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Cross-economy dynamics in energy productivity: Evidence from 47 economies over the period 2000-2015

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ADB Working Paper Series

**CROSS-ECONOMY DYNAMICS
IN ENERGY PRODUCTIVITY:
EVIDENCE FROM 47 ECONOMIES
OVER THE PERIOD 2000–2015**

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Abstract

This study investigates the long-run cross-economy dynamics in energy productivity across the world. We construct a data set comprising value-added and energy use data on 18 productive sectors in 47 economies over the period 2000–2015. First, we analyze the cross-economy distribution of energy productivity. Compared to 2000, this distribution shifted more towards the world average level in 2015. By using an index decomposition approach, we disentangle energy efficiency effect and economic structure effect as key determinants of the overall energy productivity improvement. Our results show that energy productivity progress is to a large extent driven by technological change but offset by economic structural change. Second, we explore the long-run distribution of energy productivity. Diverse patterns of energy productivity changes across these economies contradict the implicit assumption of standard convergence analysis. To address this issue, we adopt the Markov chain transition matrix. In a long-run steady state, around 64% of sample economies upgrade towards the upper end of the whole distribution, with their energy productivity performing better than the world average. Around 18% of sample economies remain at a level lower than the world average. The results suggest the persistent gap in energy efficiency across economies.

Keywords: energy productivity, decomposition, transition matrix, convergence

JEL Classification: Q01, Q56, O13

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1. INTRODUCTION

Energy is an essential factor of production. From an economic growth theory point of view, energy can directly affect total factor productivity, given the extended production function that incorporates capital, labor, and energy (Stern 2011). The extent of effectiveness to which energy resources are allocated and consumed can be measured by energy productivity – in other words, the inverse of energy intensity.¹ The improvement of energy productivity has the potential to increase economic cost-effectiveness while reducing environmental externality and is therefore a major macroeconomic concern for policymakers, the business community, and academic researchers. This study investigates the historical trends of energy productivity and their key determinant factors, and further explores the evolving distribution dynamics of energy productivity across major economies in the world.

A strand of empirical literature in economics seeks to examine the causal relationship between energy use and economic performance, e.g., GDP (Costantini and Martini 2010; Lee and Chang 2008; Ozturk 2010). However, various factors can decouple energy from economic growth, including directed technological change towards sustainability, structural changes in economic activity, changes in consumer preference, and substitution of renewable energy for fossil fuels. According to our estimates, between 2000 and 2015, the value added of the global economy increased by about 60% in productive activities, which translates to an average annual growth rate of 3.2%. As a comparison, the change in global energy use was smaller during the same period – a total growth of approximately 40.5% and an average annual growth of 2.3%. Such a disparity in growth between value added and energy use can be explained by changes in energy productivity, i.e., an increase of about 14% globally during the sample period.²

There has long been a global consensus on improving energy efficiency in the policy agenda: for example, UN Sustainable Development Goal (SDG) 7 titled “Affordable and clean energy.” Therefore, understanding cross-economy dynamics in energy productivity has important policy implications. The global tracking framework under the “Sustainable Energy for All” initiative has found that energy efficiency progress will probably remain at only two thirds of the rate that is required to achieve the 2030 target (World Bank and IEA 2017). If this cannot be changed, SDG 7 will be greatly challenged. A recent report by KAPSARC (2018) also provides an overview of the trends of industrial energy productivity in the People’s Republic of China (PRC) and Saudi Arabia, and shows the important role of industrial strategy in reducing energy intensity. This study seeks to document some crucial empirical patterns of the energy productivity dynamics.

The study will follow a two-step approach. First, we analyze energy productivity trends and drivers across 47 major economies over the period 2000–2015. Using the Logarithmic Mean Divisia Index–I (LMDI-I) index decomposition approach, we study stylized facts of the energy efficiency effect and economic structural effect – two major determinants of energy productivity. With regard to the cross-economy dynamics of energy productivity, we explore the issue of whether the difference in energy

¹ We will use energy productivity and energy intensity interchangeably in what follows from here.

² The calculations here sum up the value added (in constant 2000 US dollars) and energy use over all productive sectors (excluding the residential sector) and all economies. The data sets at our disposal are the Multi-Region Input-Output tables developed by the Asian Development Bank (ADB-MRIO, 47-economy version) and the IEA World Energy Statistics and Balances 2017. See Section 3.1 “Changing Distribution Dynamics in Energy Productivity” for a detailed discussion.

productivity between economies will narrow down. To do so, we employ well-established methods related to economic convergence in development economics. However, our analysis shows significant instability and diversity in growth patterns of energy productivity across economies. This means that the implicit assumption in the early standard convergence literature, in which the growth path of each economy is smooth, may not hold. In addition, we are particularly interested in the stable distribution of energy productivity in the long run, whereas the standard econometric convergence methodologies are not able to deal with it.

Thus, we use an alternative methodological framework, namely the Markov chain transition matrix, to investigate the long-run cross-economy distribution of energy productivity across the world. We find that the cross-economy gap in energy productivity is persistent, though most economies tend to upgrade from lower tails to upper tails in the evolving distribution dynamics by improving their energy productivity.

In this paper, we seek to document some crucial patterns regarding energy productivity and characterize the distribution of economies in the long run. We do not examine the mechanisms driving the patterns we identify, although this can be the focus of future research. The empirical findings in this paper could serve as a starting point. This paper is structured as follows. Section 2 provides a brief literature review. Section 3 applies the index decomposition analysis and documents the stylized facts regarding energy productivity across the world. Section 4 introduces the Markov chain transition matrix and discusses the findings. Section 5 concludes and discusses policy implications.

2. LITERATURE REVIEW

There is a rich body of literature on energy intensity or energy productivity. Most of these studies look into the drivers and trends of energy intensity. The economic specialization and technological competences of an economy may change during the development process. Thus, the influential drivers that affect the growth of energy productivity may change as well. Decomposition analysis, either index decomposition analysis or structural decomposition analysis, is able to distinguish between the effect due to changes in energy efficiency and other factors driving energy consumption (Ang 2005; Ang, Mu, and Zhou 2010; Ang, Xu, and Su 2015). Depending on the periods and/or countries involved, the literature finds mixed results on the importance of the energy intensity effect and economic structural effect. Some studies provide evidence of a greater role played by technological change in reducing energy consumption (Ma and Stern 2008; Voigt et al. 2014; Welsch and Ochsens 2005; Wing 2008). In contrast, structural change (for example, as measured by sectoral value-added shares) is identified as playing a greater role (Huntington 2010; Mulder and de Groot 2012). Some studies employ production theory to assess the effects due to technological change, changes in the capital-labor-energy ratio, output structure, and trade-facilitated technology spillovers in energy productivity changes (Wan, Baylis, and Mulder 2015; Wang 2013). By adopting the econometric approaches from development economics, the convergence analysis in energy economics focuses on energy-related indicators instead of income, and has generated a huge empirical literature (see, for example, Duro and Padilla (2011); Huang, Yu, and Ma (2017); Jakob, Haller, and Marschinski (2012); Liddle (2009, 2010); Miketa and Mulder (2005); Mulder and de Groot (2012)). The literature does not come to a conclusion regarding whether energy intensity converges across countries or sectors. Most previous studies support the convergence of energy intensity for the sample of developed countries but reject the convergence hypothesis if using a broader sample that includes developing countries (Le Pen and Sevi 2010).

One of the fundamental questions in development economics revolves around economic inequality across countries, namely whether the disparity in national income between countries is growing or declining as time progresses. A lot of literature has applied convergence analysis.³ The mainstream methodology in convergence literature in development economics and energy economics investigates the absolute level and growth rate of a set of variables, i.e., σ -convergence and β -convergence, as developed through a series of important works by Barro (1991), Barro and Sala-i-Martin (1991, 1992), and Sala-i-Martin (1996) on economic growth. From an economic theory point of view, the σ -convergence approach seeks to confirm the declining trend in the variation of the target variable's differentials across economies. The β -convergence approach looks at the negative correlation between the initial level of the target variable and its growth rate (Wan, Baylis, and Mulder 2015). However, the issue is whether the country would eventually "stay" in the steady state if it existed.

The standard approach that tests convergence is largely based on econometric estimations: simplify the entire dynamic process of the variable under research (for example, national income per capita or labor productivity) by using its average growth rate, then estimate the effect of the initial level of the target variable on its average growth rate while controlling for some static characteristic variables. A negative regression coefficient of the initial target variable would indicate a tendency of convergence. This is because it provides some evidence that the economy in which the target variable is lower initially tends to grow faster, assuming that the growth rate tends to decline when approaching the steady state. Such an empirical method assumes implicitly that each economy in the sample should have a smooth growth trajectory and is not affected by large external shocks except in the initial period (Quah 1993).

In addition, traditional econometric approaches will only capture the dynamics of those economies that are more influential in terms of economic size. These techniques cannot tell us anything about how the most energy-intensive economies (e.g., bottom 10%) are catching up with the most energy-efficient ones (e.g., top 10%). The empirical results based on the distribution approach are more informative as they show the long-run tendency for how economies in the sample are distributed.

3. ENERGY PRODUCTIVITY DEVELOPMENT BETWEEN 2000 AND 2015

3.1 Changing Distribution Dynamics in Energy Productivity

We use the Asian Development Bank Multi-Region Input-Output tables (ADB-MRIO)⁴ to derive the data on sectoral value added for each economy (in constant 2000 US dollars). This data set has been used in the ADB's flagship publication series of Key Indicators for Asia and the Pacific (Asian Development Bank 2017, 2018). We define 18 sectors consistently with the energy use data provided by the IEA World Energy Statistics and Balances 2017 (see the sector classifications in Appendix A). Our data set covers 47 major economies across the world for the years 2000, 2005, 2008, 2011, and 2015. The energy productivity is defined as the value added per unit of energy use (ktoe) in the

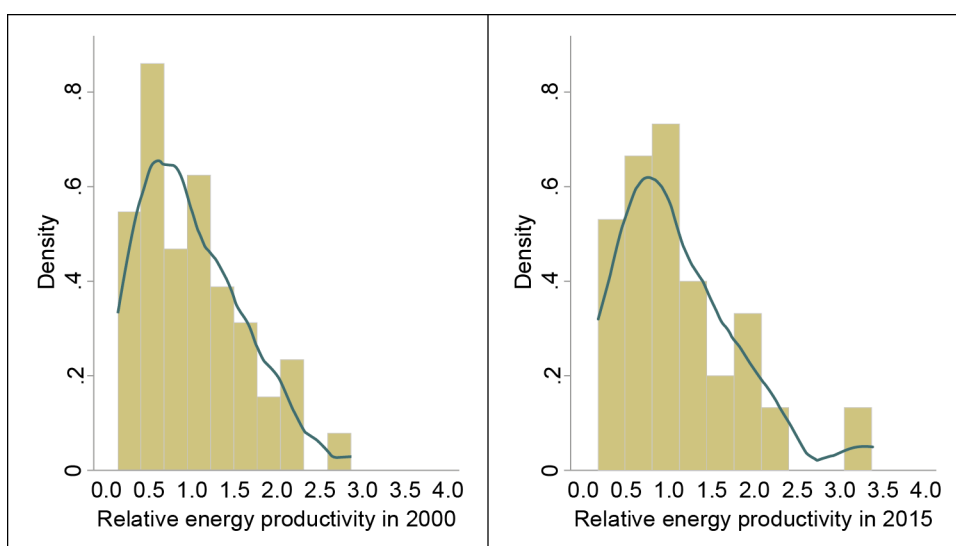
³ Recent economics literature in this area has focused less on growth rate convergence and is directed more towards the mechanisms that generate the distribution and evolution of the variable of interest (Maasoumi, Racine, and Stengos 2007).

⁴ In this paper, we use the ADB-MRIO tables that cover 47 economies. The new edition of the ADB-MRIO will be extended to a more diversified set of 62 economies across the world. However, the 62-economy version only contains the input-output tables in current prices.

productive activities of an economy. This refers to those productive sectors that generate value added (through producing physical goods or providing services). This study excludes the residential sector but includes the inland, water, and air transport subsectors.

The distributions of energy productivity in 47 economies for the years 2000 and 2015 are shown in Figure 1. Note that the value “1” on the horizontal axis reflects the world level of relative energy productivity. The findings are straightforward. In 2000, the majority of economies are concentrated in the level of energy productivity lower than the world average. Over the entire sample period, the distribution changes. The density curve slightly shifts to the right side in 2015 as compared to the year 2000, as more economies are concentrated on the world average level (i.e., the column containing the value 1).

Figure 1: Distribution of Relative Energy Productivity in 2000 and 2015



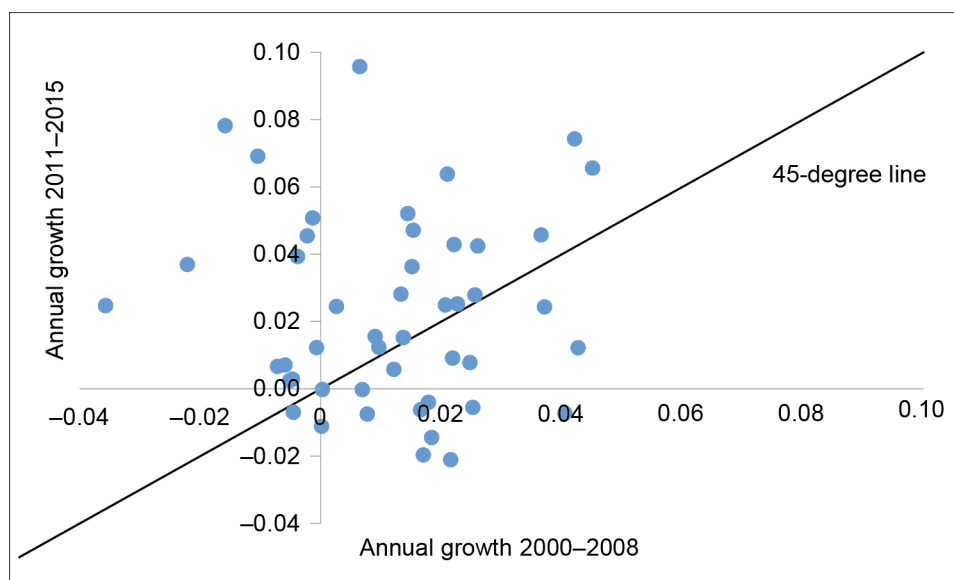
Note that (1) the energy productivity is relative to the world average; (2) the curves in the figure are kernel density estimates; (3) see Appendix B for detailed energy productivities by economy in both years.

Source: Own elaboration.

The standard approach of convergence analysis, as described in Section 2, simplifies the entire dynamics process by using a summary statistic: for example, the average growth rate of energy productivity. Further, the standard approach requires estimation of the effects of some factors (e.g., initial level of energy productivity) on the summary statistic. By doing so, however, the uncertainty or external economic shocks that take place in the process (except those in the initial period) will not be captured in the estimations. The results derived using the standard approach will not be robust if the growth patterns in some periods significantly differ from those in the initial period.

However, the growth rates of energy productivity of 47 economies over the period 2000–2015 do not show smooth time trends. The stylized facts derived from our data sample cannot satisfy this implicit assumption in the standard σ -convergence and β -convergence tests. Figure 2 graphs each economy's annual average energy productivity growth rate over 2000–2008 against that over 2011–2015. In the case of the smooth time trends, the data points of the average growth rates over these two periods will distribute around the 45-degree line and have the same changing directions. However, Figure 2 shows very different growth patterns across 47 economies: The vast majority of data points significantly scatter away from the 45-degree line. Some economies show completely opposite directions for energy productivity changes between the two periods. This indicates a great heterogeneity in the growth paths of energy productivity among these 47 economies. Imposing a smooth trend, as is done in traditional strategies, is not plausible.

Figure 2: Fluctuation of Average Energy Productivity Growth Rates among 47 Economies over the Periods 2000–2008 and 2011–2015



Source: Own elaboration.

This graph offers several crucial findings. First, the instability across economies and years is pervasive, in terms of their energy productivity growth trajectories. This implies that the stability assumption required by the standard approach might not be satisfied, and thus the results based on the econometric estimations are probably not robust and are sensitive to the selection of the initial period. Second, the fluctuations in energy productivity growth rates suggest that important disturbances – energy efficiency or economic structural change – are ongoing. Among many external shocks, the global financial crisis over the period 2007–2010 perturbed the different economies. In Section 4, we will address this issue by using an alternative distribution approach to describe the dynamics of energy productivity across economies in the long run.

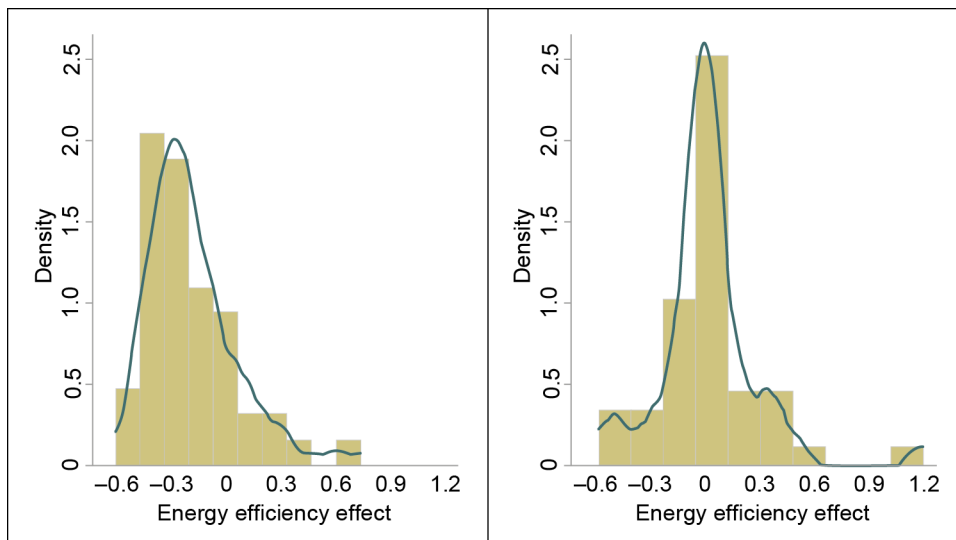
3.2 Determinants of Energy Productivity

The analysis in the above section does not show a smooth and gradual improvement in energy productivity on a global scale. Many underlying dynamics still need to be revealed, as the expected potential of progress in energy productivity predominantly results from two determinants – technological change and economic structure change. One would expect different patterns in developed and developing economies. Common sense tells us that economies at the industrialization stage may see their productive activities shift towards energy-intensive industries. Likewise, the economic structure of developed economies may expect to improve energy productivity when their economies become more services and industrial outsourcing oriented. Meanwhile, developing economies today have access to a set of efficient technologies that were not available to rich economies in the past. Increasing trade and market integration can further facilitate technology learning across economies. One may expect energy efficiency progress due to technological leapfrogging in the developing world to converge with the developed world.

These ideas frequently feature in the energy debate. Will the historical development of energy productivity support them? We adopt the well-established LMDI-I multiplicative decomposition to examine the influential factors that affect the total final energy use of productive activities in 47 economies over the period 2000–2015 (Ang 2005, 2015; Ang and Liu 2001). For this, we disentangle three factors: the effect due to changes in economic activities (as measured by changes in total value added), the effect due to changing economic structure (as measured by the changes in sectoral shares of value added in the economy), and the effect due to changes in energy efficiency (as measured by the changes in energy intensity). Figure 3 depicts the distribution of the energy efficiency effect and economic structural effect over the study period, and their combined effects on energy productivity. Across 47 economies, both the energy efficiency effect and the economic structure effect are mainly distributed in certain groups, which means the differences in these two effects between economies are small. However, the energy efficiency effect is heavily distributed on the left-hand side of the value “0,” which implies that the technological change does indeed contribute to promoting energy productivity in the vast majority of economies by lowering energy intensity. The economic structure effect, however, is more concentrated on the right-hand side of the value “0,” indicating that economic structure change tends to offset energy productivity progress, with productive activities shifting towards more energy-intensive industries or services in a wide range of economies. The magnitude of the economy-specific energy efficiency effect looks more homogeneous than that of the economic structure effect in the sample. This shows that the progress rate of energy efficiency, largely owing to technological change, does not significantly vary between developed and developing economies.

The energy efficiency effect and economic structure effect jointly lead to the improvement of energy productivity across 47 economies shown in Figure 1, but they have opposite effects on energy productivity progress. As shown in Figure 4, the combined effect of changes in energy efficiency and economic structure is mostly smaller than 0, which means energy intensity is lowered. Therefore, the distribution of overall energy productivity shifts towards the right side between 2000 and 2015.

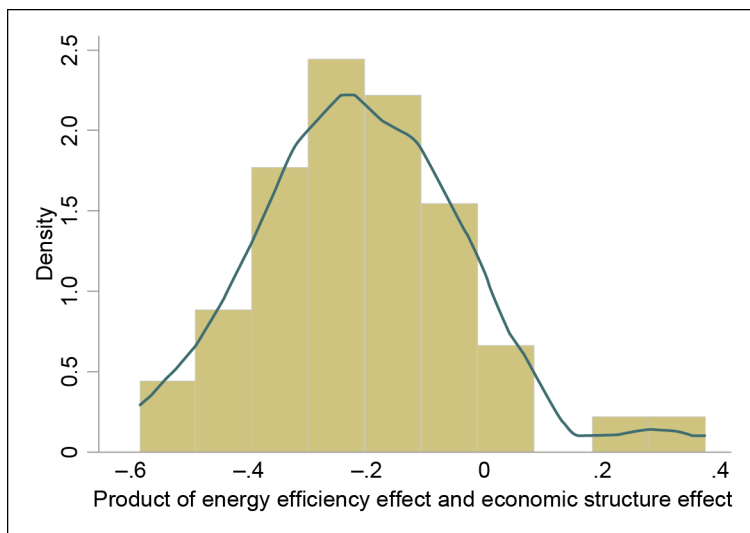
Figure 3: Distribution of Energy Efficiency Effect and Economic Structure Effect from Decomposition Analysis of 47 Economies Between 2000 and 2015



Note that the curves in the figures are kernel density estimates. On the horizontal axis, if the value is smaller (larger) than 0, it means the effect lowers (increases) energy intensity; a value of 0 indicates a neutral effect.

Source: Own elaboration.

Figure 4: Distribution of the Product of Energy Efficiency Effect and Economic Structure Effect



Note that the curve in the figure is kernel density estimates. On the horizontal axis, if the value is smaller (larger) than 0, it means the effect lowers (increases) energy intensity; a value of 0 indicates a neutral effect.

Source: Own elaboration.

Appendix B provides an overview on the economy-specific results of our decomposition analysis. The economy-specific energy efficiency effects mostly contribute to improving energy productivity, with a few exceptions, including Viet Nam, Hungary, Brazil, Luxembourg, Sweden, Austria, and Malta. However, for the economic structure change effect, the outcome looks much more heterogeneous. Out of 47 economies, 27, including major OECD and emerging economies, have seen a positive sign from the economic structural change effect, which implies that changes in productive activities worsened

energy productivity over the study period. Final energy consumptions in the PRC, Japan, the United States, and India increased by 6%, 12%, 16%, and 33%, respectively, due to economic structure change. Several economies, including Denmark, Australia, Spain, the Netherlands, Turkey, and Mexico, have shown a small or almost null effect from economic structure change. In the United Kingdom, Greece, Belgium, Hungary, and the Russian Federation, economic structure change has led to increasing final energy consumption by 3%–9%. It is important to note that our data set considers inland, water, and air transport sectors to be part of the productive activities alongside manufacturing and service sectors.⁵ Recent empirical studies have shown that large rebound effects do exist (Saunders 2015; Wei and Liu 2017). This means the growth of energy consumption is likely to be much higher than what preliminary estimates have claimed. This rebound effect, partially captured by structure change, might be more pronounced in the transport sector due to the reduced occupancy rate and a lack of energy efficiency standards for freight transport.

The following section will investigate the long-run distribution of energy productivity across the world, while addressing the methodological issue identified in Section 3.1.

4. DISTRIBUTION DYNAMICS OF ENERGY PRODUCTIVITY

Section 3 shows the limits of standard convergence analysis that assumes a stable growth path of energy productivity. To address this issue, we will adopt an alternative framework, known as the “Markov chain transition matrix,” to investigate the international dynamics of energy productivity across 47 economies over the period 2000–2015. The Markov chain transition matrix is an empirical approach used in the literature on per capita GDP convergence and productivity distribution.

This session will shed light on how the economies catch up in terms of energy productivity from the perspective of cross-distribution dynamics. To be more precise, we study how the entire distribution of energy productivity evolves across 47 major economies at a steady state over the long run. Our study will reflect the mobility of energy productivity that occurs not simply within a representative economy but across the world.

4.1 Distribution Approach

We use a distribution approach with the transition matrix to explore the mobility of energy productivity. In contrast to standard econometric approaches, it is not necessary to introduce the assumption regarding the stability of the growth path for the distribution approach. Specifically, the distribution of the target variable that maps its dynamics can be taken into account over the entire sample period. More research on convergence in development economics has shifted towards the laws that shape the distribution (Maasoumi, Racine, and Stengos 2007), but the transition matrix can provide simple but intuitive characterizations of the future distribution tendency, which is the goal of this section. This method has been a standard analytical tool applied to the areas of firm productivity (Baily, Bartelsman, and Haltiwanger 1996; Baily, Hulten, and Campbell 1992; Bartelsman and Dhrymes 1998) and income distribution (Quah 1993, 1996, 1997). This paper follows the approach proposed by Quah and applies this approach to the study of energy productivity.

⁵ The decomposition analysis considering solely industry and services will limit the ability to draw insights into transport-specific value added, which is a major part of the world economy output.

Based on Quah's method, each economy's energy productivity is compared to the average level of the world. Thus, the energy productivity disparity between economies is expressed in terms of the relative ranking in the world, rather than the exact magnitude. Let F_t denote such a distribution of economies' relative energy productivity in year t .

The relationship between F_t and its future distribution in year $t + 1$, F_{t+1} , can be expressed as follows:

$$F_{t+1} = M * F_t$$

where M is a Markov transition matrix of a 5*5 dimension.

The intuition here is that the current distribution is determined by the distribution in the previous year (i.e., Markov process). As we consider economies' rankings, all economies are allocated into five groups,⁶ from the least to the most energy efficient. Hence, the matrix M contains the probability of each economy moving from one group to another between two continuous years.

The distribution in the year $t + s$, F_{t+s} , can be described as follows:

$$F_{t+s} = M^s F_t$$

If the parameter s is sufficiently large, according to the property of the Markov process, the matrix M will converge into a stable one, namely the ergodic distribution. This also means the long-run distribution F_{t+s} will not change anymore. Note that the ergodic distribution in the analysis should only be interpreted as a characterization of the long-run tendency, rather than a precise forecast. The energy productivity disparity between economies declines if the majority of economies in the long run are distributed in the group in which the relative level of the world (i.e., 1) is located, otherwise the gap in relative energy productivity across economies is persistent.

4.2 Results and Discussions

All 47 major economies are classified into five groups related to their relative energy productivities. The grouping bonds are based on the quantiles of their initial relative energy productivities, i.e., the relative energy productivity in 2000, as shown in Table 1. By doing so, each group has 9 or 10 economies. The economies in Group 1 are the least energy efficient in the year 2000, with each of them having a relative energy productivity below the 20% quantile of the sample, i.e., 0.46. Group 3 is the group in which the world average, 1, is assigned. Group 5 is the highest relative energy productivity group (top 20% of the sample).

⁶ Quah's method requires each group to be (almost) the same size.

Table 1: Group Bounds Based on Relative Energy Productivity in 2000, Relative to World Level

Group 1: [0, 0.46)	0 – 20% quantile	9 economies
Group 2: [0.46, 0.70)	20% – 40% quantile	10 economies
Group 3: [0.70, 1.10)	40% – 60% quantile	9 economies
Group 4: [1.10, 1.58)	60% – 80% quantile	10 economies
Group 5: ≥ 1.58	80% – 100% quantile	9 economies

Note that: (1) the world level is 1 and located in Group 3; (2) the year 2000 is the initial year; (3) the group bounds are fixed over the entire period, so the groups are almost equal sized only in the initial year; (4) the economies in each group are listed in Appendix B.

Source: Own calculations.

Table 2 below presents the ergodic distribution in the long run for all economies in our sample. The groups in the row and column headers represent the places in which economies are located in year t and $t + 1$, respectively. The value in such a 5*5 matrix indicates the probability of economies shifting from the row group to the column group after one period, given the data over the period 2000–2015. Then, the last column gives the number of economies that have been located in the row group over the period 2000–2015. If the transition takes place many times, each row of the 5*5 transition matrix will converge to the same limit, which is the ergodic distribution presented in the last row.

It is not surprising that there is a persistence in the energy productivity mobility in the short run. The values on the diagonal of the transition matrix range between 0.7353 and 0.8462, suggesting that an economy from a certain group is very likely to stay in the same group after one period (with a probability of at least 0.7353). For example, the economy in Group 1 has a probability of 0.8333 of staying in the same group in the next period, and a probability of 0.1667 of moving to Group 2. A similar finding can also be found in Group 5. The economies initially located in Groups 2–4 might move up/down to neighboring groups, but the probability of moving up is higher than that of moving down. This implies that for economies in Groups 2–4, there is a tendency to improve relative energy productivity. The long-run distribution of economies is shown in the ergodic distribution.

Table 2: One-Period Transition Matrix of Relative Energy Productivity, Relative to World Level, 2000–2015

	Group 1	Group 2	Group 3	Group 4	Group 5	Total Number
Group 1	0.8333	0.1667	0	0	0	30
Group 2	0.0513	0.7949	0.1538	0	0	39
Group 3	0	0.1176	0.7353	0.1471	0	34
Group 4	0	0	0.0870	0.7391	0.1739	46
Group 5	0	0	0	0.1538	0.8462	39
Ergodic	0.0420	0.1365	0.1785	0.3018	0.3412	

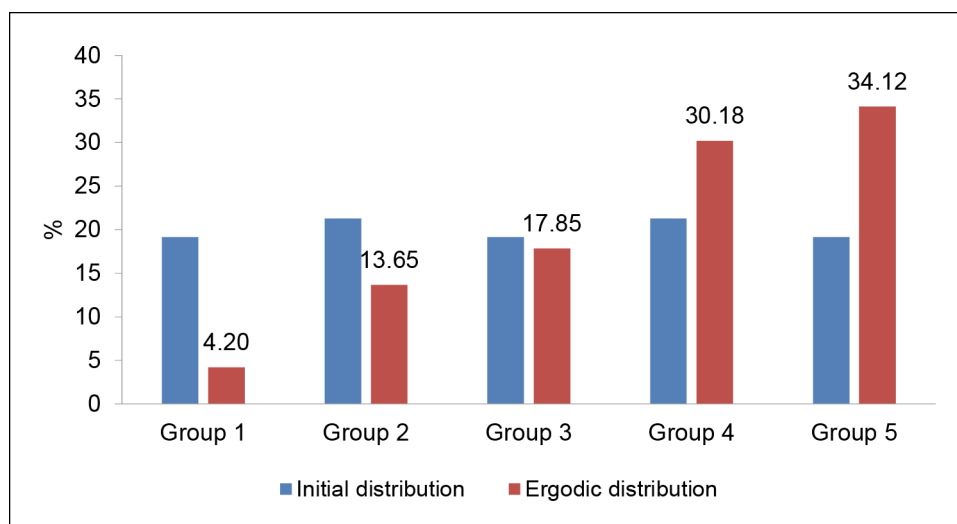
Note that: (1) Group 1 contains the economies that are least energy efficient (below the bottom 20% quantile); (2) Group 5 is the most energy efficient (top 20% of the sample); (3) Group 3 contains the relative energy productivity of the world, i.e., 1.

Source: Own calculations.

The figure below compares the initial distribution with ergodic distribution of economies in each group. In the initial year, each group contains about 20% of all 47 economies. However, the distribution changes hugely in the long run. More economies tend to be distributed in the groups with higher relative energy productivity. For example, most economies are concentrated in very high relative energy productivity groups, i.e., Group 4 and Group 5, in which shares grow to 30.18% and 34.12%, respectively. In the lower-than-average groups, the changes in shares show similar tendencies. In Group 1, the group with the lowest relative energy productivity, the share of economies drops dramatically from about 20% to 4.2%, whereas the share decreases on a smaller scale in Group 2 (from 20% initially to 13.65% in the ergodic distribution). The share in Group 3, in which the world average is assigned, also declines slightly to 17.85% in the long run.

The comparison clearly shows that most economies tend to improve their energy productivities enormously, but there is no tendency for the energy productivity disparity to decline over time. In total, 17.85% of economies in our sample would be distributed in the groups below the world average level. Our data set covers mostly advanced economies and large emerging economies. The majority of emerging economies and the least developed economies are not considered in the current analysis, as the data are not detailed enough.

Figure 5: Comparison Between Initial Distribution and Ergodic Distribution



Note that (1) group bounds are summarized in Table 1. (2) Grouping based on relative energy productivity in 2000, relative to world average.

Source: Own elaboration.

5. CONCLUSIONS AND POLICY IMPLICATIONS

This paper focuses on the distribution of historical energy productivity across major economies over the period 2000–2015. The majority of the distribution in 2000 shifted towards higher energy productivity, with a trend moving toward the world average level in 2015. By using an LMDI-I decomposition approach, we further identified that the combined effect of energy efficiency change and economic structure change have affected the historical trends of energy productivity in opposite directions. Energy productivity progress has been driven to a large extent by technological change but offset by economic structure change.

We use the Markov chain transition matrix to investigate future distribution dynamics of energy productivity across our sample economies. Our results show that around 64% of sample economies will upgrade towards the upper end of the whole distribution in the long run, with their energy productivity performing better than the world average, while around 18% of sample economies will stay at a level lower than the world average. However, in a long-run steady state, the gap in energy productivity across economies will be persistent despite these improvement trends of energy productivity. These results have profound policy implications. Speeding up policies and activities on energy efficiency in different jurisdictions will not automatically lead to narrowing the gap in global energy productivity. We suggest that a strong international cooperation mechanism is required to share knowledge and best practice from around the world. More coordinated actions, such as technology transfer and harmonization of energy efficiency standards, have to be in place to reduce the disparity in energy productivity across economies. Also, policymakers should strengthen the existing successful policies and revise those that are out of date.

It is important to note that the Markov chain transition matrix approach is based on extrapolating historical trends of energy productivity without considering randomness and potential interventions. It is not plausible to expect that the future will strictly follow the trends of the past. For example, radical innovations may occur in the future (with uncertainty) and bring “creative destruction” that greatly improves energy productivity and thus reshapes the economic structure. Emerging policy interventions that promote directed technological change with environmental targets would play a crucial role in changing the energy productivity.⁷ Likewise, changes in consumer preferences and behaviors can play a crucial role in shaping future economic structure.⁸ The future distribution dynamics in energy productivity presented in this study can be considered a base case scenario if no such external disturbances occur. Thus, this study will provide a meaningful benchmark to compare with any forecasting studies. With better access to sector-specific data, future research may better assess the impact of economic structural change on the shape of cross-economy distribution in energy productivity.

⁷ See Acemoglu (2002) and Acemoglu et al. (2012) for a detailed discussion.

⁸ Allcott and Mullainathan (2010) discuss the implications for energy policy in terms of consumer behaviors.

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APPENDIX A: ECONOMIES SECTOR CLASSIFICATION

Table A1: Economies in the ADB-MRIO

ISO Code	Economy	ISO code	Economy
AUS	Australia	LTU	Lithuania
AUT	Austria	LUX	Luxembourg
BAN	Bangladesh	MAL	Malaysia
BEL	Belgium	MLT	Malta
BRA	Brazil	MEX	Mexico
BGR	Bulgaria	MON	Mongolia
CAN	Canada	NLD	Netherlands
TAP	Taipei,China	PRC	People's Republic of China
CYP	Cyprus	PHI	Philippines
CZE	Czech Republic	POL	Poland
DNK	Denmark	PRT	Portugal
EST	Estonia	ROM	Romania
FIN	Finland	RUS	Russian Federation
FRA	France	SVK	Slovak Republic
DEU	Germany	SVN	Slovenia
GRC	Greece	ESP	Spain
HUN	Hungary	SRI	Sri Lanka
IND	India	SWE	Sweden
IDN	Indonesia	THA	Thailand
IRL	Ireland	TUR	Turkey
ITA	Italy	GBR	United Kingdom
JPN	Japan	USA	United States
KOR	Republic of Korea	VIE	Viet Nam
LVA	Latvia		

Source: Own elaboration based on the ADB-MRIO (47-economy version).

Table A2: Sector Classification

Sector Classification in This Paper	Sector Classification in IEA World Energy Balances	Sector Classification in ADB-MRIO
Sector 1	Agriculture/forestry Fishing	Agriculture, hunting, forestry, and fishing
Sector 2	Mining and quarrying	Mining and quarrying
Sector 3	Food and tobacco	Food, beverages, and tobacco
Sector 4	Textiles and leather	Textiles and leather
Sector 5	Wood and wood products	Wood and products of wood and cork
Sector 6	Paper pulp and printing	Pulp, paper, printing, and publishing
Sector 7	Chemical and petrochemical	Chemicals and chemical products
Sector 8	Nonspecified industry	Nonspecified industry (rubber and plastics, manufacturing, nec; recycling)
Sector 9	Nonmetallic minerals	Nonmetallic minerals
Sector 10	Nonferrous metals Iron and steel	Basic metals and fabricated metal (nonferrous metals and iron and steel)
Sector 11	Machinery	Machinery (machinery, nec, electrical and optical equipment)
Sector 12	Transport equipment	Transport equipment
Sector 13	Construction	Construction
Sector 14	Road Rail Pipeline transport	Inland transport (road, rail, and pipeline transport)
Sector 15	World marine bunkers Domestic navigation	Water transport (world marine bunkers and domestic navigation)
Sector 16	World aviation bunkers Domestic aviation	Air transport (world aviation bunkers and domestic aviation)
Sector 17	Nonspecified transport	Other supporting and auxiliary transport activities; activities of travel agencies
Sector 18	Comm. and public services	Comm. and public services
Sector 19	Residential	Residential

NEC = not elsewhere classified.

Note that: (1) the sectors used in this paper may include multiple sectors in the IEA World Energy Statistics and Balances or ADB-MRIO; and (2) Sector 19, the residential sector, is not included in the analyses.

Source: Own elaboration based on IEA World Energy Balances and ADB-MRIO (47-economy version).

APPENDIX B

Figure B1: Comparison Between Energy Productivity in 2000 and 2015

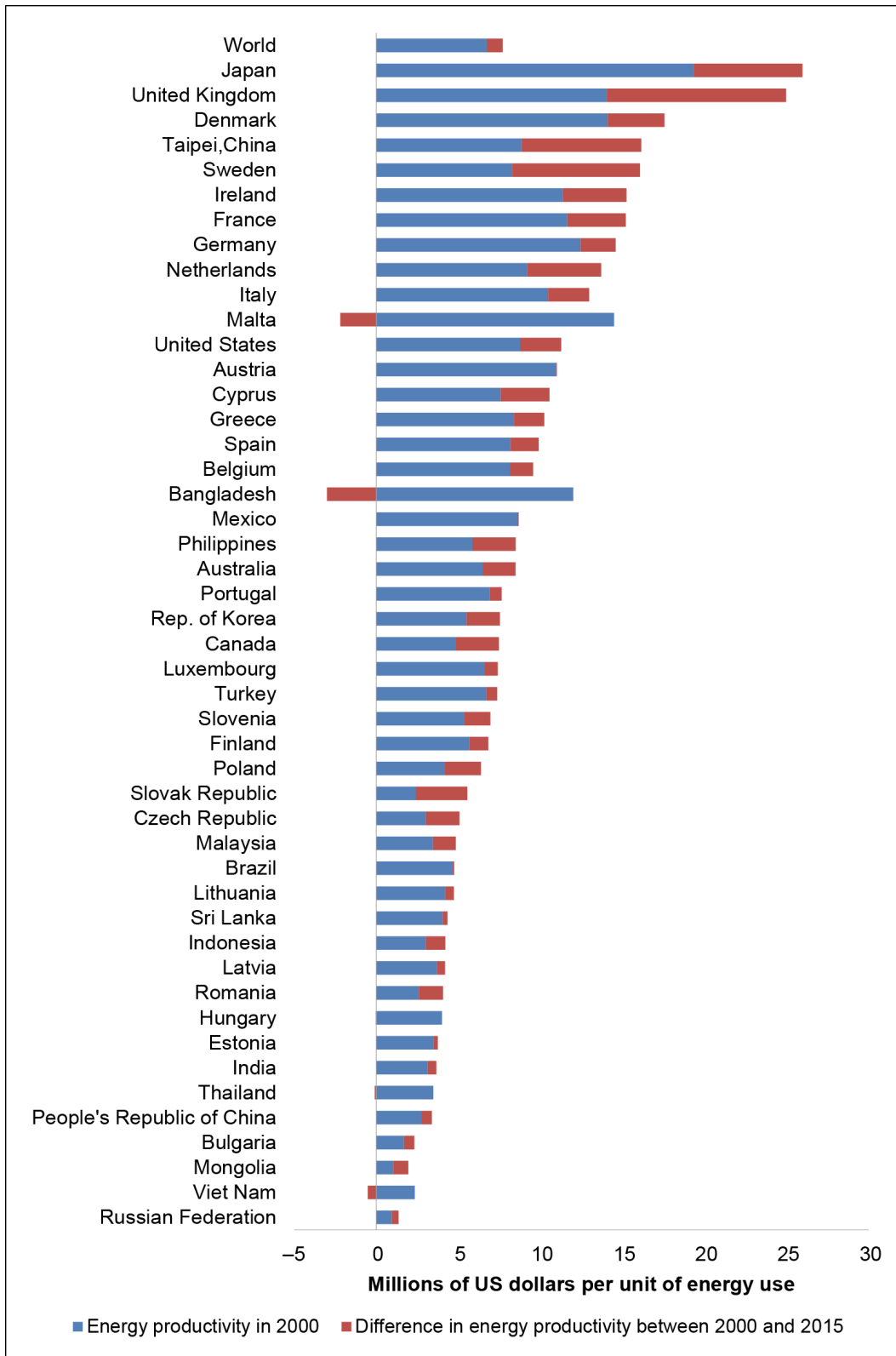
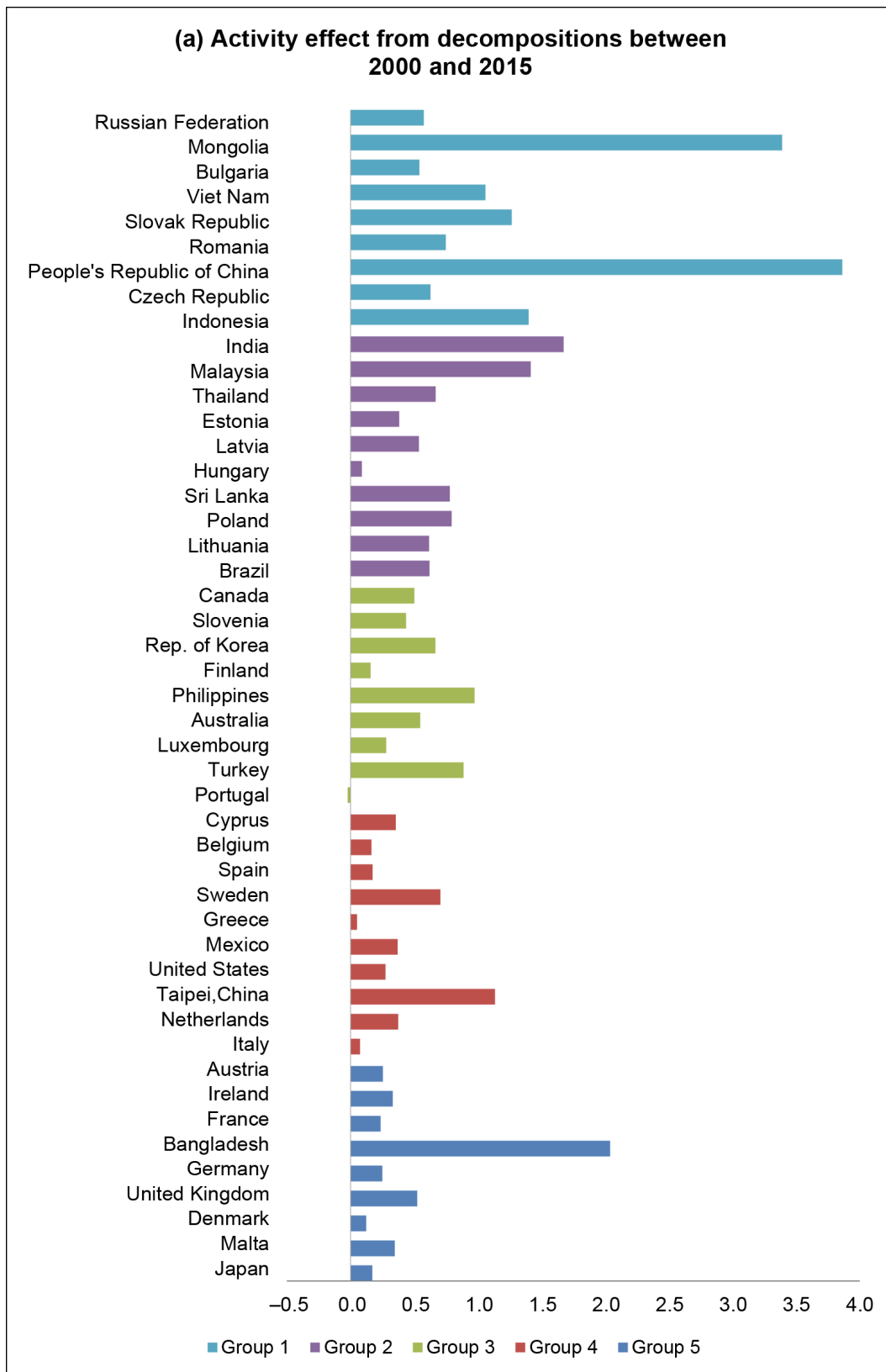
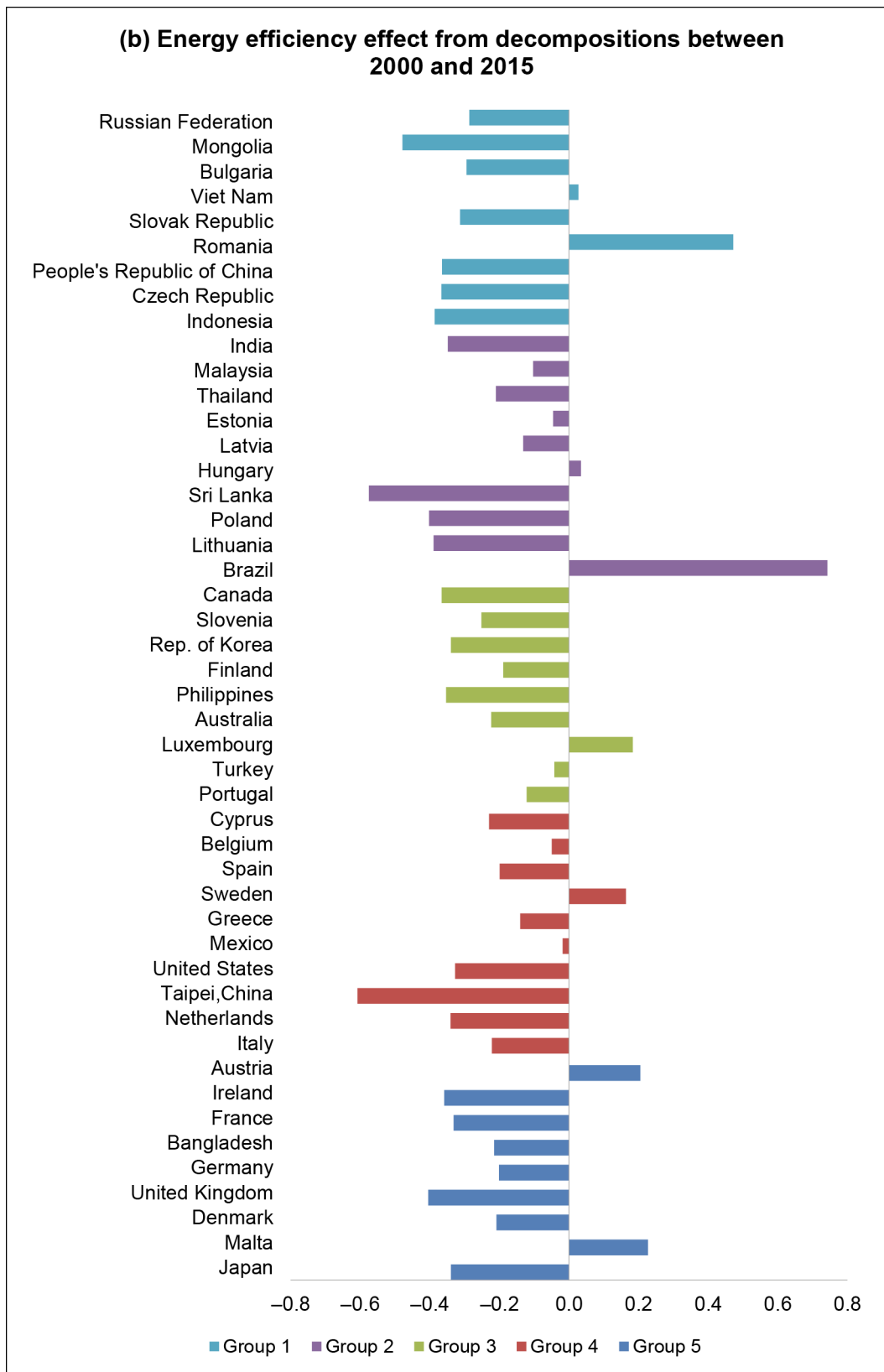


Figure B2: Decomposition Results Between 2000 and 2015



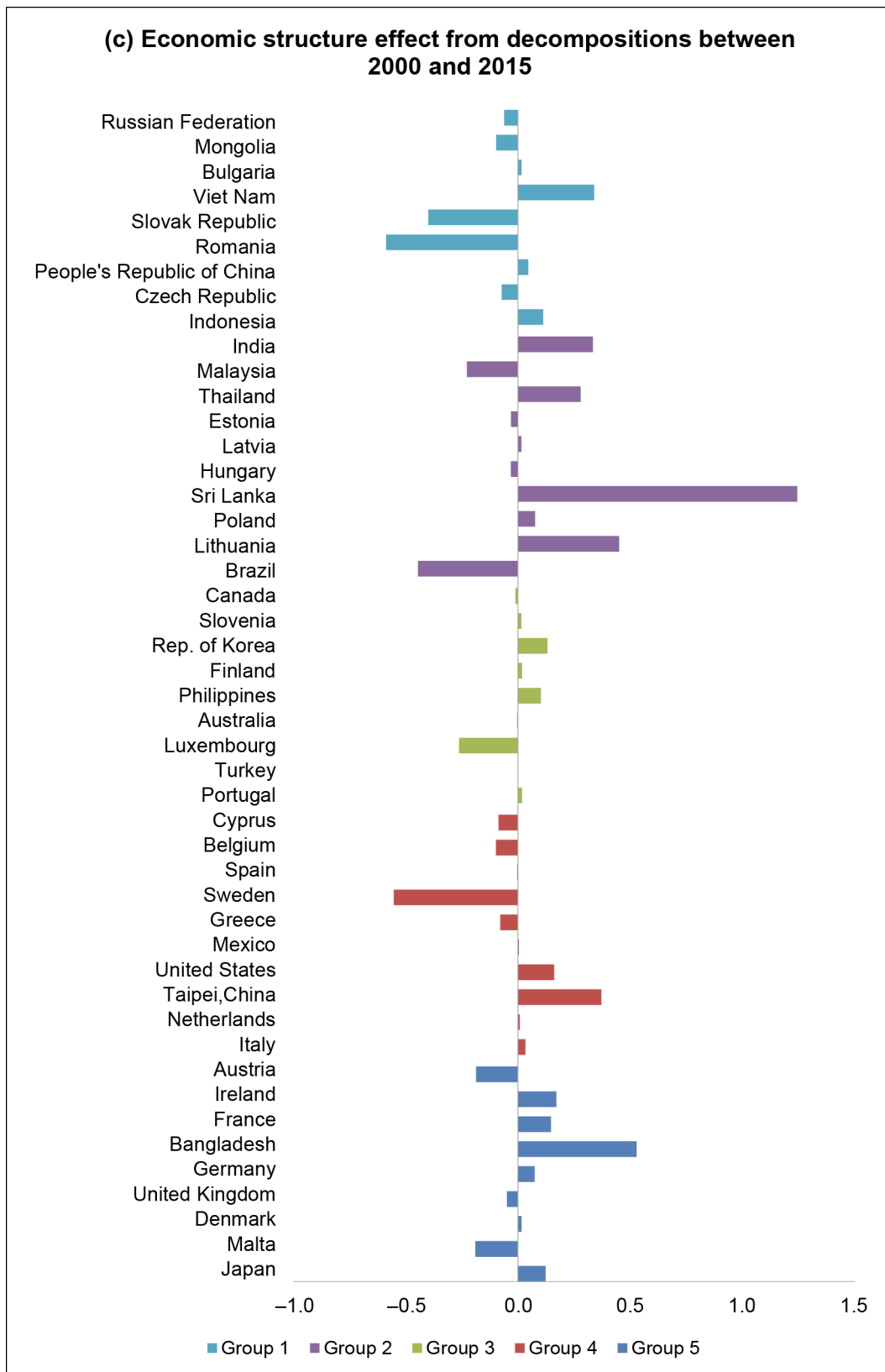
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Figure B2 continued



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Figure B2 continued



Note that: (1) the grouping is based on the energy productivity in 2000, the initial year; (2) the values on the Y axis in each panel represent the ratio of energy use between 2015 and 2000.

Source: Own elaboration.