic kernel approach. One issue of the former is that the selection of grid values is an arbitrary process, therefore the demarcation of the state is not objective which, in turn, can affect the analytical results. The latter is deemed to be much better as the process of demarcation can be performed objectively (Cheong and Wu, 2018). As a result, the stochastic kernel approach is employed in this study. The bivariate kernel estimator can be represented by equation (1).

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

Where x is a variable representing the relative CO2 emissions of a country at time t, y is a variable representing the relative CO2 emissions of that country at time t+1, $X_{i,t}$ is an observed value of relative CO2 emissions at time t, and $X_{i,t+1}$ is the observed value of relative CO2 emissions at time t+1, n is the number of observations. Furthermore, K is the normal density function, and h_1 and h_2 are the bandwidths which are computed by the approach developed by Silverman (1986). The approach of the adaptive kernel with flexible bandwidth is also used in this study to consider the sparseness of the data (Silverman, 1986). This procedure is made up of two stages: (1) the computation of a pilot estimate, and (2) the recalculation of the bandwidth by a factor that reflects the kernel density. Assuming that the evolution is first order and time-invariant such that the distribution at time $t+\tau$ depends on t only and not on any previous distribution, the relationship between the distributions at time t and time $t+\tau$ can be represented as equation 2.

$$f_{t+\tau}(z) = \int_0^\infty g_\tau(z|x) f_t(x)dx \quad (2)$$

Where $f_t(x)$ is the kernel density function of the distribution of relative CO2 emissions at time t, $f_{t+\tau}(z)$ is the τ-period-ahead density function of z conditional on x, and $g_\tau(z|x)$ is the transition probability kernel which maps the distribution from time t to $t+\tau$. It is worth noting that annual transitions are used in this study as the sample size will be larger and the estimation results will be more reliable. The ergodic density function, given that it exists, can be calculated by the following equation.

$$f_\infty(z) = \int_0^\infty g_\tau(z|x) f_\infty(x) dx \tag{3}$$

Where $f_\infty(z)$ is the ergodic density function when τ is infinite. The ergodic distribution can be viewed as a forecast of the steady-state distribution of relative CO2 emissions and it can be used for making predictions.

The mobility Probability Plot (MPP) developed by Cheong and Wu (2018) offers three unique advantages. First, it produces precise information about the probability mass distribution. Second, it facilitates comparisons of carbon emissions' transitional dynamics across periods and cross-sections such that we can identify countries with different socioeconomic profiles (urbanisation and agricultural production) and a high probability of moving above (or below) the global average CO2 emissions and how these vary over time. Third, multiple MPPs can be superimposed in one graph, which, in turn, enables easier comparison across groups of countries and periods. This is unachievable with traditional visual tools of distribution dynamics (e.g., three-dimensional plots).

Due to the above, since its first introduction, the MPP has been employed extensively for analyzing transitional dynamics in areas such as energy, coal, or electricity consumption (Cheong et al., 2019; Shi et al., 2021b, 2021c) per capita GDP (Wu et al., 2021), housing affordability (Liu et al., 2022), information transparency (Williams et al., 2022) or credit ratings (Lee et al., 2021). The MPP can be computed by the net upward mobility probability which is represented by $p(x)$ as per equation (4).

$$p(x) = \int_x^\infty g_\tau(z|x) dz - \int_0^x g_\tau(z|x) dz \tag{4}$$

Accordingly, in this study, the MPP plots the net upward mobility probability against the relative CO2 emissions. It is worth noting that a negative value of net upward mobility probability means that the country has a net probability of moving downwards in the distribution, and a positive value means that the country has a net probability of moving upwards. Furthermore, the MPP is expressed in percentage with a range from -100 to 100[4].

4. Results and Discussions

In this section, we discuss the distribution dynamics of country-level CO2 emissions[5] using three display tools: a contour map of the transition probability kernel, an ergodic distribution, and the MPP. We group the countries according to their urban and agrarian structures by using

[4] Please refer to Cheong and Wu (2018) for more details on the MPP.

[5] We use two alternative measures of carbon emissions: relative carbon intensity (REPGDP), and relative per capita carbon emissions (REPC).

two variables commonly used in prior studies (e.g., Rafiq et al., 2016; Wang and Wang, 2021), i.e., urban population as a percentage of the total population and agriculture sector's contribution to GDP.

4.1. Relative CO2 emissions per capita (REPC) vis-à-vis countries' urbanisation levels

Fig. 1 offers a glimpse into the transition probability kernel for REPC. We group the sample countries by quartiles of urbanisation with the first (fourth) quartile corresponding to the groups of countries with the lowest (highest) urbanisation levels. We can observe that the probability kernel shown in panels (a) and (b) has three peaks and one peak, respectively. It is worth reiterating that the REPC value above (below) one implies that country's per capita carbon emissions are above (below) the global average. Thus, the locations of the major peak in panel (a) and the sole peak in panel (b) indicate that most of the countries with below-the-average urbanisation ratio cluster around extremely low REPC values of less than 0.25, i.e., significantly below the global average.

Moving on to the third quartile countries, we can observe that many entities congregate around a REPC value of 0.5 (the location of the major peak) but some entities cluster around a REPC value of 1.5 (the location of the minor peak). As for the fourth quartile countries, two out of four peaks in panel (d) are situated at very high REPC values of 2 and 4. However, many of the entities from the fourth quartile congregate close to the global average - that is, a range of REPC units from 1 to 1.3 (the location of the major twin peaks). Moreover, Fig. 1 shows that the outermost contour lines reach the lowest (highest) value of 0.6 (6.5) as we move from the transition probability kernel for countries with the lowest (highest) urbanisation ratio. This, in turn, implies the largest and the smallest cross-country differentiation in terms of per capita carbon pollution levels amongst the most and the least urbanised countries, respectively.

[Insert Fig. 1 here]

To find out if the results presented in Fig. 1 hold in the long-run, we use the ergodic distribution tool which displays the long-run steady-state equilibrium in investigated variable under the assumption of no changes in transitional dynamics. Accordingly, a comparison of the four panels in Fig. 2 delivers valuable insights into the long-run cross-country evolution in REPC.

We can observe that most of the peaks in Fig. 1 remain in Fig. 2. This means that across the board, many countries will congregate in the long-run to the above-discussed clusters of REPC. Because each of the ergodic distributions is multimodal (between two and four peaks per distribution), we can expect the emergence of convergence clubs in the long run and thus only conditional '*within the group*' inter-country convergence in the future in all four groups of countries.

Furthermore, the trend of increasing '*within the group*' variability observed in Fig. 1, finds correspondence in Fig. 2 which presents the least dispersed REPC distribution in the least urbanised group of countries. Moreover, panel (a) shows that the four peaks (moving from the most to the least pronounced) are located around the REPC values of 0.04, 0.25, 0.5, and 1.15. Summing up, the results suggest the most significant long-run convergence for the entities from the first quartile group with a great majority of these countries maintaining extremely low emissions proxied by REPC in the long run.

Panel (d) delivers mixed findings from the carbon convergence perspective. The good news is that the major peak's location is around the REPC value of one, meaning that many highly urbanised countries converge to the global mean in the long-run. The bad news, however, is that the remaining two peaks occur at very high REPC values of 2 and 4, i.e., far above the global average, whilst the distribution shown in panel (d) is the most dispersed.

Summing up, Fig. 2 suggests that except for some of the most urbanised economies, a long-run international convergence to the global mean in per capita carbon emissions is not going to take place without changes to its transitional dynamics. Instead, convergence clubs occur within each of the investigated groups of countries. Moreover, Fig. 2 shows that as we move from the least to the most urbanised groups of countries, the distribution becomes more dispersed, whilst peaks occur at higher REPC values. This latter propensity stands in contrast with Wang et al. (2022) who document that the club towards which low-urbanisation countries converge is located at around 2.5 times higher carbon emissions than the club towards which high-urbanisation countries converge.

[Insert Fig. 2 here]

The MPP tool offers detailed, precise, and user-friendly information about the probability mass' location in the variable's transitional dynamics. Specifically, the MPP shows the exact probability of moving up or down in the distribution for the full spectrum of country-level REPC in years to come[6]. Fig. 3 shows that the red-coloured MPP representing transitional dynamics of REPC for the first quartile entities is the most volatile with four (five) steep-slope peaks (troughs) along with a sharp '*zigzag pattern'*. Furthermore, the red plot is the most compressed and extends to a maximum REPC unit of 5.2. On the other hand, the yellow-coloured MPP (fourth quartile countries) is the least volatile, and the most spread out, with its right end reaching an extraordinarily high REPC value of 21.5[7]. Such saliently different patterns for REPC in the least (the most) urbanised entities imply the highest (lowest) aggregate net mobility probability in years to come for the former (latter) group of countries.

Moreover, the shapes of the MPPs largely correspond with the shapes of the respective ergodic distributions shown in Fig. 2. For example, most of the intersections between the MPPs and the horizontal axis occur at approximately the same REPC values as the peaks observed in the ergodic distributions[8]. Such a strong similarity between the two display tools is not

[6] The horizontal axis in Fig. 3 measures the REPC units, while the vertical axis indicates the probability of moving upward (above the horizontal axis) and downward within the distribution (below the horizontal axis). Therefore, the net upward mobility probability ranges from +100 to -100.

[7] The yellow plot reaches its last local maximum at a value of 14. From there the MPP slopes down at a relatively straight line ending at the value of 21.5. For the sake of readability, the graph's area has been constrained to the range of relative emission values from zero to 10.

[8] This is because the countries with REPC values to the left (right) from the intersection between the MPP and the horizontal axis tend to move upward (downward) within the distribution in the coming years. Thus, these countries' REPCs will congregate around the intersection points.

coincidental and indicates that the transitional dynamics captured by the MPP largely determine the shape of the long-run ergodic distribution.

The intersection and tangent points between the MPPs and the horizontal axis together with sections of MPPs with '*above the global average*' REPC values positioned above the horizontal axis are important from the policy perspective aiming at carbon convergence and reduction. That is because these points help pinpoint carbon emitters with a detailed range of above-the-average REPC and specific probabilities to further diverge from the global average in the following years. Thus, such entities merit special attention and a place on the '*policy priority list*'. Accordingly, countries from the first (second) quartile group with REPC units between 1.9 and 2.85 (4.6 and 6.55) require special attention[9]. In the same manner, the countries from the third (fourth) quartile group by urbanisation ratio and REPC values between 1.3 and 1.6 (between 3.25 and 3.85) merit a place in the '*policy priority list*'.

Other important sections of each of the MPPs shown in Fig. 3 are those reaching the net upward mobility probability of -100, which, in turn, translates to the so-called '*development trap*' in country-level REPC. Specifically, the country's REPC value cannot fall below the '*development trap*' threshold. Instead, upon reaching this value, the country is destined to experience a decrease in its REPC, i.e., a downward move within the distribution in the following years. Thus, in the context of carbon emissions, the '*development trap'* constitutes a piece of positive news. We can observe that the red-, blue-, and green-coloured MPP reach the net mobility probability of -100 at the emission value of 5.2, 6.6, and 9.8, respectively. As mentioned above, the yellow MPP's maximum REPC value is equal to 21.5 where it reaches the '*development trap'*.

[Insert Fig. 3 here]

4.2. REPC vis-à-vis countries' agrarian orientation

In this section, we split the countries into four groups (quartiles) based on the countries' agriculture sector's value-added (agrarian orientation). Fig. 4 paints an overall picture with patterns similar to those observed in Fig. 1 but taking place in reverse order by quartiles. For instance, Fig. 4 informs us that the outermost contour lines reach the smallest (largest) REPC value of 0.3 (7.5) in the transition probability kernel for the group of countries with the highest (lowest) degree of agrarian orientation[10], i.e., the fourth (first) quartile group. This finding translates into the largest (smallest) intra-country variability in REPC amongst the least (most) agrarian-oriented entities. Furthermore, the location of the major peaks in Fig. 4 highly resembles the location of peaks in Fig. 1 subject to the opposite (reverse) quartile-by-quartile order. Specifically, we can observe that many of the most (least) agrarian-oriented countries congregate around the REPC value of 0.025 (1.3 and 2), i.e., significantly below (above) the

[9] It is worth adding that the further above the mean is the country's REPC and the greater its probability of moving upward, the higher the place in the priority list. For instance, the first (second) quartile entities with REPC values of around 2.2 (5.5) and an upward mobility probability of 65% (32%) are the most worrisome and as such merit a high position in the list.

[10] It is worth noticing that the outermost contour lines with the lowest (highest) REPC unit of 0.3 (6.5) in Fig. 1 are shown in the kernel of the first (fourth) group of entities by urbanisation ratio. Hence, the above-mentioned reverse order.

global average. Summing up, the reverse order by quartiles amongst the transition probability kernels in Fig. 1 vis-à-vis Fig. 4, is not surprising, given a negative correlation between the urbanisation and agriculture sector contribution to GDP.

[Insert Fig. 4 here]

Fig. 5 indicates that the less agrarian-oriented group of countries, the more dispersed the ergodic distribution, i.e., the less significant intra-group long-term convergence of REPC. This again translates to the above-discussed '*reverse order by quartiles'* vis-à-vis ergodic distributions from Fig. 2. A reverse pattern also applies to the location of the major peaks. Specifically, the tallest (major) peaks in the four panels of Fig. 5 move leftward or decrease in REPC values starting with a value of 1.3 in panel (a) and ending with a value of 0.04 in panel (d). This, in turn, implies that the largest group of the least (most) agrarian-oriented countries converge to REPC values of around 1.3 (0.04) – that is, inconsiderably above (extremely below) the global average per capita carbon emissions in the long-run. Thus, the above results are broadly consistent with prior studies (Rafiq et al., 2016; Ben and Ben, 2017; Dar and Asif, 2020; Cai et al., 2022) reporting the reducing effect of agricultural contributions (as % of GDP) on carbon emissions, whereas inconsistent with Liu et al. (2017) who find a positive association between agriculture sector and emissions.

Furthermore, each of the distributions shown in Fig. 5 is characterised by two to four peaks, i.e., the convergence clubs occur in the long run, thereby indicating a conditional convergence with groups of entities converging to various REPC levels. The bad news (from convergence to the mean policy perspective) is that one of the minor peaks in panels (b) and (d) occurs at the REPC value of 2.7 and 2.4, respectively, i.e., significantly above the global average.

[Insert Fig. 5 here]

Fig. 6 shows that the yellow-coloured MPP (fourth quartile by agrarian orientation) is the most volatile, compressed, and except for the range of REPC units from 1.7 to 2.4 lies below the three other MPPs. The above high volatility (low location) of the MPP implies the highest aggregate net mobility probability (higher tendency to move downward) over time in REPC for the countries with the largest degree of agrarian orientation. On the other hand, the red-coloured MPP for most of its length lies above the remaining three plots and is the least volatile. In other words, we can infer a strong negative association between the degree of agrarian orientation and the upward mobility of REPC, somewhat consistent with prior studies (Rafiq et al., 2016; Ben and Ben, 2017; Dar and Asif, 2020; Cai et al., 2022). Furthermore, the MPPs of the second and third-quartile countries follow a near-identical pattern with several intersections among them, thereby indicating that overall, the transitional dynamics of REPC for these two groups of entities are not significantly different.

On the one hand, the good news (from the carbon convergence policy perspective) is that all four MPPs reach the '*development trap'* or the net upward mobility probability of -100. On the other hand, the locations of these '*development traps'* vary widely from the lowest REPC value of 3.1 (yellow-coloured MPP) to an extremely high REPC value of 21.5[11] (red-coloured MPP). Moving on to the issue of the '*policy priority list*', the countries from the first (second) quartile by agrarian orientation with the REPC value of around 1.8 (between 2.2 and 2.6) require special attention. By the same token, the entities from the third (fourth) quartile with REPC values between 1.2 and 1.5, 2.15 and 2.55 (1.7 and 2.3) merit a place on the '*policy priority list'*. It is worth mentioning that from the convergence to the mean perspective, the most worrisome will be the most agrarian-oriented countries with REPC values around 1.9 due to their extremely high (80%) probability of further divergence in carbon emissions over time.

[Insert Fig. 6 here]

4.3. Relative carbon intensity (REPGDP) vis-à-vis countries' urbanisation levels

In multilateral negotiations on climate change, the two most popular allocation schemes used to establish countries' share in the global carbon mitigation obligation are per capita carbon emissions and carbon intensity (Frankel, 2007; Mattoo and Subramanian, 2012; Bhattacharya et al., 2020). However, as Parker and Bhatti (2020) point out, it is not uncommon for carbon intensity and per capita carbon emissions to take divergent paths even concerning the same country or group of countries. Against the above backdrop, Figs. 7 to 12 are based on the relative carbon intensity variable (REPGDP).

Fig. 7 suggests that the transition probability kernels of countries' REPGDP grouped by the quartiles of urbanisation ratio are relatively similar. In other words, there is no evidence of the salient disparities forming an apparent trend of increasing variability observed amongst kernels of REPC shown in Fig. 1. Furthermore, we can observe that the width of the transition probability kernel in panels (a), (b), and (d) is very narrow while the density mass clusters along the 45-degree line (diagonal), meaning a considerable persistence in REPGDP for these three groups of countries. This, in turn, implies a very slow convergence process. Moreover, Fig. 7 shows that in each of the four panels, the significant peak is located around a similar range of REPGDP values between 0.5 and 0.7, i.e., below the global average but not extremely far from it. Lastly, the existence of minor peaks in the transitional distribution of REPGDP in the first, third and fourth quartile countries implies that some entities in these groups congregate around two to three different clusters of REPGDP.

[Insert Fig. 7 here]

The examination of ergodic distributions presented in Fig. 8 does not indicate the presence of inter-quartile trends similar to those based on REPC as reported in Fig. 2. However, each of the ergodic distributions in Fig. 8 is multimodal (between two and four peaks), whilst the number, location and significance of the peaks vary largely. Consequently, in each of the four groups, multiple clubs emerge, signifying clusters of countries converging to different REPGDP in the long run. Such results are broadly in line with Bhattacharya et al. (2020) who

[11] Once more, for the sake of interpretation and comparability, the scale on the horizontal axis in Fig. 6 ends with the value of 14, from where the red MPP descends further until it reaches the REPC value of 21.5.

find two (three) convergence clubs in consumption- (territory) based carbon intensity in a sample of 70 countries.

As for the prospects of convergence to the global average, the REPGDP value of one corresponds to the saddle in between the major twin peaks of the second quartile countries, meaning that some entities will converge to this desirable target – that is, assuming the distribution dynamics remain unchanged. Another piece of good news stems from the fact that a minor peak in panels (a) and (d) is also located at the REPGDP value of one. Nonetheless, in each of the panels, we also observe peaks situated above and below the global average ranging from the highest location around the REPGDP value of 2.2 in panel (b) to the lowest location around the REPGDP value of 0.4. This, in turn, suggests considerable long-run differentiation in REPGDP within each of the groups. Interestingly, Fig. 8 also suggests that ergodic distributions representing countries with the highest and the lowest urbanisation level bear a fair degree of resemblance which is at odds with the results based on the REPC variable shown in Figure 2. This similarity between the two distributions is also at odds with Bhattacharya et al. (2020) who document that as urbanisation increases, so does the prospect of a country belonging to a low carbon intensity club.

[Insert Fig. 8 here]

Fig. 9 informs us that all four MPPs intersect with the horizontal axis for the first[12] time at a range of low REPGDP values (from 0.42 to 0.68). Furthermore, in all four plots, the net upward mobility probability is highly positive only for the REPGDP values far below the global average. In other words, regardless of the urbanisation level, only countries with very low REPGDP values have a significant tendency to move upward within the distribution in the coming years. This is a positive piece of information from the carbon reduction policy perspective. Interestingly, we can observe a fair degree of resemblance between the patterns of the yellow- and red-coloured MPP. In other words, the overall annual mobility probability dynamics for these two groups of countries are not that different, despite very different urbanisation rates.

As for the '*policy priority list'*, Fig. 9 paints a generally positive picture. Specifically, the first, second and fourth quartile countries with a similar (and narrow) range of above-the-average REPGDP values between 1.4 and 1.9, 1.4 and 1.6, 1.5 and 1.85, respectively, have low probabilities of up to 5% to diverge further away from the global mean in coming years. Therefore, in comparison with MPPs based on the REPC variable (see Fig. 3), the '*policy priority list*' is significantly less concerning and consists of a shorter range of REPGDP values.

Another major disparity in the MPPs based on two alternative measures of carbon emissions applies to the location of '*development traps*' with Fig. 9 painting a more optimistic picture than Fig. 3. For instance, the yellow-coloured MPP in Fig 9 reaches a net upward mobility probability of -100 at the REPGDP value of 4.2 (much lower than the corresponding REPC value of 22.2 in Fig. 3).

[12] In the case of the MPP for second quartile countries, there is only one intersection point with the horizontal axis.

[Insert Fig. 9 here]

4.4. REPGDP vis-à-vis countries' agrarian orientation

We can observe that the pattern of declining intra-group transitional variability of REPC previously spotted in Fig. 4 (from the least- to the most agrarian-oriented countries) is not present in Fig. 10. Additionally, the locations of the significant peaks in the four panels of Fig. 10 are fairly similar and ranging from the lowest REPGDP value of 0.45 in panel (a) to the highest value of 0.7 in panel (b). However, in each panel of Fig. 4, the significant peak occurs at a significantly more dispersed range of REPC values[13]. Finally, the number peaks, their heights, and the width of the corresponding kernels differ significantly when compared between Figs. 4 and 10. Overall, we can conclude that the results based on the transition probability kernels for REPC vis-à-vis REPGDP are saliently dissimilar.

[Insert Fig. 10 here]

Fig. 11 shows that long-term distributions for the REPGDP are also different to those observed in Fig. 5 (the REPC variable). For instance, the locations of the major peaks in the four panels of Fig. 11 do not decrease drastically when moving from panel (a) to panel (d) as it happens in Fig. 5. Instead, we can infer that many countries in each of the four groups converge in the long-run to '*below the average'* REPGDP values.

Furthermore, the ergodic distribution in panel (a) of Fig. 11 is the only unimodal distribution in this study, and the narrowest of the four panels with a peak situated at the REPGDP value of 0.45. Thus, Fig. 11 suggests that in the long-run steady-state equilibrium, the absolute convergence of REPGDP is possible among countries with the least agrarian profile[14], assuming no changes in transitional dynamics. However, the three remaining distributions are characterized by two to four peaks, i.e., the convergence clubs emerge in the long run, thereby indicating conditional convergence.

[Insert Fig. 11 here]

The comparison of the MPPs presented in Fig. 12 with their equivalents based on REPC presented in Fig. 6, conforms with the prior finding derived from the comparison of Figs. 10 and 11 vis-à-vis Figs. 4 and 5. In other words, we can observe some prominent disparities in the results based on two alternative measures of CO2 emissions. For instance, Fig. 12 shows that the yellow- and red-coloured MPP is the most compressed and the most spread out, respectively. Moreover, the '*development trap'* is reached by the yellow plot at a very high REPGDP value of 12. However, for the red plot, the highest probability of moving downward is 95% and occurs at a much lower REPGDP value of 5.6. The above findings are in stark contrast to those presented in Fig. 6. Summing up, the comparison of results based on the REPC (Figs. 4 to 6) vis-à-vis REPGDP variable (Figs. 10 to 12) corroborate the argument raised by

[13] The locations of the major peaks in Fig. 4 range from the lowest REPC value of 0.025 in panel (d) to the highest REPC values of 1.3 and 2 (twin peaks) in panel (a).
[14] The above findings are at odds with those based on the ergodic distribution for REPC in panel (a) of Fig. 5 which suggest that the least agrarian-oriented group of countries is the most problematic from the perspective of carbon convergence and low carbon transition policy goals.

Parker and Bhatti (2020) who claim that these two popular measures of CO2 emissions can follow opposite routes for the same country or group of countries.

As for the entities that merit a place in the '*policy priority list'*, we can pinpoint countries from the first (second) quartile group with REPGDP values between 3.5 and 4.35 (1.5 and 2.15). By the same token, countries from the third (fourth) quartile with REPGDP values between 1.5 and 1.6 (1.55 and 1.95 and between 6 and 7) should be included on the priority list. Consequently, the results suggest that in terms of the REPGDP, some of the most and the least agrarian-oriented high emitters will be more prone to diverge further away from the global mean, thereby requiring special attention and actions from the decision-makers.

[Insert Fig. 12 here]

5. Conclusion

This study aims to investigate the nexus between country-level urbanisation, agrarian orientation and two popular measures of carbon emissions around the world. The examination is entrenched in a panel dataset covering 217 countries from 2000 to 2016. The pattern and progress of each country inside the distributions in various blocs are then revealed using a distributional dynamics analysis. The convergent dynamic characteristics of relative per capita carbon emissions (REPC) and relative carbon intensity (REPGDP) in countries with different urbanisation levels and agrarian orientations are subsequently identified. In addition, the mobility probability plots (MPPs) are used to provide specific insights into the likelihood of a shift in future carbon emissions. There are four major findings of this research.

First, except for the ergodic distribution of REPGDP in the least agrarian-oriented group of countries, the study documents two to four convergence clubs for REPC and REPGDP alike. That is, in the long run, there will be groups of countries forming convergence clubs around different carbon emission levels regardless of the grouping variable (urbanisation level and agrarian orientation) or the CO2 emissions measure. Second, the majority of the above clusters occur at values far from (below and above alike) the global average level. Specifically, concerning urbanisation levels, the clubs located the furthest below and above the global average occur around the REPC (REPGDP) values of 0.04 and 4 (0.4 and 2.2). However, concerning countries' agrarian orientation, the clubs located the furthest below and above the global average are observed around the REPC (REPGDP) values of 0.04 and 2.7 (0.3 and 2.3). Such findings deliver a generally grim message to the policymakers hoping for global convergence of carbon dioxide emissions.

Third, the study pinpoints countries from the first (second) quartile group by urbanisation with high REPC values ranging from 1.9 to 2.7 (4.9 to 6) to have alarmingly high probabilities between 20% and 65% (20% and 32%) of further diverging above the global average emissions in years to come. Because of such high-risk emission/divergence profiles, these countries require monitoring from policymakers and thus merit a high position in the '*policy priority list'*. By the same token, the countries with the most (least) agrarian profile and with a REPC

(REPGDP) value of around 1.9 (4) deserve a place on the '*policy priority list'* due to high 80% (30%) probability of further divergence away from (and above) the global average.

Fourth, the results based on the REPC vis-à-vis the REPGDP variable are largely different. For instance, concerning the REPC variable, the long-run distribution of the least urbanised group of countries is the least dispersed with the majority of countries becoming members of three clubs located around very low REPC values of 0.04, 0.25, and 0.5. On the other hand, the distribution of the most urbanised group of entities is the most spread out with many entities clustering around three clubs with much higher REPC values of 1, 2, and 4. However, such stark differences between emissions of the least and the most urbanised groups of countries are not observed when the REPGDP variable is analysed. Instead, the ergodic distributions of REPGDP in these two groups of countries bear a high degree of resemblance. Likewise, the results based on the REPC (REPGDP) variable suggest that the least agrarian-oriented group of countries are the most (least) worrisome from the perspective of policies aiming at carbon convergence and low carbon transition. Therefore, this study underscores the significance of using alternative measures of country-level carbon emissions and supports the argument for considering both as a suite of future multilateral climate negotiations and policies.

The policy recommendations of this study are as follows. First, the research findings identify the sources and potential future growth trends of national per capita carbon emissions and carbon intensities. Thus, this study could be helpful for governments to effectively allocate capital and technical resources to promote their reduction, regardless of which measure is used as a basis to share in the global carbon mitigation burden. Second, instead of a '*one-size-fits-all'* policy, the decision-makers should focus their efforts on monitoring carbon emissions in countries from the '*policy priority list'* and formulating timely, bespoke and proactive climate policies. For instance, some of the most agrarian-oriented low-income countries from the '*policy priority list'* should receive coordinated international aid (technological and financial) to improve the energy efficiency and energy mix used in the agriculture sector (e.g., cleaner technology, renewable sources of energy, biofuels). Finally, this research delivers nascent evidence in favour of employing display tools of the distribution dynamics approach in periodic (preferably annual) exercises to help identify the future positions and responsibilities of different countries in global cooperation on climate change.

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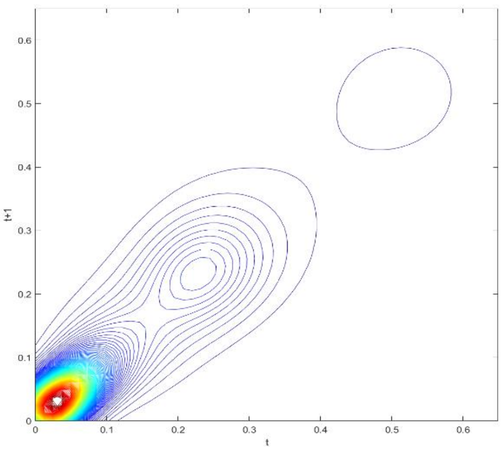
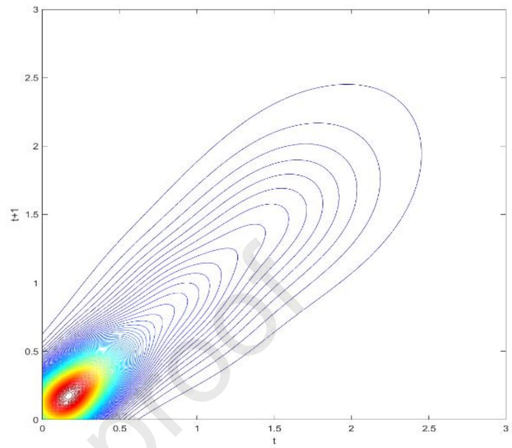
Fig. 1. Contour maps of transition probability kernel for REPC by the quartiles of urbanisation ratio.

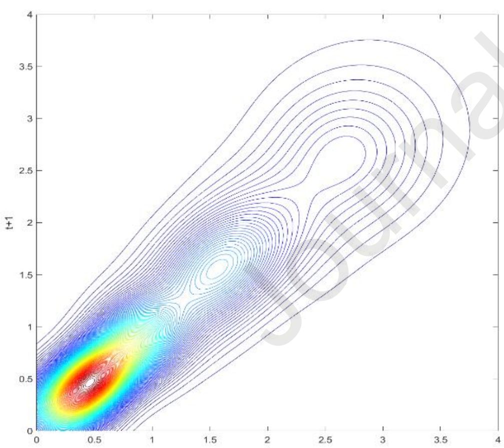
(a) First quartile countries



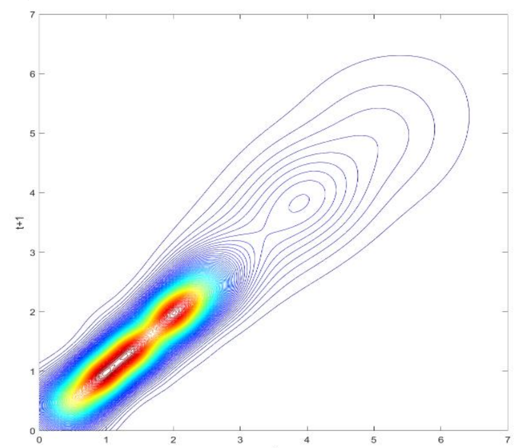
(b) Second quartile countries



(c) Third quartile countries

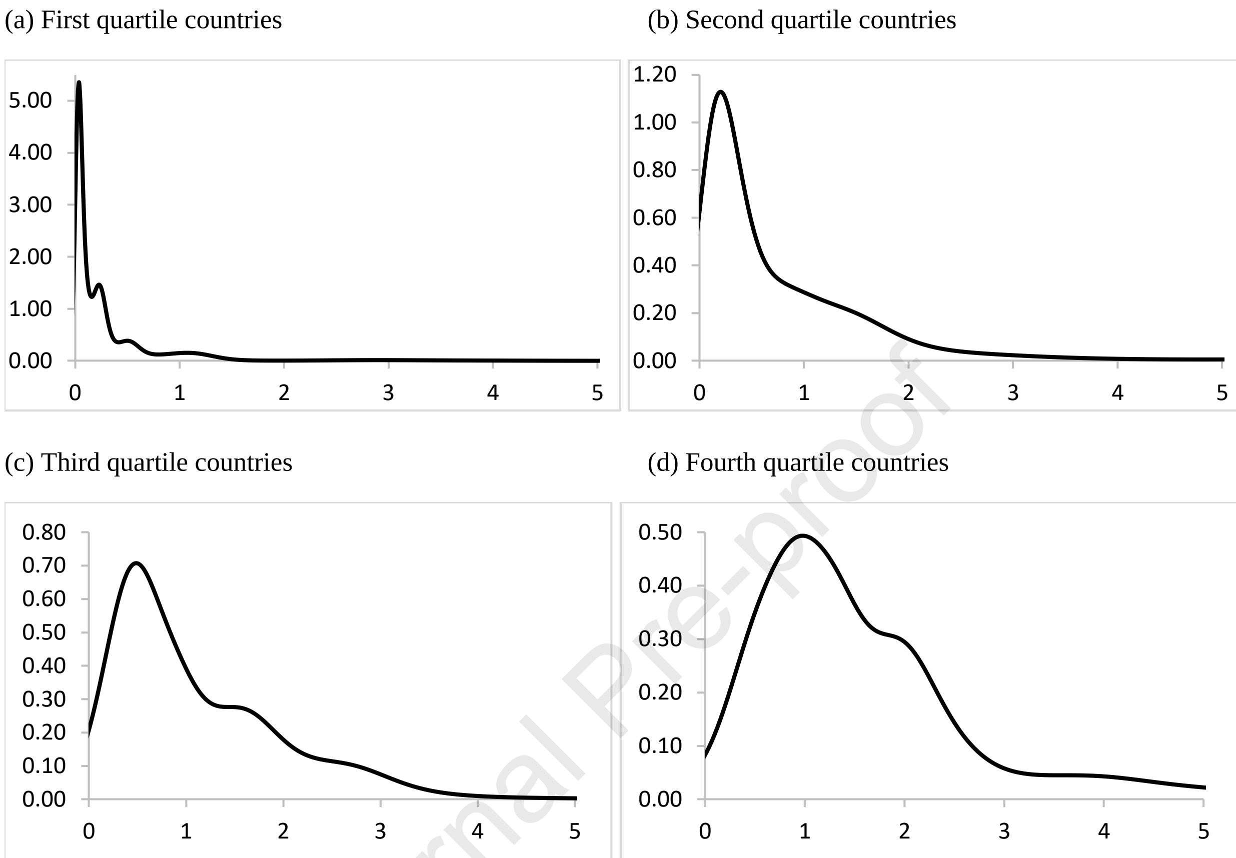


(d) Fourth quartile countries



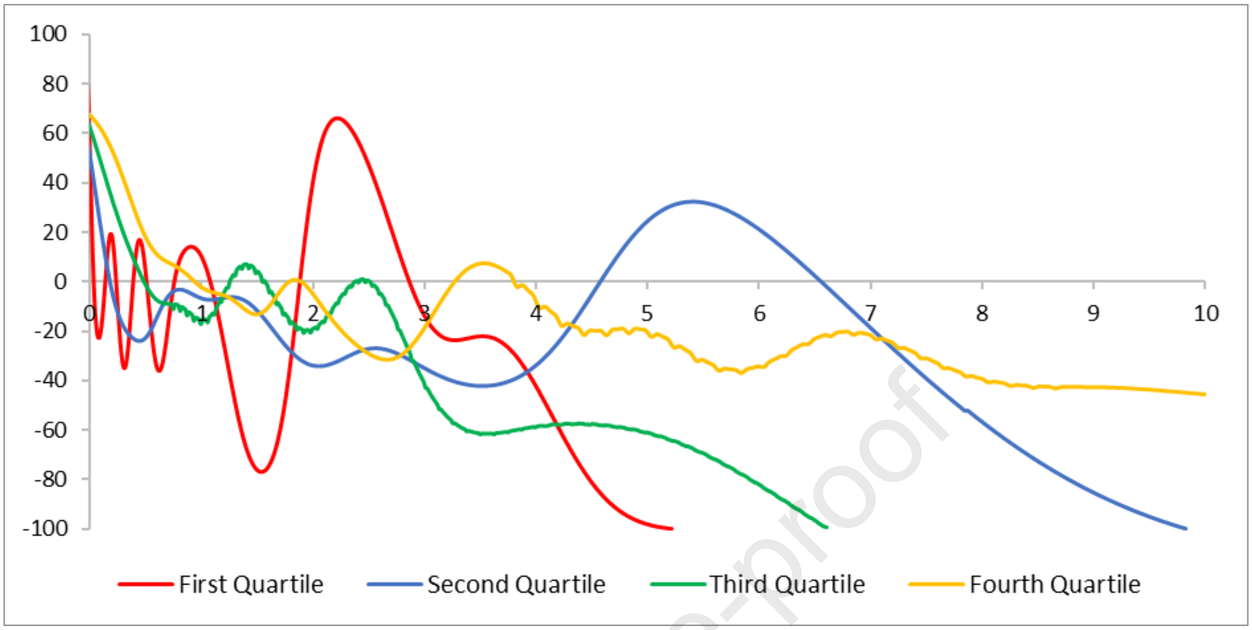
Notes: The horizontal axis represents the value of REPC at time t, whilst the vertical axis represents the value of REPC at time t+1.
Source: Authors' calculations

Fig. 2. Ergodic distributions for REPC by the quartiles of urbanisation ratio.



Notes: The horizontal axis represents the value of REPC, whilst the vertical axis represents the proportion.
Source: Authors' calculations

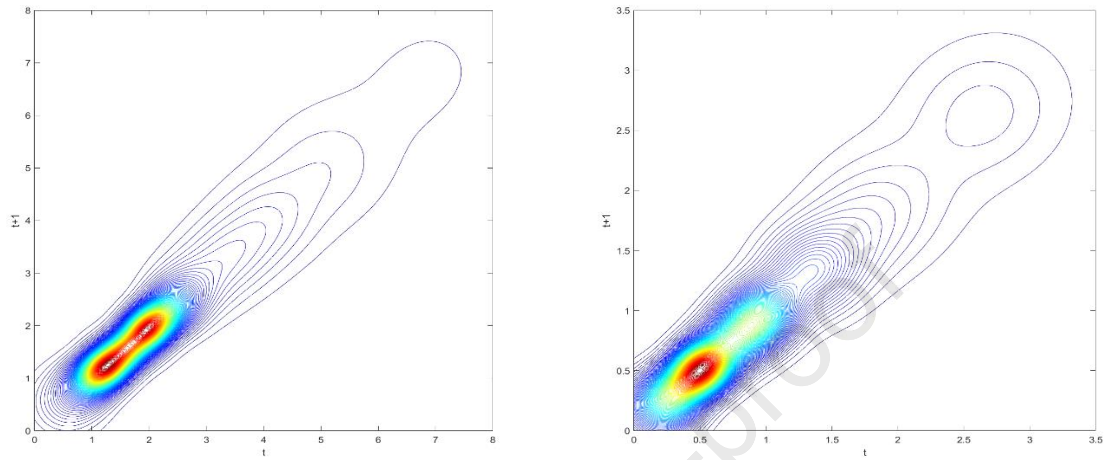
Fig. 3. Mobility Probability Plots (MPP) for REPC by the quartiles of urbanisation ratio.



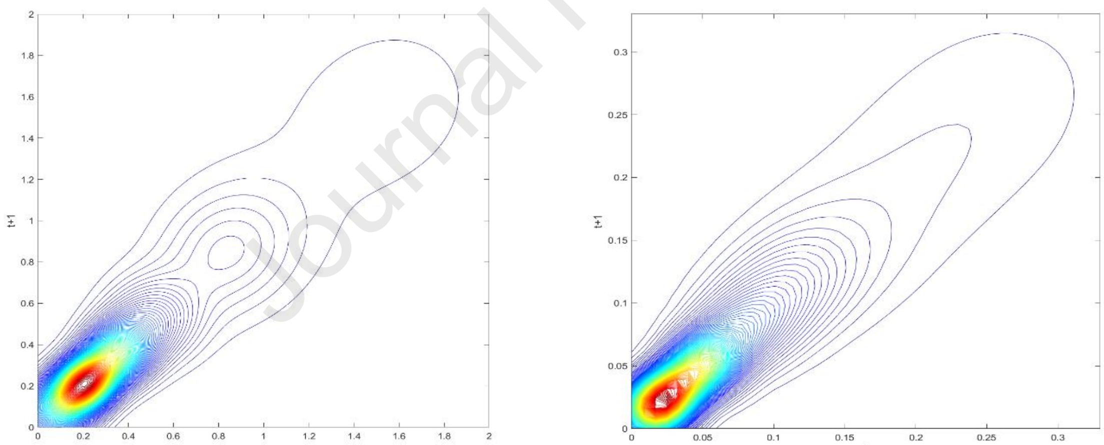
Notes: The horizontal axis represents the value of REPC, whilst the vertical axis represents the MPP.
Source: Authors' calculation

Fig. 4. Contour maps of transition probability kernel for REPC by the quartiles of agrarian orientation.

(a) First quartile countries (b) Second quartile countries



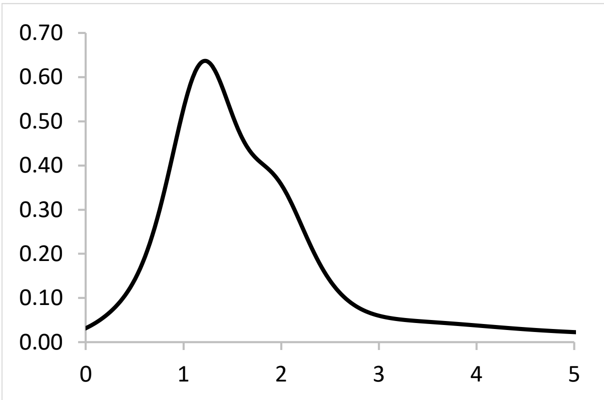
(c) Third quartile countries (d) Fourth quartile countries



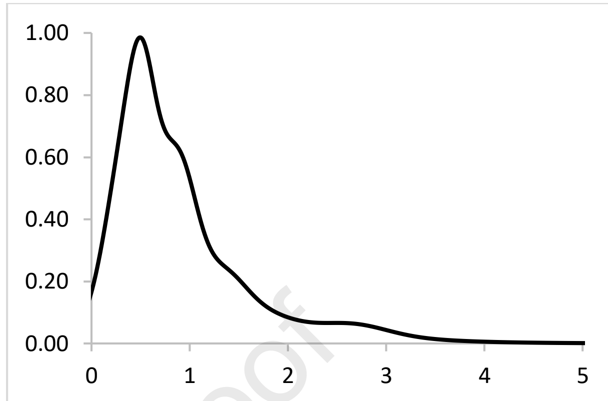
Notes: The horizontal axis represents the value of REPC at time t, whilst the vertical axis represents the value of REPC at time t+1.
Source: Authors' calculations

Fig. 5. Ergodic distributions for REPC by the quartiles of agrarian orientation.

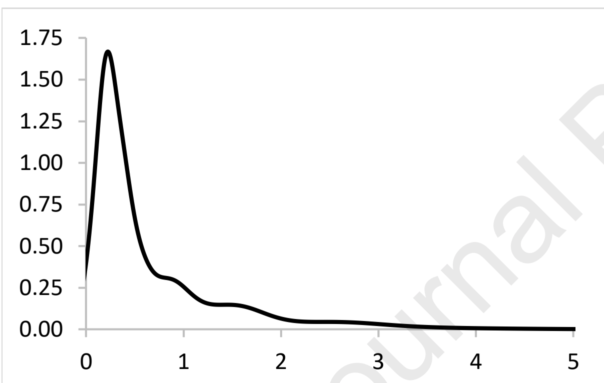
(a) First quartile countries



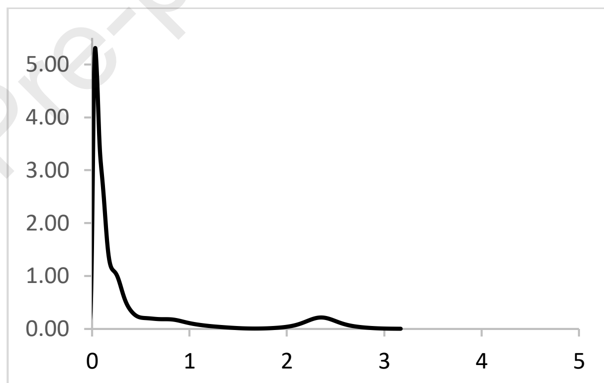
(b) Second quartile countries



(c) Third quartile countries

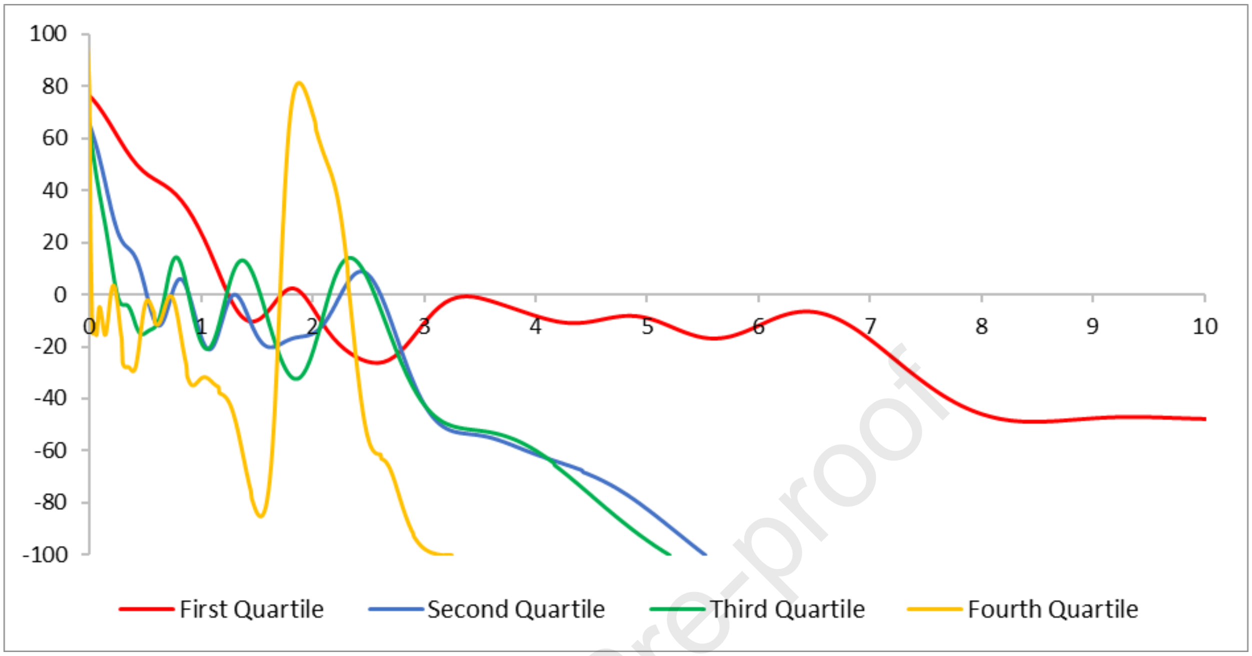


(d) Fourth quartile countries



Notes: The horizontal axis represents the value of REPC, whilst the vertical axis represents the proportion.
Source: Authors' calculations

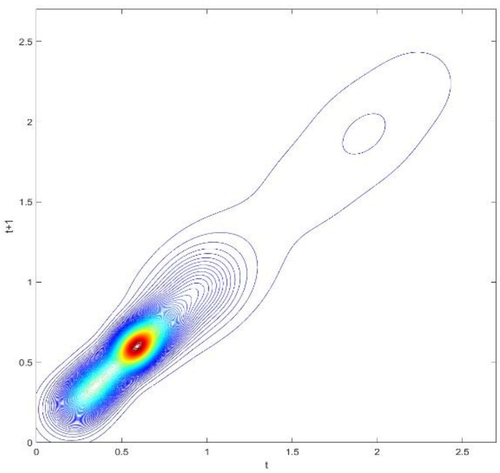
Fig. 6. Mobility Probability Plots (MPP) for REPC by the quartiles of agrarian orientation.



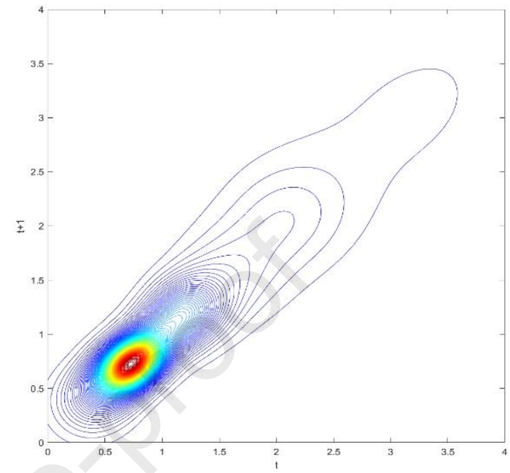
Notes: The horizontal axis represents the value of REPC, whilst the vertical axis represents the MPP.
Source: Authors' calculations

Fig. 7. Contour maps of transition probability kernel for REPGDP by the quartiles of urbanisation ratio.

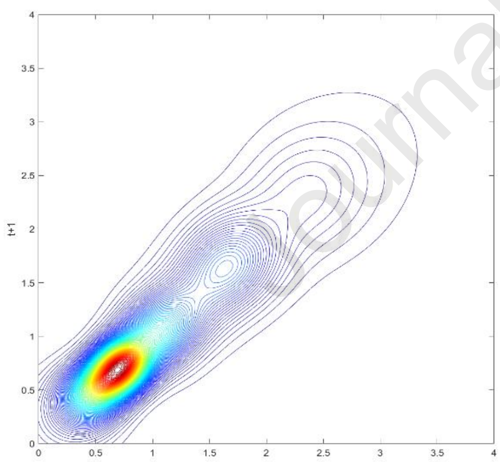
(a) First quartile countries



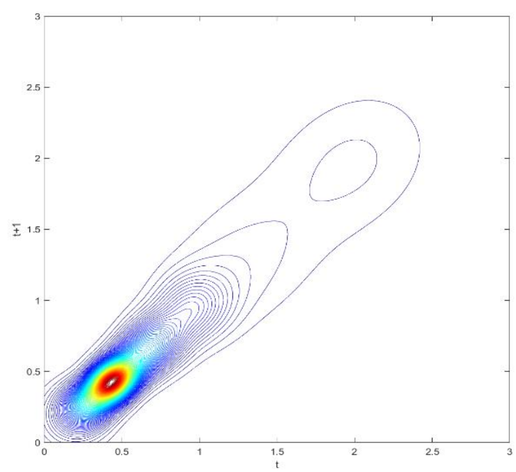
(b) Second quartile countries



(c) Third quartile countries

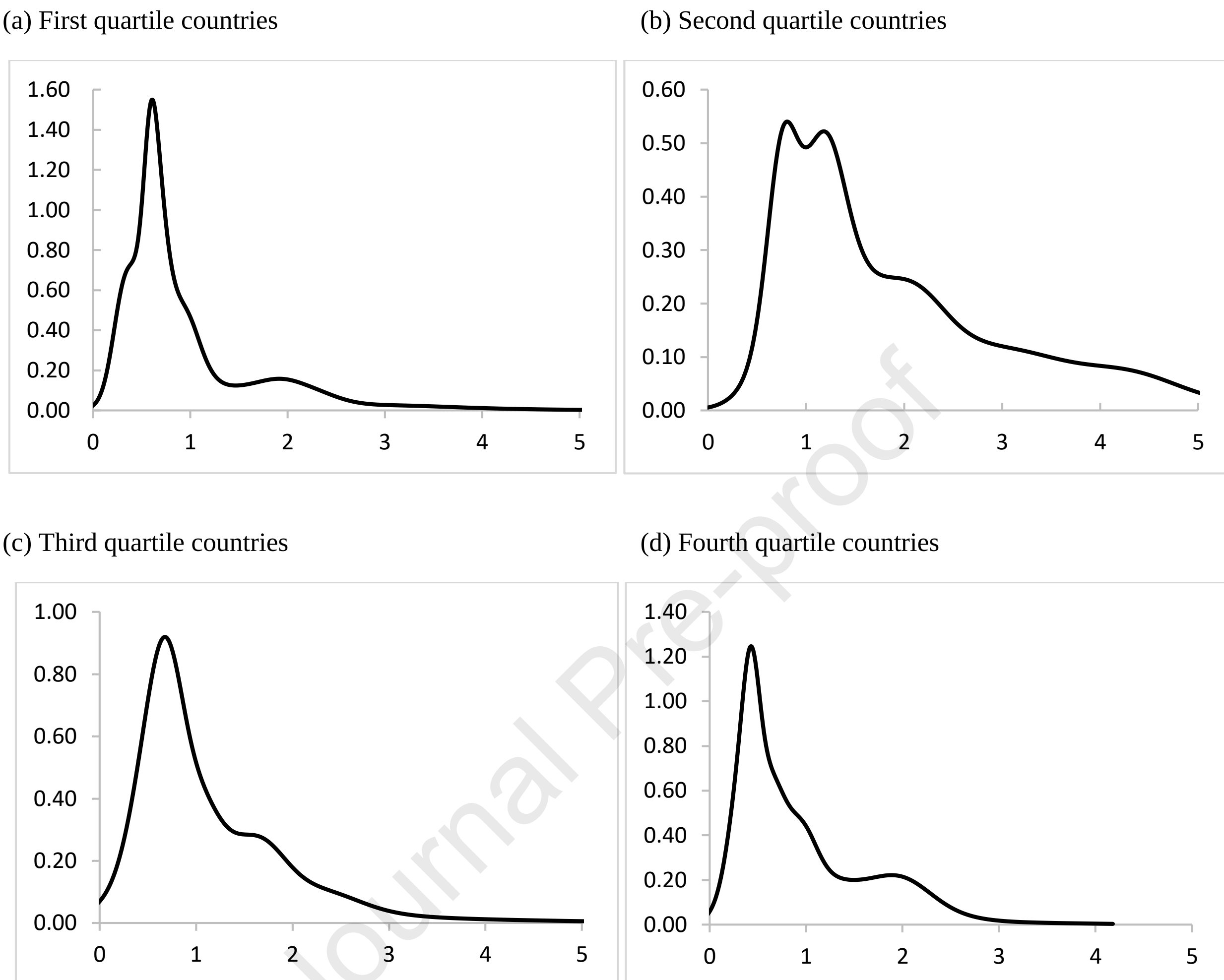


(d) Fourth quartile countries



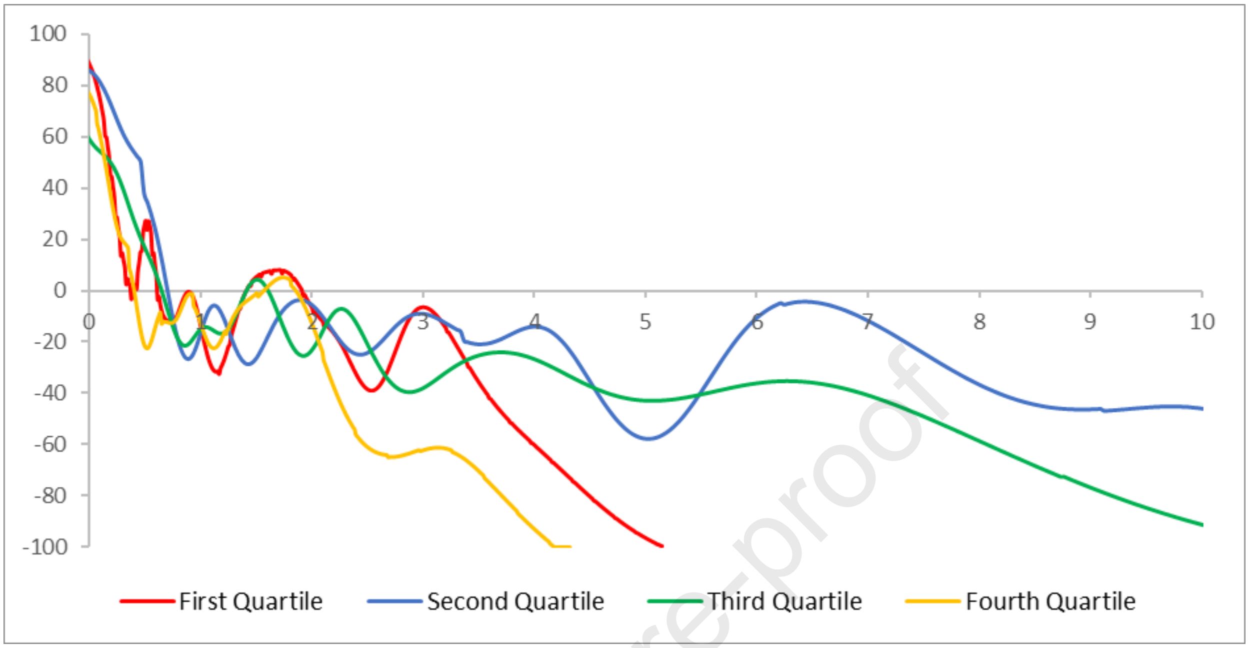
Notes: The horizontal axis represents the value of REPGDP at time t, whilst the vertical axis represents the value of REPGDP at time t+1.
Source: Authors' calculations

Fig. 8. Ergodic distributions for REPGDP by the quartiles of urbanisation ratio.



Notes: The horizontal axis represents the value of REPGDP, whilst the vertical axis represents the proportion.
Source: Authors’ calculations

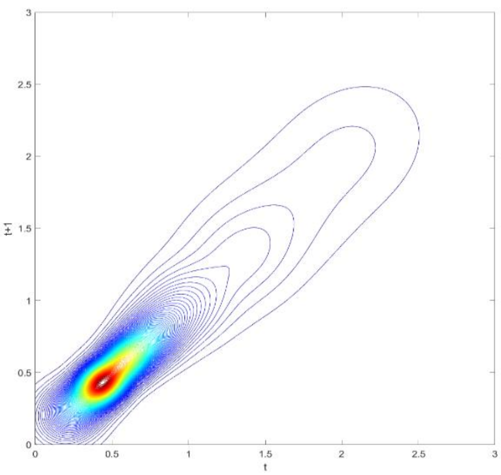
Fig. 9. Mobility Probability Plots (MPP) for REPGDP by the quartiles of urbanisation ratio.



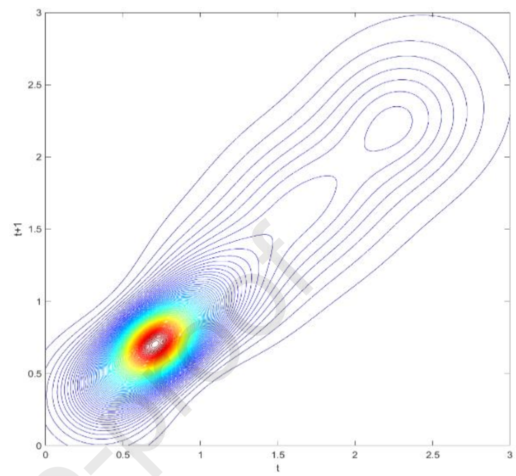
Notes: The horizontal axis represents the value of REPGDP, whilst the vertical axis represents the MPP.
Source: Authors' calculations

Fig. 10. Contour maps of transition probability kernel for REPGDP by the quartiles of agrarian orientation.

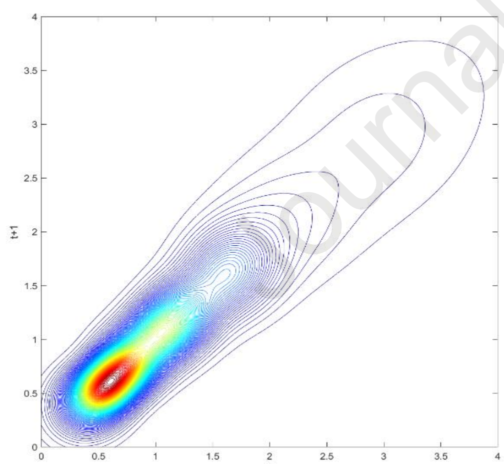
(a) First quartile countries



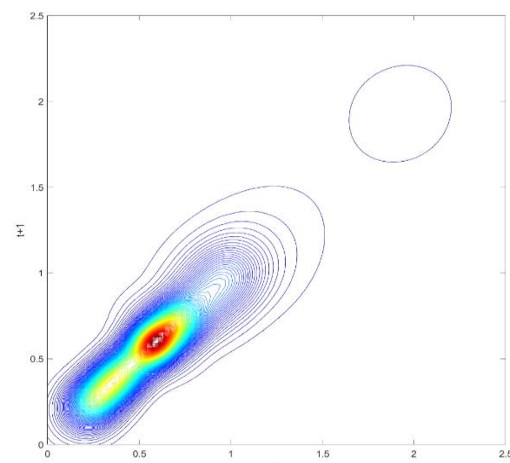
(b) Second quartile countries



(c) Third quartile countries



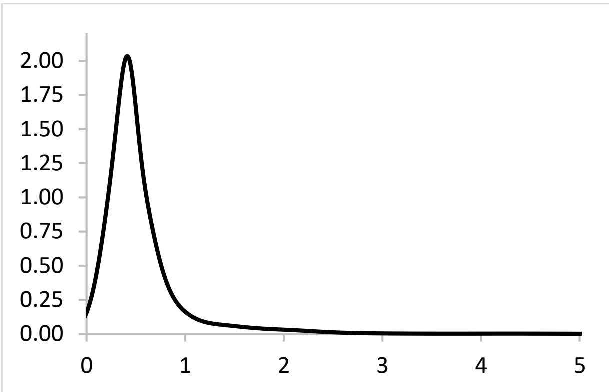
(d) Fourth quartile countries



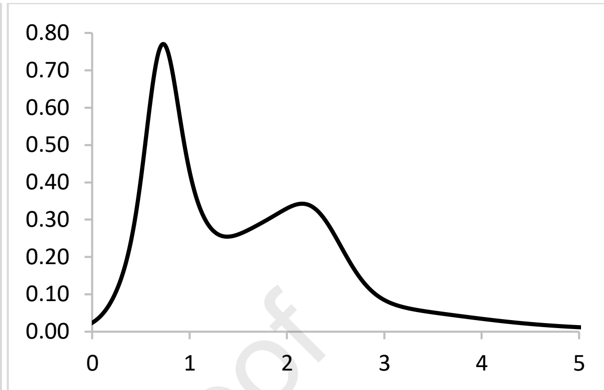
Notes: The horizontal axis represents the value of REPGDP at time t, whilst the vertical axis represents the value of REPGDP at time t+1.
Source: Authors' calculations

Fig. 11. Ergodic distributions for REPGDP by the quartiles of agrarian orientation.

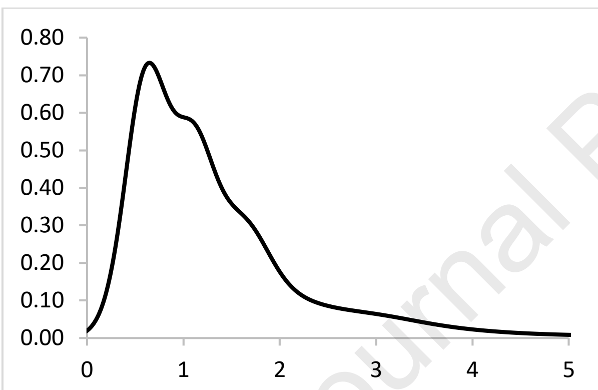
(a) First quartile countries



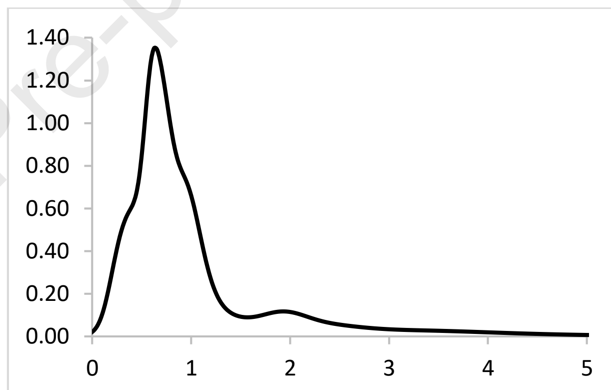
(b) Second quartile countries



(c) Third quartile countries

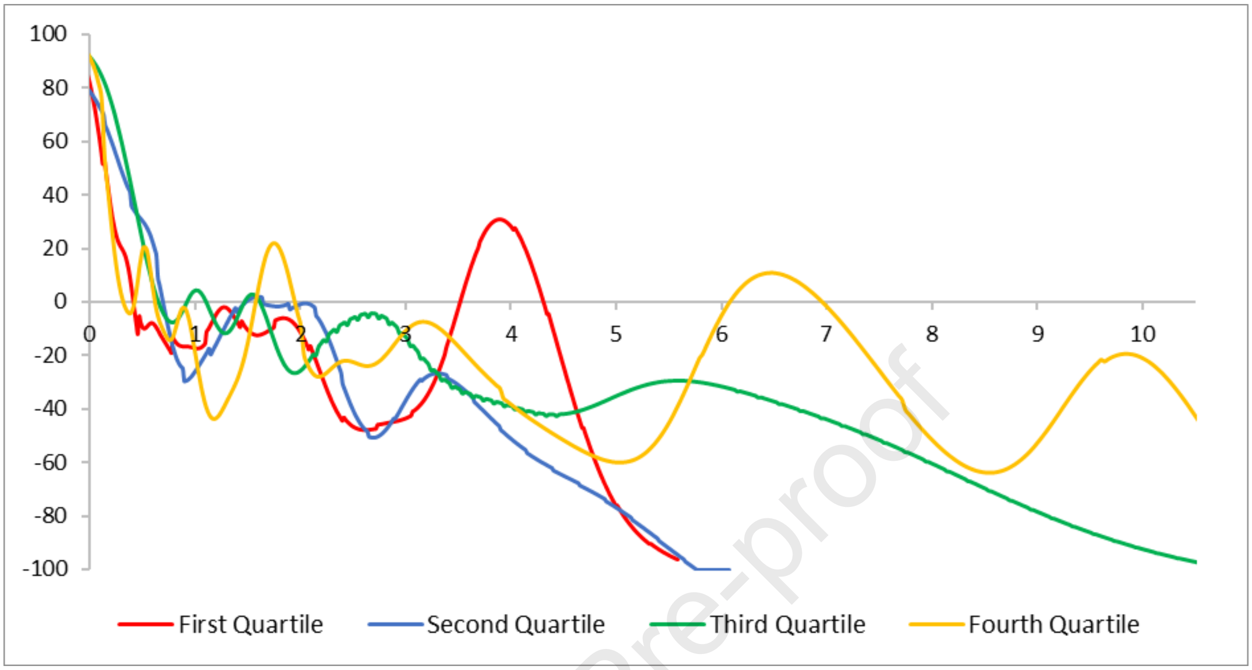


(d) Fourth quartile countries



Notes: The horizontal axis represents the value of REPGDP, whilst the vertical axis represents the proportion.
Source: Authors' calculations

Fig. 12. Mobility Probability Plots (MPP) for REPGDP by the quartiles of agrarian orientation.



Notes: The horizontal axis represents the value of REPGDP, whilst the vertical axis represents the MPP.
Source: Authors' calculations

- Multiple convergence clubs for both measures of CO_2 emissions in the long run
- CO_2 emissions distribution is the least dispersed for the least urbanised countries
- Most clusters occur at CO_2 emission values far from the global average

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: