Evolution of Future World Coal Consumption: Insights from a Distribution Dynamics Approach

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Abstract

Global efforts in limiting coal consumption will be undermined if new major coal users emerge, however, very few studies have been conducted on the emergence of prospective coal users. The objective of this paper is thus to investigate how likely some developing countries will emerge to be significant coal users. The distribution dynamics approach is adopted to examine the evolution and transitional dynamics of coal consumption. Ergodic distributions and mobility probability plots are constructed for each grouping so as to provide detailed information on the current pattern and future development. Our study finds that some low-income and lower middle-income economies may increase their coal consumption in the future if coal remains to be a cheap energy source, while the countries in other income groups have entirely different behaviours. The findings suggest that global policy coordination focusing on the prospective coal users should be adopted.

Keywords

Coal consumption; growth potential; distribution dynamics; mobility probability plots

1. Introduction

Since coal is one of the primary local air polluters and has the highest emission intensity among fossil fuel, its utilisation is subject to mounting environmental pressure in the past few decades. The Chinese coal sector, which accounts for half of the global production and consumption, has been subjected to growing pressure in the past two decades. Despite a boom in the early 2000s due to restructuring of the industry and China's surge in energy demand (Shi, 2010, Shi and Grafton, 2010), China is leading the cut of coal consumption in line with its international commitment to peak CO2 emissions by 2030 (Shi et al., 2018, Shi et al., 2019, Qiao et al., 2019). The data has demonstrated a decoupling trend between coal consumption and economic growth in China (Zhang et al., 2018). The development of the carbon market in China (Sun et al., 2019), further ruins coal's prospect. The world's third-largest coal consumer, the US, has been continuously on the path of reducing coal consumption due to the cost competitiveness of natural gas (EIA, 2016). Overall, the gravity of energy production has been moving toward the southeast (Wang et al., 2014).

While the current major coal users have initiated significant efforts to limit coal use, the global efforts in limiting coal consumption will be undermined if substantial new coal users emerged. Despite that coal is heading downhill in the Global North, the mining, trade, and consumption of coal are increasingly developed in the Global South, which includes countries like India, South Africa, Colombia, Turkey and Southeast Asian countries (Cardoso and Turhan, 2018). Globally, more than 1.2 billion people did not have access to electricity in 2015 (IEA, 2016). According to the current international practice, the need for essential energy should not be sacrificed to climate change efforts (UNFCCC, 2010). For these governments that need to electrify their communities, coal will become an attractive option if the retreat of big users slashes its price. Therefore, India and Southeast Asian countries are expected to leading the future global growth in coal (IEA, 2017). For example, in India, around 70 percent of power production comes from coal. The country has made it clear that it does not intend to agree to phase out fossil fuels by 2100 and that it will "not be bullied into accepting the position of developed countries" (Cosgrave, 2015). With the fourth largest reserve in the world, coal consumption in India is expected to increase 360 Mton by 2035, the second-largest global growth after Southeast Asia (Bhattacharya et al., 2017).

One major strategic question is how likely some developing countries will increase their use of coal consumption during their future economic growth, as the past and current major coal users did. The question was originated from the observed spill-over effects of coal consumption cut in the US: coal that has been crowed out from the US market by cheap gas found their destination in Europe, mainly Germany (Lang and Mutschler, 2014). Such spillover effects could be further extended to countries that are not using much coal currently but may attempt to do so in the future when coal price is even lower and becomes the cheapest energy source.

Using the global coal consumption data for major economies from 1965-2015, this paper will investigate the evolution and transitional dynamics of coal consumption for major countries and regions in the world. The paper will make the following contributions to the literature. First, it introduces the distribution dynamics approach to the study of the convergence of coal consumption by providing a new perspective. Ergodic distributions and mobility probability plots (MPPs), which are a new methodologies that have been developed in the past few years by Cheong and Wu (2015), are then constructed for each grouping, which provide detailed information on the current pattern and future development of coal consumption. The method can complement the econometric study by evaluating consumption from a new angle.

Second, it investigates the convergence process in the case of coal consumption for the overall sample of countries as well as differentiating between countries in different income levels. Third, it offers a forecast of future evolution for countries with a high level of coal consumption. The findings derived can provide important policy implications in formulating a global strategy in mitigating the effects of climate change. Fourth, it provides information for energy and climate policymakers to examine those prospective coal users, which is only possible with the methodology in this paper. Such information on prospective coal users is vital for shaping future policies. Lastly, the MPPs can pinpoint the trend and its future change in consumption for each country. It provides information on the probability of an increase and decrease of use for each economy. The policymakers can then allocate resources in combating climate change according to results derived from the MPP.

The paper is organized as follows. The next section presents a brief survey of the literature. Section 3 introduces the methodology and data. Section 4 discusses the results. The last section concludes the paper with policy implications.

2. Forecasting of coal consumption: a literature review

Forecasting of coal consumption often conducts in two distinctive approaches. One is a top-down approach. With this approach, energy consumption is first predicted according to factors such as economic growth, industry structure, etc with time series econometric methods. For example, (Wang and Li, 2017) use a time series model to investigate China's coal consumption and finds it has been peaked in 2014. The coal consumption is then estimated based on the prediction of its share in the future energy mix (Crompton and Wu, 2005). Variety of VARs models were used for such forecasting, such as Crompton and Wu (2005), Jiang et al. (2018) and Chan and Lee (1997).

The other approach for forecasting is a bottom-up approach, which is often used by outlooks (IEA, 2016, Kimura, 2011) and some academic papers (Wang and Li, 2008). In this approach, coal consumption is estimated based on major sectoral users, such as power generation, cement, chemistry, and building materials or by functions such as heating, lighting, and transportation. Such forecasting often relies on a large model with sector output as the key driving factors. It needs a significant amount of data inputs which are often beyond the scope of one single paper.

Sometimes mixed of both approaches are used. For example, coal consumption could also be estimated by regions, mainly in the case of big counties like China, such as Cattaneo et al. (2011) and Hao et al. (2015). Such regional estimation is still more or less a top-down approach. A summary of the literature on forecasting China's coal consumption can be found in Wang et al. (2018).

Variables included in forecasting coal consumption depend on methodology, but GDP (often in per capita term) is often the minimal and essential variables. In a VAR framework of forecasting of coal consumption, the variables often included energy consumption, real fuel price, real GDP, and population (Crompton and Wu, 2005). In the case of spatial econometrics, other variables including share of second industry (value-added to GDP), urbanization rate, and trade openness, are frequently used (Hao et al., 2015, Chan and Lee, 1997). Per capacity GDP and energy elasticity are used to predict coal consumption as well (Wang and Li, 2008).

The major sensitive part in forecasting consumption is the relationship between those drivers and coal consumption. Elasticities will have to be assumed and such elasticities will have to be varied over time to account for energy efficiency improvement. One of the most critical elasticities, income elasticity--the relationship between economic growth and coal consumption, has seen no consensus regarding the direction of causality between energy consumption and economic growth (Wolde-Rufael, 2010). Many studies find that the relationship between coal consumption and GDP is not linear (Hao et al., 2015).

The majority of the previous studies are based mainly on econometric analysis, which has its limitations. The majority of econometrics methodology is based on the first-moment characterization. It provides only partial information and can lead to deceiving results when the distribution of the indicator is not unimodal (Wang, 2011, Quah, 1997). One major issue is that it can only provide a summary of the statistics but cannot provide information on the shape of the distribution, which is essential to policymakers (Quah, 1993b). Econometric analyses can show the level of significance of the independent variables, but cannot reveal information on the world distribution itself (which is a two-dimensional entity). Moreover, it cannot offer information on the change in the shape of the distribution across time. The information on the overall distribution is fairly important as it can offer an overall picture of the consumption for all the countries in the world.

In the past, some scholars study the convergence by using regression, but this method is subject to many criticisms (Quah, 1993a). Alternatively, papers that predict coal supply using curve-fitting models (Patzek and Croft, 2010, Lin and Liu, 2010, Wang et al., 2013) are based on a strong assumption of the underlying distribution. The conclusion may prove incorrect if the underlying distribution of the population is different from the mathematical form, which was assumed in these analyses.

This paper adopts the distribution dynamics approach to fill in the gap in the literature and provide another perspective for examining the world's coal consumption patterns. Compared with other non-parameter methods, the distribution dynamics approach does not make any assumption of the underlying distribution of the population, so that the results derived from distribution dynamics analysis will not suffer from this issue. The distribution dynamics approach is also adopted in this paper because it can pinpoint the countries which have a high probability of increasing their consumption in the future, and it can show the probability of an increase or decrease in coal consumption for each country. As a result, this study can inform the policymakers about the future transitional dynamics of prospective coal users who will shape the future policy debate on coal and climate change.

Although the distribution dynamics approach has many merits as mentioned above, no literature can be found for its application in projecting coal consumption, although some scholars used this approach to examine the convergence of CO_2 such as Nguyen Van (2005) and Evans and Kim (2016). Other scholars employed this approach to explore the change in the energy sector, such as Wang (2011), Ezcurra (2007), Herrerias (2012) and (Shi et al., 2020b). Given that the distribution dynamics approach was not employed before in investigating coal consumption, the purpose of this paper is to take a look at the distribution dynamics of coal consumption at the world level and thus fill in the gap in the literature.

3. Data and Methodology

The data of this study is based on the information provided in the *BP Statistical Review of World Energy* (BP, 2016). This dataset is very comprehensive and contains the data of coal consumption for all the major economies and aggregated regions in the world from 1965 to 2015. It was then combined with the population data obtained from the World Development Indicators (WDI) database (supplied by the World Bank) to compute the coal consumption per capita for each country. However, the population data of Taiwan was not available from the World Bank, and was downloaded from the website of Population City. Similarly, the average consumption of the world was calculated by dividing the world consumption by the world population. However, as the aim is to investigate the disparity in consumption amongst the countries, the data of the coal consumption of each country was further divided by the world average to determine the relative coal consumption per capita (RCCPC).

In the first stage, the analysis covers all the countries and regions to provide an overall picture of the consumption pattern, trend, and future development. In the second stage, the analysis is based on those countries with an extremely high level of coal consumption. In the final stage, the dataset was divided into four sub-samples according to the income level of each country. This can reveal the relationship between the distribution dynamics of a country and its income. The stepwise approach offers a comprehensive investigation of coal consumption in all the economies in the world.

The classification of the income level is based on the information supplied by the World Bank. There are four classifications for national income, namely, the Low Income, the Lower Middle Income, the Upper Middle Income, and the High-Income groups. To observe the transition in detail, the classification of the income group is based on the prevailing income status of a country for that stage. For example, China was classified as a low-income country in 1996, and then it moved to the lower-middle-income group from 1999 to 2009, and finally became an upper middle-income country from 2010 onwards. In the second stage of analysis, a dataset of countries with high consumption was compiled. The analysis derived from this dataset can offer valuable information on the consumption patterns of those countries which consume more than 1% of the world's total consumption every year, and it can thus reveal the future trend of these major economies in great detail.

Distribution dynamics analysis was first developed by Quah (1993a). Distribution dynamics analysis was first developed by Quah (1993a). It is worth noting that distribution dynamics analysis can reveal a lot of information which is not available from conventional econometric analysis. Although time series econometric analysis can provide a forecast of the dependent variable, however, the forecast is only a point estimation; and thus econometric analysis cannot be used to prepare a forecast for the overall shape of a distribution which is a two-dimensional entity. On the contrary, distribution dynamics analysis can offer a prediction of the shape of a distribution; therefore it is better for investigating the change. Moreover, distribution dynamics analysis can also provide information on the movement of the entities within the distribution, thereby revealing the underlying trend behind the change in great detail." The distribution dynamics approach can be further divided into the traditional Markov chain analysis approach and the stochastic kernel approach. The stochastic kernel approach is thus developed to circumvent the issue of demarcation of the state which is an inherent problem of the traditional Markov chain analysis by incorporating kernel analysis in the process. A bivariate kernel estimator is employed and the formula is:

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

where x is a variable representing the RCCPC of a country at time t, y is a variable representing the RCCPC of that country at time t+1, $X_{i,t}$ is an observed value of RCCPC of a country at time t, and $X_{i,t+1}$ is the observed value of the RCCPC of that country at time t+1, h_1 and h_2 are the bandwidths, n is the number of observations, and K is the Epanechnikov kernel function. The optimal values of the bandwidth were selected according to the procedure suggested by Silverman (1986).

It is worth mentioning that another thorny issue of the distribution dynamics analysis is the unbalanced shape of the distribution. The actual shape of the distribution coal consumption is not balanced, but is skewed and has a very long right tail. This can affect the estimation of the stochastic kernel because over-smoothing may appear in regions with many entities, whereas under-smoothing may occur in regions with only a few entities. Therefore, the sparseness of the data is taken into consideration by employing the technique of adaptive kernel with flexible bandwidth (Silverman, 1986).

Assuming that the evolution is time-invariant and first order, that is, the distribution at time $t+\tau$ does not depend on any previous distributions save the distribution at time t only, and so the distribution at time $t+\tau$ can be represented as:

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

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

The ergodic distribution is the long-run equilibrium distribution, and its formula is:

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

where $f_\infty(z)$ is the ergodic density function when τ is infinite.

The ergodic distribution shows the distribution of RCCPC in the long-run given that the distribution dynamics remain unchanged. This is the steady-state distribution and so it can be used to prepare a forecast of the shape of a distribution in the future. By comparing the shape of the current distribution and that of the ergodic distribution, the proportion change in different parts of the distribution can be known, thereby revealing the change in shape and its underlying trend in great detail.

In order to analyse the mobility of RCCPC for each country, we employ the mobility probability plot (MPP) technique that was developed by Cheong and Wu (2018) . This technique has been employed in many research areas in analysing distribution dynamics, such as industrial output (Cheong and Wu, 2018), investment (Cheong et al., 2018a), rural household income (Li and Cheong, 2016), housing price and affordability (Li et al., 2017, Cheong and Li, 2017) and also in energy economics (Cheong et al., 2018b) and many studies focusing on carbon dioxide emissions (Cheong et al., 2016, Wu et al., 2016). This technique can provide important information which is not available from econometric analysis and other traditional approaches, thus it can complement existing studies on coal consumption.

The MPP shows the net upward mobility probability of RCCPC for each country, and is expressed as percentage. It ranges from -100 to 100, and can be computed as $p(x)$:

$$p(x) = \int_{x}^{\infty} g_{\tau}(z|x)dz - \int_{0}^{x} g_{\tau}(z|x)dz \qquad (4)$$

If a country has a positive MPP, it implies that the country has a net probability of increasing relative coal consumption in the future. In contrast, a negative value of MPP signifies that the country has a net probability of reducing its relative consumption. Therefore, by observing the MPP value, one can know the change in coal consumption of each country and can even make a prediction of the consumption into the future.

4. Results

4.1 Full sample: all economies

Stochastic kernel analyses are performed to compute the transitional dynamics for each economy. Figure 1 shows the three-dimensional plots of the coal consumption distribution of all economies, while Figure 2 displays the associated overhead view of the contour map. The width of the transition probability kernel in Figure 2 is widely dispersed with the density mass concentrated along 45 degree diagonal line. This indicates that future coal consumption trend will vary significantly among all economies. However, there is only one peak in Figure 2, which is clustered at around 0.05. The implication is that the coal consumption of most of the countries and regions in the world will be below the world average (among the clustered group), while a few economies will have an extremely high level of coal consumption.

[Please insert Fig. 1]

[Please insert Fig. 2]

To further explore the future trend of coal consumption around the world, ergodic distribution is used to estimate the distribution dynamics. Figure 3 shows the ergodic distribution of the world's coal consumption, which is its long-run steady-state. The peak of 0.05 is more clearly observed in the ergodic distribution. While the ergodic distribution in Figure 3 has shown the existence of one peak for all economies, the mobility of future coal consumption cannot be identified by the ergodic distribution. The new framework of MPP can effectively tackle this problem and offer a direct interpretation of the mobility of the entities. In Figure 4, the MPP on distributions of the probability mass is above zero only when the coal consumption level is no more than 0.08. It suggests that many countries will reduce coal consumption except those with a consumption level lower than 0.08 of the global mean. However, this result alone does not suffice to say that global coal consumption will decline, as the volume of consumption of the major coal consumers can be very high though the number of these major consumers is few in number.

[Please insert Fig. 3]

[Please insert Fig. 4]

4.2 High consumption countries

To better understand the pattern of major coal consumers, Figure 5 displays the three-dimensional plots of coal consumption for economies with consumption at least 1% of the world total, while Figure 6 displays their relevant contour map. The width of the transition probability kernel for all the three property sizes and regions are dispersed with the density mass concentrated along the 45-degree diagonal line. Unlike the global distribution of all economies, the distribution of economies consuming at least 1% world total has three peaks in the dimensional plot. The three peaks are at the values around 0.53, 1.55 and 4.18, respectively.

[Please insert Fig. 5]

[Please insert Fig. 6]

To capture the long-run distribution of economies consuming at least 1% coal of the world total, Figures 7 and 8 provide their ergodic distribution and mobility probability plot, respectively. For those that consume more than 1% of the world's coal, we observe the existence of three convergence clubs in Figure 7. Combined with the MPP in Figure 8, it is evident that for economies with consumption levels from 50% to 92% of the world average, they tend to reduce their coal consumption. But for those with consumption level from 0.92 to 1.5, they will increase their consumption; and for economies with consumption level from 1.5 times to 2.55 times of the world average, they tend to reduce their coal consumption. Yet for economies consuming 2.55 times to 4.14 times of the world average, they tend to increase their future coal consumption. Briefly speaking, although a majority of economies will reduce their coal consumption, a number of economies will increase their consumption and some will even reach an alarming level of four times and above (as shown by the third peak in the distribution).

[Please insert Fig. 7]

[Please insert Fig. 8]

4.3 Different income groups

We divide the economies into four categories to further investigate whether the income levels have played a pivotal role in differentiating the diverse consumption patterns among various income groups.

Figure 1 to Figure 8 has indicated a sharp contrast between the reduction of coal consumption for the majority of economies and the increase of coal consumption for several economies with an extremely high level of consumption. It is thus essential to explore whether the income levels have played a pivotal role in differentiating the diverse consumption patterns among various income groups. We, therefore, divide the economies into four categories: low income, lower middle income, upper middle income, and high-income economies. Figure 9 provides the three-dimensional plot of transitional probability kernels by different income groups. It is worth noting that the distribution of coal consumption is often bimodal, which justifies the importance of conducting a distributional analysis to avoid deceiving results (Quah, 1997).

[Please insert Fig. 9]

Figure 10 displays the associated contour maps of transition probability kernels by different income groups. The low-income economies converge at lower energy intensity ratios, which are less than 0.5. In the case of high-income economies there are two convergence clubs, one in the lowest level of energy intensity and another with higher levels of energy intensity.

[Please insert Fig. 10]

To explore the future evolution trend of coal consumption patterns for different income groups, Figure 11 displays the ergodic distribution for different income levels. In Figure 11a, the values of the peaks are 0.02, 0.32 and 1.33 for the low-income economies. Figure 11b shows the ergodic distribution of the lower middle-income economies, while Figure 11c shows the one for the upper middle-income economies. In Figure 11b, the values of the peaks are 0.05 and 1.98 for the lower middle-income economies. The values of the peaks are 0.06 and 3.92 for the upper middle-income economies as shown in Figure 11c. Turning to Figure 11d which shows the ergodic distribution of the high-income economies, the values of the peak are around 0.51 and 1.8.

[Please insert Fig. 11]

There are several salient findings derived from this study. It can observe that convergence clubs will emerge within all the income groups implying that the disparity in consumption will persist in the long run. Moreover, the highest peaks in all the figures are below the value of 1, thereby signifying that most of the economies will have a consumption level lower than the global average. However, the value of the highest peak is the lowest (0.02) for the low-income economies, and this value increases with the income level. It reaches the value of 0.51 for the high-income economies. Therefore, it shows that the proportion of economies rely on coal is positively correlated with the level of income.

Figure 12 shows the MPP for different income groups. There is a considerable variability of consumption dynamics in the low-income economies. In comparison, the distribution and evolution of coal consumption for the upper-middle and high income economies are more straightforward. In Figure 12a, the MPP for low-income economies is below zero when the coal consumption intensity is ranged from 0.03 to 0.20. Yet for the range of 0.20 to 0.32, the MPP lies above zero which shows a net probability of moving upward. The MPP becomes negative again when the coal consumption intensity falls into the range of 0.33 to 0.64. It then displays a net tendency to move upward in the coming periods back for the range of 0.65 to 1.31. Once again, the MPP turns negative for the range of 1.32 to 1.78, before it moves upward for the range of 1.79 to 2.03. Afterward, the MPP displays a net tendency to move downward in the coming periods again for consumption intensity greater than 2.04.

[Please insert Fig. 12]

According to Figure 12b, it shows that the MPP for lower-middle-income economies is below zero when the coal consumption intensity is ranged from 0.07 to 0.88. For the range of 0.89 to 1.85, the MPP lies above zero, which shows a net probability of moving upward. Afterward, the MPP displays a net tendency to move downward in the coming periods again for consumption intensity greater than 1.85.

Figure 12c shows that the MPP for upper-middle-income economies is below zero when the coal consumption intensity is ranged from 0.11 to 3.0. For the range of 3.0 to 3.64, the MPP lies above zero; and shows a net probability of moving upward. Afterward, the MPP displays a net tendency to move downward in the coming periods again for consumption intensity greater than 3.64.

In Figure 12d, the MPP for high-income economies stays above the horizontal axis initially and intersects the horizontal axis at 0.53. Afterward, it lies below the horizontal axis all the way down except the range of 1.57 to 1.86 where MPP has a net tendency of moving upwards. Generally, high-income economies have a tendency to reduce their coal consumption (except only the economies with consumption form 1.86 to 2).

There are some prominent findings derived from a careful analysis of the MPP. Firstly, it shows that most of the high and upper-middle-income economies would reduce their consumption in coal in the long run. Secondly, the disparity in consumption for the lower-middle-income economies will increase in the future as Figure 12b shows that the economies with a consumption level lower than the global mean will reduce their consumption, while the economies with a consumption level higher than the global mean will increase their consumption. Indeed, the convergence clubs in the ergodic distribution as shown in Figure 11b can be explained satisfactorily by referring to the movement of the MPP in Figure 12b. Thirdly, huge variability can be observed for the low-income economies.

By examining future evolution of coal consumption through the use of MPP and transitional dynamics for different income groups, one can reach a key conclusion that the high-income economies are much richer than the other countries, so they can choose to employ whatever energy sources that they like without relying on coal. However, the poor economies do not have adequate funds to pursue their ideal energy mix, but need to rely heavily on the energy source with the lowest cost. As a result, for those developing countries with abundance in coal, they will increase their consumption in coal; however, for those developing countries with abundance in other non-coal energy sources, they will increase their reliance on these non-coal sources. This can be confirmed by the high variability of the MPP as observed for the low-income groups. The central message is that to reduce global consumption in coal, financial support should be provided to the low-income countries to help them reducing coal consumption as they do not have the required funds to pursue the employment of other forms of clean energy. It thus calls for international cooperation and financing in mitigating the adverse effects of increased coal consumption.

5. Conclusion

The objective of this paper is to investigate how likely some developing countries will emerge to be major coal users. A transitional dynamics approach is adopted in this study to examine the evolution and transitional dynamics of coal consumption for major countries and regions in the world. An overview of coal consumption is presented first, followed by the results derived from different groupings to evaluate the impacts of national income. Ergodic distributions and mobility probability plots (MPPs) are further constructed for each grouping so as to provide detailed information on the current pattern and future development of coal consumption.

The coal consumption of most countries and regions in the world will be below the world average, while a few countries will have an extremely high level of coal consumption. This suggests that some high intensive major coal users may even further increase their consumption intensity in the future.

Our findings show that there is a considerable variability of consumption dynamics in the lower-middle and low-income economies. Our results show that both low-income economies that consume more than 0.65 times of the world average, and lower-middle-income economies that consume 0.89 times of the world average, will increase their coal consumption intensity to more than the world average.

Our study suggests that the transition from coal to lower carbon fuels is not a natural process. The policymakers and the public should not take the energy transition for granted. Due to a lack of funds to pursue their ideal energy mix, poor countries need to rely heavily on the energy source with the lowest cost. Some low-income countries and lower-middle-income economies may increase their coal consumption in the future if coal remains to be a cheap energy source, while the countries in other income groups have entirely different behaviours. This transition could be further boosted by lower coal prices due to the retreat of major coal users. This is contradictory to the Paris Agreement that requires a substantial decline in coal power generation by 2030 (Shi et al., 2020b).

The results suggest that policy intervention from both production and consumption sides, and both national and international perspectives are needed:

First, the global policy to contain coal consumption should not just focus on current major coal users, but also on those prospective coal users, i.e. low-income economies with abundant coal resources. While they are not intensive coal users for the time being, their internal dynamics may turn them into major coal users (in terms of intensity) in the future if coal is still the cheapest energy source. This concern is supported by a recent study that found that the gravity of emission is moving from developed countries to developing countries (Song and Zhang, 2019).

Second, an inclusive global policy coordination is needed to control coal consumption in the future. Prospective intensive coal users are not above the horizon yet. If we push coal out of the energy mix in the current intensive users, it may be shifted to those prospective users and the issues with coal consumption will not be solved at the global level. It is necessary to engage these prospective intensive coal users in the current global battle of climate change, which hopefully can prevent them from emerging as future intensive coal users. Engaging them into the current dialogue on limiting coal use will prevent entrance to path-dependent coal consumption patterns due to misinformation.

Third, international cooperation among both higher and lower-income countries are crucial to prevent the surge of coal consumption in low-income countries. The literature, such as Han et al. (2018), has shown that energy cooperation between developed and developing countries can improve the environmental performance of developing countries. It is often the case that even those prospective coal users have the intention to limit their coal consumption. Yet, they often do not have the technical and financial capacity to set policy interventions due to low development levels. The global community needs to assist low-income countries to increase their financial and technical capacity to not jump to the path of growing coal consumption through intensive investment in coal-related sectors. International cooperation is also needed to help low-income countries in improving their energy efficiency level as they often lack the institutional and technical capacity to improve their energy efficiency performance (Shi, 2015, Shi, 2014).

Lastly, economic and market mechanisms should be adopted to facilitate the phase-out of coal from both supply and demand sides. Some recent studies show that a capacity permit and its trading system can significantly minimize the costs of cutting coal production capacity (Shi et al., 2019, Shi et al., 2020a). On the supply side, a properly designed emission trading policy can reduce the demand for coal and other high carbon energy sources in developing countries (Sun et al., 2019).In addition to carbon prices, further taxes should be levied to account for the adverse health impact of coal use (Hendry et al., 2020).

The current study, however, does have some caveats. The current methodology relies on the own dynamics of coal evolution, which is appropriate for the current study for examining long-term and highly aggregated dynamics. The most popular method of forecasting coal consumption, the time series econometric method, has demonstrated that changes in energy consumption have been reflected in time series data/patterns. However, a lack of consideration of specific technological progress and policy interventions would make it challenging to predict the trend in a specific case. This could be a direction for future studies.

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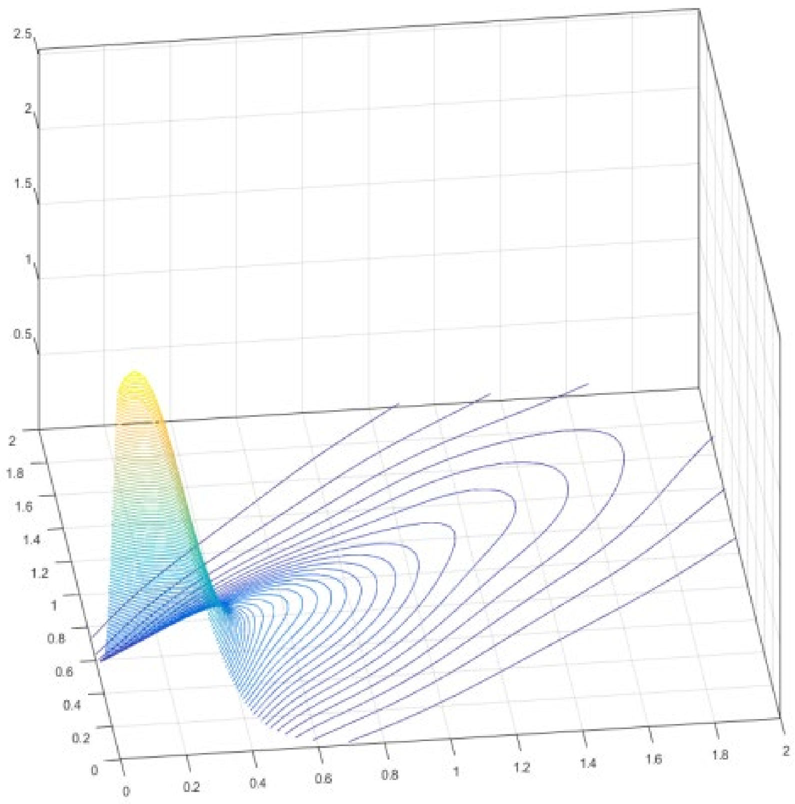


Fig. 1. Three-dimensional plot of transitional probability kernel for coal consumption (all economies)

Note: horizontal axis represents time t, vertical axis represents time t+1, and height represents kernel density.

Source: authors' calculation.

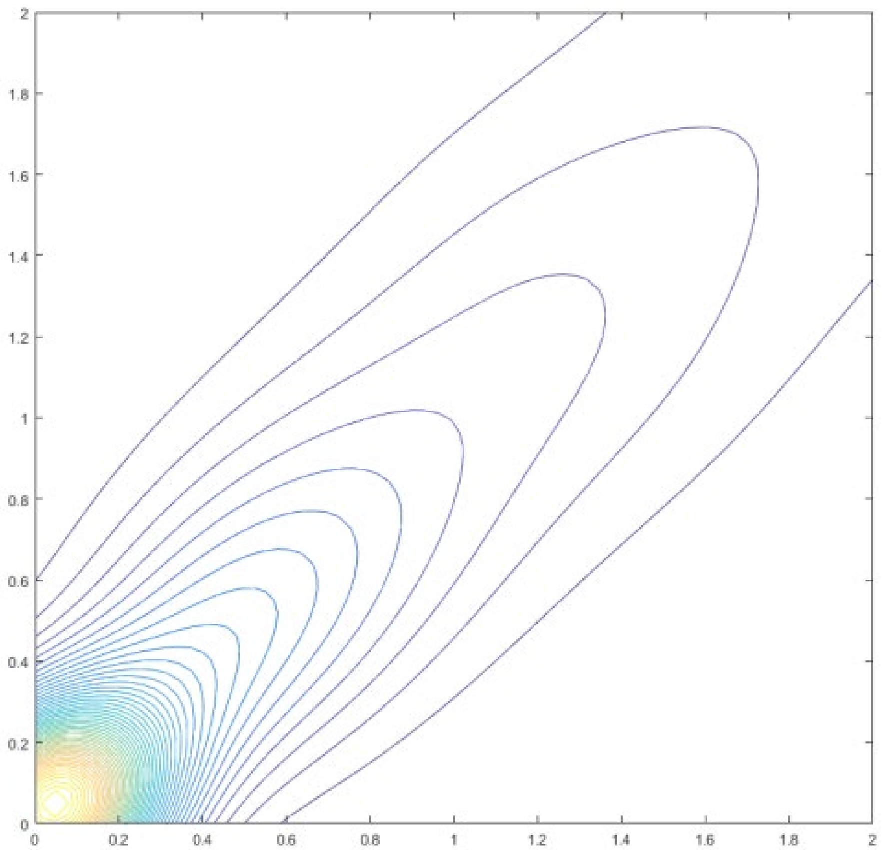


Fig. 2. Contour map of transitional probability kernel for coal consumption (all economies)

Note: horizontal axis represents time t, vertical axis represents time t+1.

Source: authors' calculation.

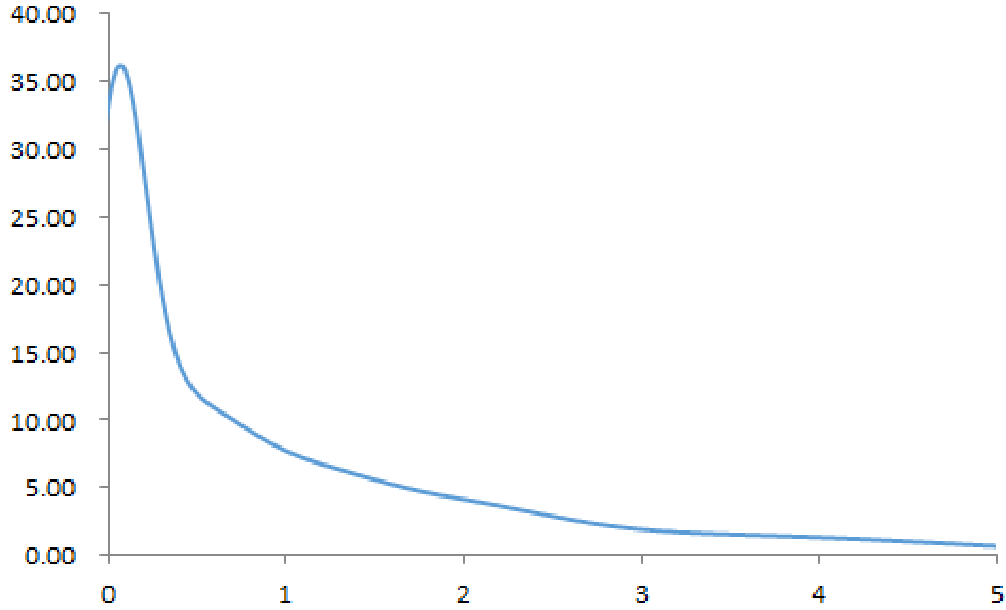


Fig. 3. Ergodic distribution of coal consumption (all economies))

Note: horizontal axis represents relative consumption, vertical axis represents proportion.

Source: authors' calculation.

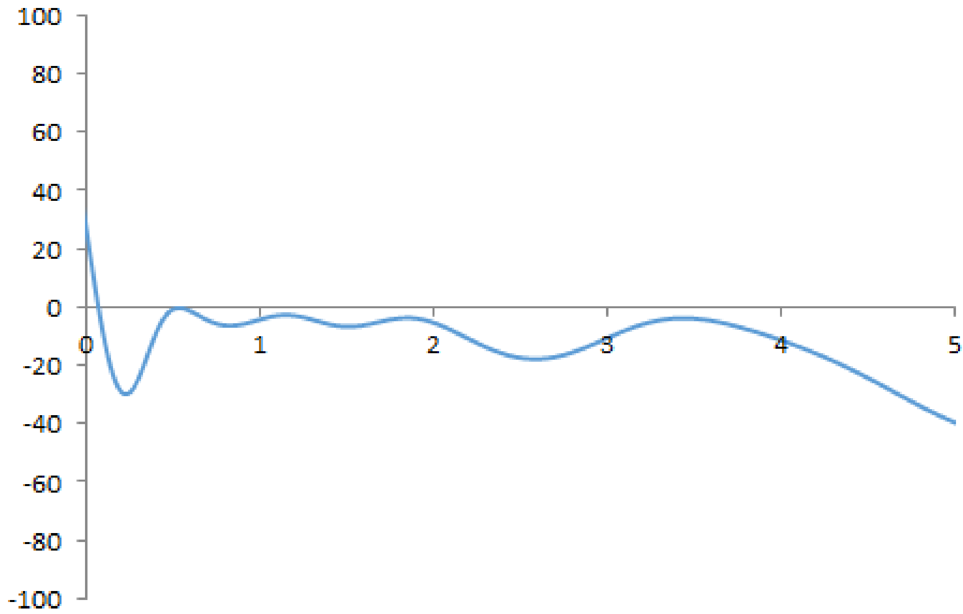


Fig. 4. Mobility probability plot of coal consumption (all economies)

Note: horizontal axis represents relative consumption, vertical axis represents MPP.

Source: authors' calculation.

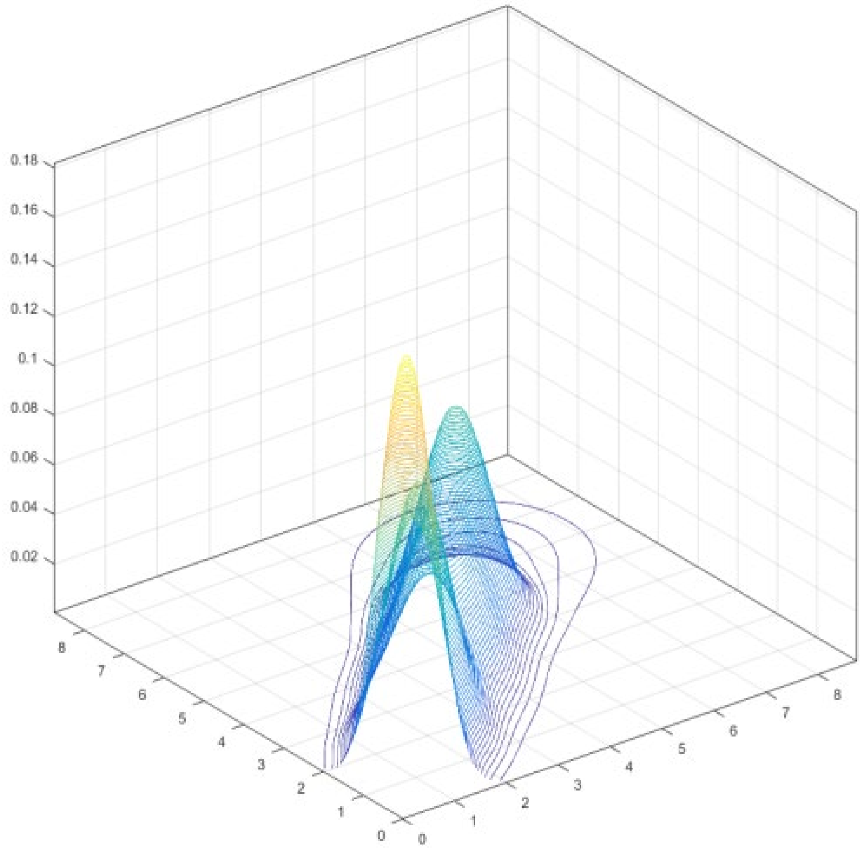


Fig. 5. Three-dimensional plot of transitional probability kernel for coal consumption (economies with consumption greater than 1% of world total)

Note: horizontal axis represents time t, vertical axis represents time t+1, and height represents kernel density.

Source: authors' calculation.

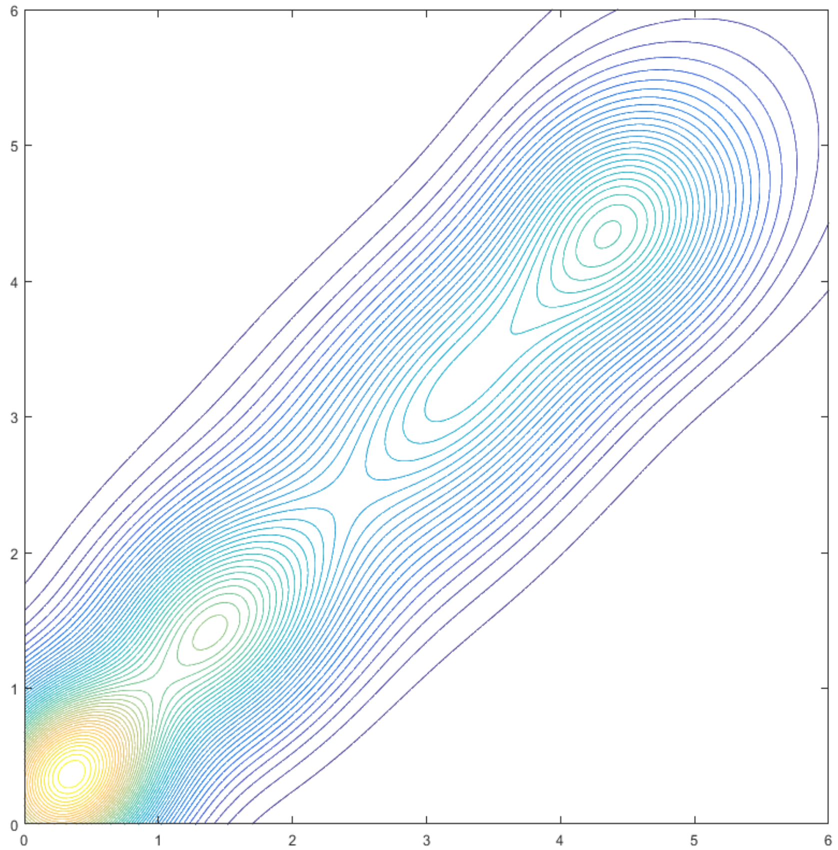


Fig. 6. Contour map of transitional probability kernel for coal consumption (economies with consumption greater than 1% of world total)

Note: horizontal axis represents time t, vertical axis represents time t+1.

Source: authors' calculation.

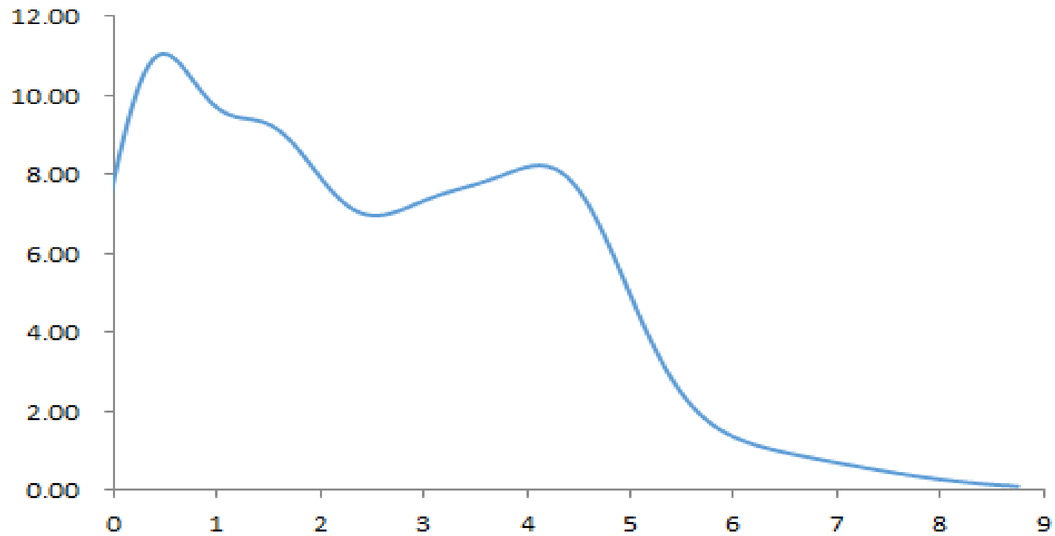


Fig. 7. Ergodic distribution of coal consumption (economies consuming more than 1% of world total)

Note: horizontal axis represents relative consumption, vertical axis represents proportion.

Source: authors' calculation.

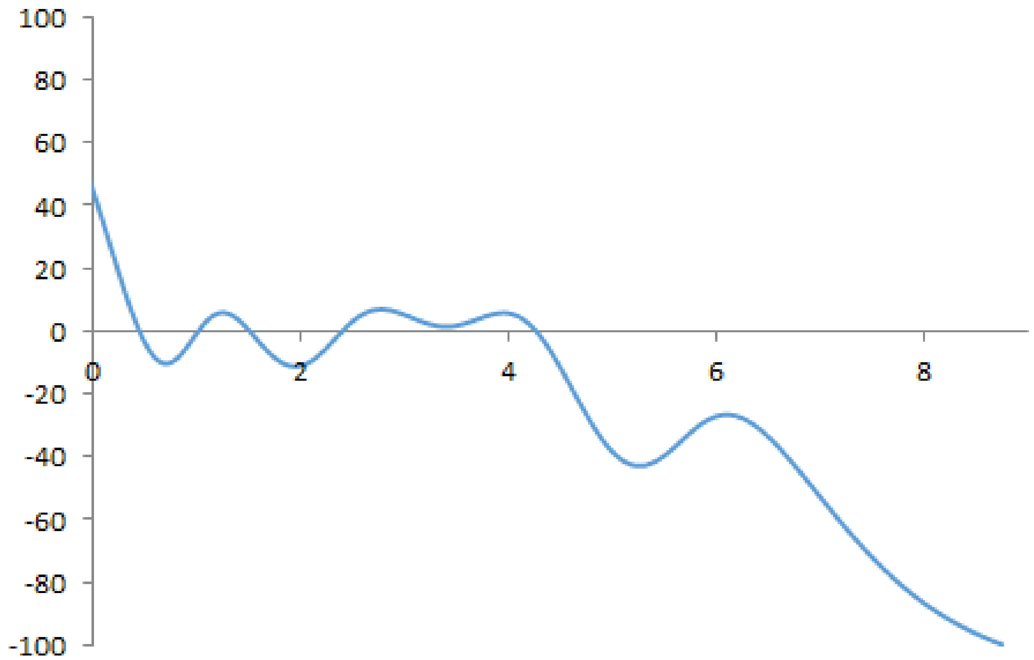
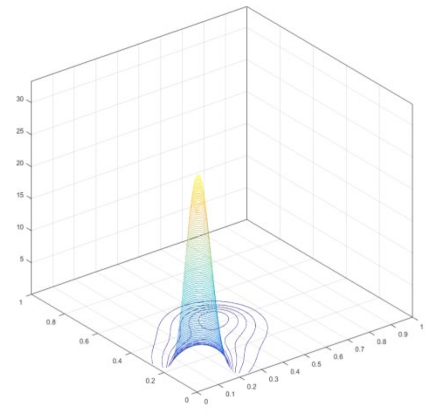


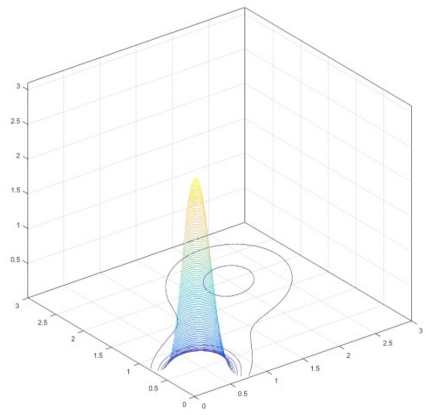
Fig. 8. Mobility probability plot of coal consumption (economies consuming more than 1% of world total)

Note: horizontal axis represents relative consumption, vertical axis represents MPP.

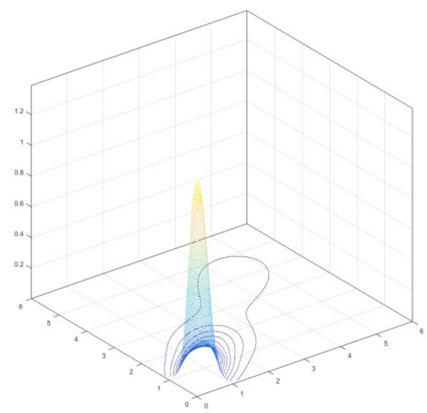
Source: authors' calculation.



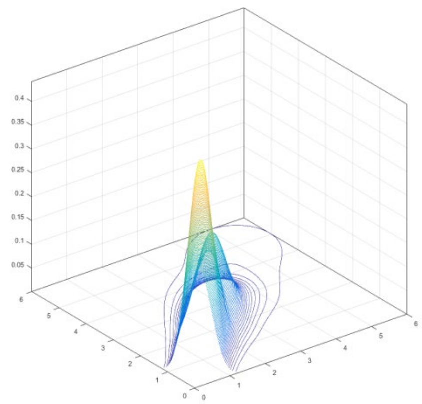
a) Low income economies



b) Lower middle income economies

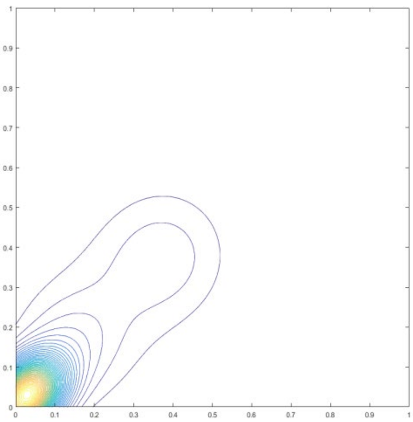


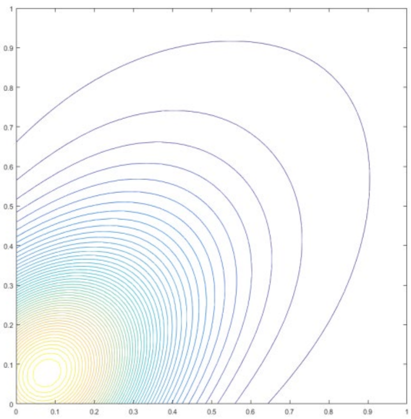
c) Upper middle income economies



d) High income economies

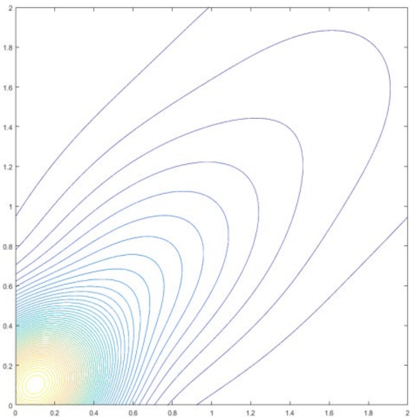
Fig. 9. Three-dimensional plot of transitional probability kernel for coal consumption (all economies by different income groups)
Note: horizontal axis represents time t, vertical axis represents time t+1, and height represents kernel density.
Source: authors' calculation.

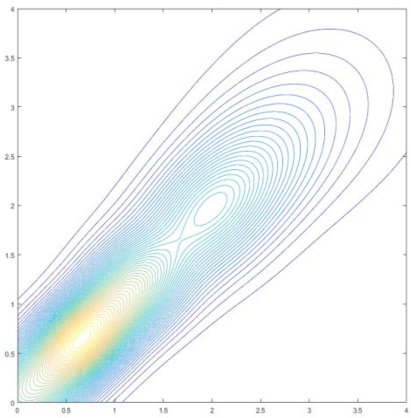




a) Low income economies

b) Lower middle income economies

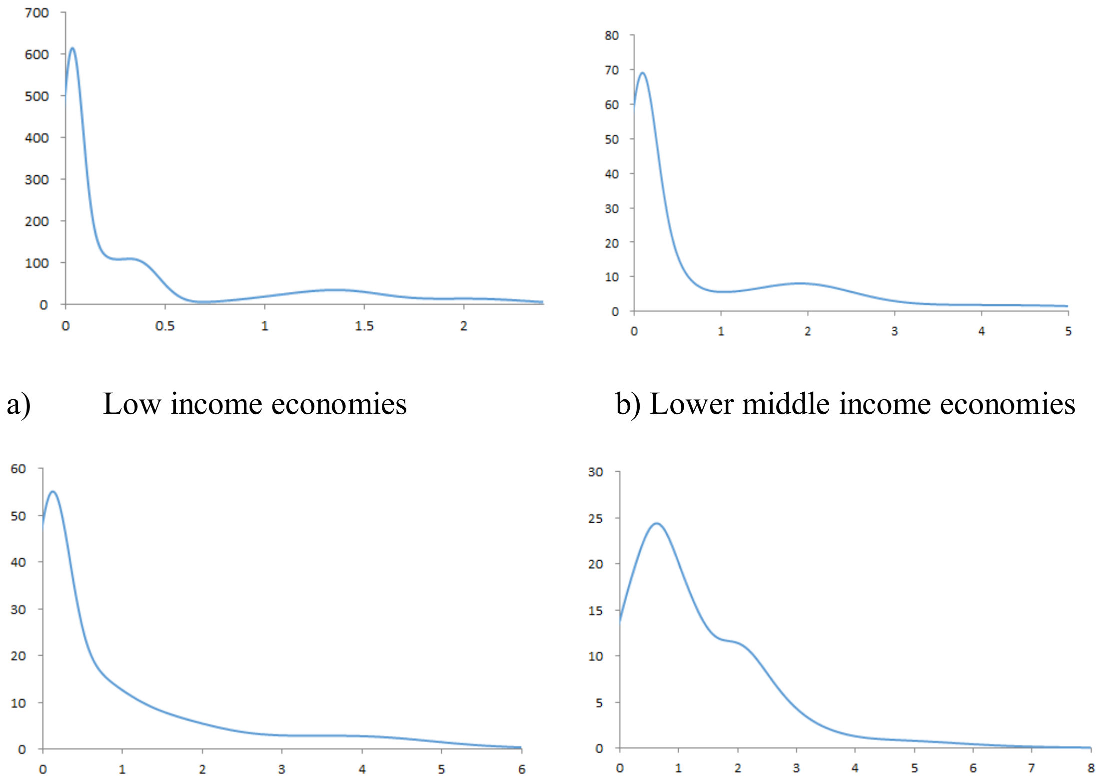




c) Upper middle income economies

d) High income economies

Fig. 10. Contour maps of transition probability kernels for coal consumption (all economies by different income groups)
Note: horizontal axis represents time t, vertical axis represents time t+1.
Source: authors' calculation.



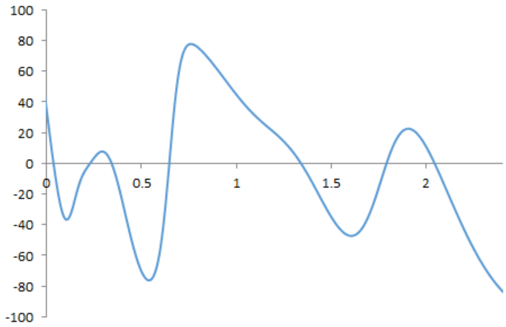
a) Low income economies

b) Lower middle income economies

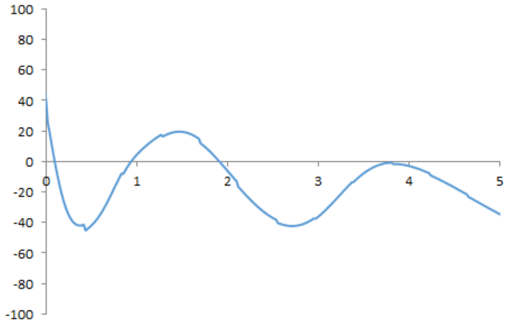
c) Upper middle income economies

d) High income economies

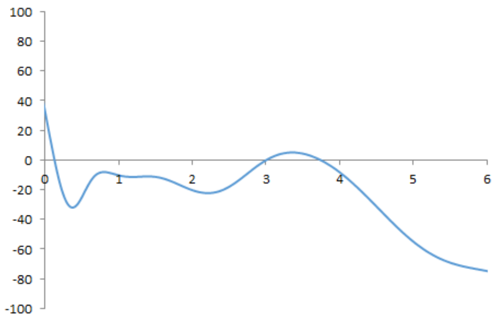
Fig. 11. Ergodic distributions of coal consumption (all economies by different income groups)
Note: horizontal axis represents relative consumption, vertical axis represents proportion.
Source: authors' calculation.



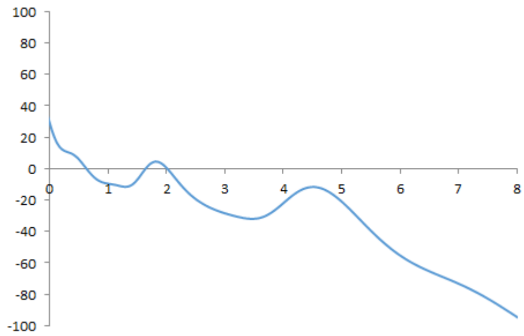
a) Low income economies



b) Lower middle income economies



c) Upper middle income economies



d) High income economies

Fig. 12. Mobility probability plots of coal consumption (all economies by different income groups)
Note: horizontal axis represents relative consumption, vertical axis represents MPP.

Source: authors' calculation.