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The Impact of Income Inequality on Carbon Emissions in Asian Countries: Non-Parametric Panel Data Analysis

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Abstract

Widening income inequality and environmental degradation are two of the most important problems that threat the sustainable development. For that, this study aims to examine the effect of income distribution on CO_2 emissions in seven Asian countries over the period 1971-2014 using a non-parametric panel estimation method and time-varying coefficients. Specifically, we apply the local linear dummy variable estimator (LLDVE) approach that allows evaluating the coefficients which vary over time for the panel data models. The results reveal that there is a strong non-linear correlation between income inequality and per capita CO_2 emissions. The non parametric model suggest that there is a negative relationship between income inequality and environment degradation over the whole study period expect for the period 1988-1997 which was positive. Our findings broadly support the existence of the "equity-pollution dilemma", whereby income redistribution induces environmental pollution. This dilemma has potential implications for policies designed to promote redistribution in the selected Asian countries.

Keywords: CO_2 emission, Income inequality, Non-parametric panel data, Asian countries.

JEL classification: C14, C33, O1, O4, Q3.

1. Introduction

The concerns about sustainable development have increased since the environmental quality is increasingly affected due to economic activities. Global warming and climate change have been the most important environmental problems in our ages. The high carbon dioxide emission (CO_2) is the major contributor to the greenhouse effect. Since the industrial revolution, the majority of CO_2 emission has recorded in the industrialized countries. Due to the rapid economic growth, the shares of developing country emissions exceeded those of industrialized economies recently (IEA, 2015).

From the beginning of industrialization, economic growth has been accompanied with high energy consumption and high carbon dioxide emissions in many parts of the world. Therefore, the nexus between CO_2 emission, energy consumption and economic growth has been the subject of much academic research. This nexus is closely related to verify the validity of the environmental Kuznets curve (EKC) hypothesis, which assumes an inverted U-shaped link between economic growth and environmental pollution. From this perspective, the environmental pollution level increases with per capita income during the early stages of economic growth, and then declines after reaching a threshold of a certain per capita income due to high demand and affordability for better environmental quality (Grossman and Krueger, 1995).

However, the current period is characterized not only by the growing environmental crises, but also by social crises caused by the unequal income distribution. Income inequality means that the income created in a country for a period, cannot be equitably shared between citizens, regions, or social classes. In both developed and developing countries, the inequitable income distribution contributes to economic and social problems (Piketty, 2003; Piketty and Saez, 2003; Stiglitz, 2012). A rise in income inequality can depress the aggregate demand and contributes to economic stagnation (Fitoussi and Saraceno, 2010). Besides, the unequal income distribution increases criminality, health inequalities and high school dropout rate (Feldstein, 1998; Wolde-Rufael and Idowu, 2017).

Widening income inequality and growing environmental crises pushed the researchers to investigate the relationship between them. In the literature, there are various

approaches through which income distribution can affect the environmental quality. The high level of income inequality can positively or negatively affect CO_2 emissions.

The first approach is based on power weighted social decision rule introduced by Boyce (1994) to investigate the effect of income distribution on environmental degradation. He suggests that the environment quality depends on income and the distribution power between different social classes. In society with a high level of income inequality, the rich recklessly use the natural resources. Likewise, in favor of their interests, the rich can also often skew national decision-making which can be more aligned with harmful policies to the environment. Therefore, environmental decisions become dominated by the rich and that leads to environment pollution. Magnani (2000) argued that the low level of income inequality can boost the voice of the powerless and allow them to be more productive within the political process. Moreover, egalitarian income distribution raises the demand for better environment by creating an ecological awareness. Therefore, income inequality increases the level of pollution than within a more egalitarian society.

The second approach that describes the relationship between income distribution and environment degradation is based on the marginal propensity to emit (MPE) which suggests that the environmental degradation varies with the equitable distribution of income, and the economic behavior of households. Some studies (Ravallion et al., 2000; Heerink et al., 2001; Berthe and Elie, 2015) suggest that the high level of income inequality can ameliorate the environmental quality through the marginal propensity to emit. Grunewald et al. (2017) and Jorgenson et al. (2017) noted that MPE varies according to income level, an increase in income decreases MPE. Likewise, Jorgenson et al. (2017) pointed out that the MPE has been also affected by marginal propensity to consume (MPC). If high-income households have a lower MPC, redistribution of income from poor to rich will improve the environmental quality as suggests the standard Keynesian model.

The third approach suggests that the increase of income inequality may affect negatively the environmental quality by raising the consumption competition which contributes to a rise in energy consumption and CO_2 emissions (Chao and Schor, 1998). The rise of consumption is due to the Veblen effect which suggests that products are used not for their functional utility but to signal a social status desired by

the consumer; the rich consume luxurious brands to show wealth. Besides, the additional working hours in society with high level of income inequality have increased the consumption of energy and CO_2 emissions due to economic growth and greater consumption by household (Bowles and Park, 2005, Fitzgerald et al., 2015; Knight et al., 2013; Jorgenson et al., 2017).

Although the contradictory theoretical views, clearly show that income inequality is closely linked to environmental pollution. Various studies have empirically investigated the relationship between income inequality and environmental degradation and present interesting results. Some studies have highlighted a negative relationship between income inequality and environmental pollution (Ravallion et al., 2000; Heerink et al., 2001; Boyce, 2007; Breannlund and Ghalwash, 2008; Andrich et al., 2010; Qu and Zhang, 2011; Masud et al. 2018; Demir et al., 2019; Hailemariam et al., 2020), while others have reported a positive relationship between income inequality and environmental pollution (Baek and Gweisah, 2013; Zhang and Zhao, 2014; Hao et al., 2016; Kasuga and Takaya, 2017; Knight et al., 2017; Zhu et al., 2018; Liu et al., 2019; Uzar and Eyuboglus, 2019; Padhan et al., 2019). Others studies suggest that there is no correlation between income inequality and environmental deterioration (Borghesi, 2006; Jorgenson et al., 2017; Wolde-Rufael and Idowu, 2017; Barra and Zotti, 2018).

Growing income inequality and environmental pollution in relation to economic growth become more and more pressing issues especially in Asian countries. Asia is considered as the "growth center of the world". It has recorded the highest average GDP growth rate of all developing region in the world since 1990. For that this region includes three of the five biggest CO_2 emitters in the world (China, India and Japan). The rapid economic growth experienced in Asia over the last twenty years is a remarkable success story in the fight against poverty. But this growth has also greatly widened the gap between the rich and the poor. Developing countries in Asia have recorded the highest level of income inequality among six world developing regions. Likewise, there is no study that estimates the time-varying correlation between income inequality and environmental pollution non-parametrically in Asian countries. To our knowledge, the only study that investigated the link between CO_2 emission

and income inequality on G7 countries using non-parametric model was presented by Uddin et al. (2020).

According to the existing environmental economics literature, the majority of subsequent empirical studies have investigated the environmental impact of income inequality with a parametric approach (see Table A1 in Appendix A). Whereas, the parametric model has a restrictive functional form that may result in a specification errors. However, the correlation between income inequality and environment degradation can change over time. This relationship can be influenced by many factors such as technological advances to protect the environment, awareness and attitudes towards climate change and preferences for a clean environment, changes in the rate of urbanization, all of which are sources of non-linearities in the long run. The widespread rise of income inequality and environmental degradation are two serious threats for the Sustainable Development especially in Asian region. For that, the purpose of this paper is to investigate non parametrical association between income inequality, economic growth and environment degradation using the local linear dummy variable estimator (LLDVE) by focusing on seven Asian countries. This technique was invented by Li et al. (2011). It allows evaluating the coefficients which vary over time for the panel data models.

The rest of the paper is organized as follow: Section 2 describes the data. Section 3 presents empirical specification and methodology in both parametric and non-parametric modeling. The empirical results are summarized and discussed in section 4. The conclusion is provided in Section 5.

2. Data description

We employ annual dataset for seven Asian countries, consisting of India, Japan, Korea, Malaysia, Pakistan, Philippines, and Sri Lanka, for the period spanning from 1971 to 2014. The choice of the sample and the time period is strictly based on the data availability. The data has been gathered from five databases. The per capita CO_2 emissions (expressed in metric tons) data for the whole period are extracted from the Carbon Dioxide Information and Analysis Centre (CDIAC) database (Boden et al., 2017). The Gini coefficient as measure of income inequality is extracted from the SWIID database (Solt, 2020). In this database, a distinction is made by Solt (2020)

between pre- and post-tax Gini coefficients, given that post-tax Gini coefficients tend to be weak due to social re-distribution. For that, in this study, we have used the after-tax Gini coefficient data, given that our main objective is to verify whether income re-distribution has an effect on CO_2 emissions. The data of real GDP per capita (expressed in 2011$) and population are collected from Maddison Project Database (Maddison, 2020). The data on trade openness (expressed in percentage of GDP) and data on financial development, measured by Domestic credit to private sector (in percentage of GDP) are extracted from the World Development Indicators (World Bank, 2020) database. Finally, the Economic Freedom of the World Index (EFWI) which is used as instrumental variable for income inequality is collected from the Fraser Institute (Gwartney et al., 2020)[1].

Trends in income inequality and per capita CO_2 emissions in the considered Asian countries during the period 1971-2014 are illustrated in Fig. 1. This figure suggests that income inequality and carbon emissions are strongly correlated over this period. However, the trends in these two variables exhibit significant versatility. The trend in income inequality is decreasing, while the trend in carbon emissions is increasing, for the period from 1971 to the end of the 1980s in almost all countries except Japan and Sri Lanka, which are experiencing the opposite situation. Then, throughout the 1990s, the trends are moving in the same way. Afterwards, at the beginning of the 2000s, the situation is similar to that of the first period, but with a lower magnitude. Accordingly, in the overall picture, an inverse correlation between income inequality and CO_2 emissions predominated throughout the 1971-2014 period for these selected Asian countries.

[insert Fig.1 here]

3. Methodology description

3.1. Non-parametric panel data specification

Following the modelling strategy used by Churchill et al. (2019) and Uddin et al. (2020), our econometric specification linking income inequality to CO_2 emissions takes the following form:

[1] Prior to 2000, the Fraser Institute provided the economic freedom index only every five years, so we interpolate the economic freedom data up to 1970 through the "ipolate command" in Stata.

$$Y_{it} = f_t + \beta_{t,1} lnineq_{it} + \beta_{t,2} lngdppc_{it} + \beta_{t,3} lnpop_{it} + \beta_{t,4} lntr_{it} + \beta_{t,5} lnfd_{it} + \alpha_i + u_{it}. \quad (1)$$

Let $Z_{it} = (lnineq_{it}, lngdppc_{it}, lnpop_{it}, lntr_{it}, lnfd_{it})$ and $(\beta_t = \beta_{t,1}, \dots, \beta_{t,5})$. Eq.(1) can be written under matrix representation such as:

$$Y_{it} = f_t + \beta_t Z_{it}^T + \alpha_i + u_{it}. \quad (2)$$

where Y_{it} is the natural log of per capita CO_2 emissions, $f_t = f_i(\frac{t}{T})$ are unknown economy-specific trend functions, while $\beta_{t,j} = \beta_j\left(\frac{t}{T}\right) = (\beta_{t,1}, \dots, \beta_{t,5})^T$ are an unknown time varying coefficients. $lnineq_{it}$, $lngdppc_{it}$, $lnpop_{it}$, $lntr_{it}$, and $lnfd_{it}$ are the natural log of income inequality, real GDP per capita, population, trade openness and financial development, respectively. α_i and u_{it} indicate the non-observed individual effects and the disturbance term, respectively. The $\sum_i^N \alpha_i$ is assumed equal to zero for the purpose of identification.

Following the example of Churchill et al. (2019) and Uddin et al. (2020) among others, the common trend f_t and the time varying coefficients $\beta_{t,j}$ will be estimated in a non-parametric manner using the LLDVE method proposed by Li et al. (2001). Silvapulle et al. (2017) and Uddin et al. (2020) provide a well-detailed formulation of the LLDVE method; however, our study differs from that of Uddin et al. (2020) concerning the selected country sample and the control variables used in the model. It should also be noted that the quadratic term of GDP per capita is not considered in our non-parametric modelling, as this method is specifically designed to capture non-linearities of the data, including non-linearities in the GDP-CO_2 emissions nexus across time.

Nevertheless, checking for the existence of nonlinear trends in our series is a relevant step before the execution of LLDVE method. For that, we apply the Maan-Kendall trend test (M-K test). This test, proposed by Mann (1945) then taken up by Kendall (1975), is non-parametric and allows a priori the detection of trends that are not necessarily linear. With the advantage that the data are not necessarily normally distributed or linear, the M-K test tests the null hypothesis that there is no trend against the alternative hypothesis that there is a downward (or upward) trend in the one-tailed test. For the time series x, The M-K statistic (S) is defined as follows:

$$S = \sum_{k=1}^{n-1} \sum_{l=k+1}^{n} sign(x_l - x_k) \tag{3}$$

where n is the length of the series, x_k and x_l two generic values of sequential data and the function $sign(x_l - x_k)$ is defined by:

$$sign(x_l - x_k) = \begin{cases} +1 \;\; if \; (x_l - x_k) \; > 0 \\ 0 \;\;\; if \; (x_l - x_k) = 0 \\ -1 \;\; if \; (x_l - x_k) < 0 \end{cases} \tag{4}$$

So, the S-statistic represents the gap between the number of positive differences and the number of negative differences found in the analyzed time series. If the series has a tendency to increase (decrease), the S-statistic should take on positive (negative) values. If the hypothesis is null, there is no trend in the correlation data between the considered variables and time, each order in the data set being equally alike. Under this assumption, the S-statistic is approximately a normal distribution with the mean E(S) = 0.

3.2. Parametric panel data specification

Our main focus in this study is to examine the impact of income inequality on environmental degradation (which is measured by the per capita CO_2 emissions) in a non-parametric way. However, to provide a benchmark for the results obtained by this method, we will present first the parametric point estimations. In this case, our parametric model, derived from the original EKC model and including income inequality as another determinant of per capita CO_2 emissions, is as follows:

$$\begin{aligned} lnCO_{2_{it}} = \beta_0 + \beta_1 lnineq_{it} + \beta_2 lngdppc_{it} + \beta_3 lngdppc\_sq_{it} + \beta_4 lnpop_{it} \\ + \beta_5 lntr_{it} + \beta_6 lnfd_{it} + u_{it}. \end{aligned} \tag{5}$$

where $lngdppc\_sq$ is the natural log of the quadratic term of GDP per capita included to capture the non linear impact of the GDP per capita variable. $u_{it} = \delta_i + \gamma_t + e_{it}$, where δ_i indicates the individual fixed effect, γ_t refers to the time effect and e_{it} is the specific-country disturbance term. In order to choose the appropriate method to estimate the parametric panel model (5), we should, first of all, implement some panel

test namely, cross-sectional dependency test, panel unit root test and panel cointegration test.

To test the presence or absence of cross sectional dependency (CSD) across countries, we use the Pesaran's (2004) CD test. Indeed, the CD test's hypotheses are as follows: H_0: absence of cross sectional dependency across countries against H_a: existence of cross sectional dependency across countries. One conclusion of this test is that it allows us to choose which panel unit root test will be applied to examine the stationarity of the variables. However, if we reject H_0, second generation panel unit root tests will be used in this case. Outcomes of the CD test outlined in Table 1 does not accept the null hypothesis in 1% threshold of significance for all variable, with exception of the income inequality variable ($lnineq$) which reject H_0 at 10% level, which allows to conclude that our panel data are cross-sectional correlated.

[insert Table 1 here]

In the presence of CSD, we employ the second generation panel unit root test proposed by Pesaran (2007), namely cross-sectional Augmented IPS test (CISP), as it considers heterogeneity as well as cross-sectional dependency issues that exists in our panel data. The CIPS test tests the null hypothesis that the series for each country has a unit root against they do not has a unit root as an alternate hypothesis. Table 2 presents the results of the CIPS test with intercept and trend indicating that the null hypothesis is accepted at the level but rejected at the first difference. Therefore, based on these results, we suggest that our variables are stationary in their first difference.

[insert Table 2 here]

As for the panel cointegration test, we use the bootstrap panel cointegration test proposed by Westerlund and Edgerton (2007). This test is considered suitable for CSD in the data by computing robust p-values from bootstrap replications. Westerlund and Edgerton (2007) augmented four normally disturbed tests which are used to test the null hypothesis of no cointegration. Two, such as between groups (G_t) and among groups (G_a), present group-mean tests, while the other two, namely between panels (P_t) and among panels (P_a), for the whole panel tests. We implement this test using 500 bootstrap replications to control CSD in order to compute robust critical values. Table 3 provides the findings of this test and shows that there is no

evidence of cointegration among groups and among panels tests (i.e. G_a and P_a), whereas between groups and between panels (i.e. G_t and P_t) tests, panel cointegration relationship exists at the 1% and 5% threshold of significance, respectively. Then, the results suggest the existence of long-run associations among variables. Once the panel evidence of cointegration is confirmed, we can proceed to estimate the panel parametric model. Accordingly, we employ the CCEMG estimator proposed by Pesaran (2006) as it accounts for CSD and also it accommodates for heterogeneity or endogeneity issues which can be observed in panel data.

[insert Table 3 here]

4. Results and discussion

4.1. Parametric specification results

The baseline long-run results from the CCEMG estimator are given in Table 4. As our main objective is to examine the association between income inequality and CO_2 emissions under the EKC hypothesis, whereas to verify the robustness of our parametric analysis, we have attempted to expand the model by including further control variables, namely trade openness and financial development. Thus, we have three models to estimate. In column 1, the model is without trade openness and financial development; in column 2, the model without trade openness; finally, in column 3, the model with all variables. For all specifications, the results suggest that income inequality does not show any significant impact on CO_2 emissions in the seven selected Asian countries. This suggests that the impact of income inequality on CO_2 in these Asian countries could be non-linear with a possible switch between positive and negative values and time-averaging point estimates. Our findings are corroborated with those obtained by Uddin et al. (2020), revealing that in their parametric analysis, income inequality does not affect CO_2 emissions in the G-7 countries.

Findings from all specifications indicate also negative and positive coefficients for $lngdppc$ and $lngdppc\_sq$ at different significance level respectively which is like a normal U-shaped relationship among CO_2 emissions and economic growth. Therefore EKC's assumption does not valid. Besides, we find the population variable has a significant and positively signed coefficient, indicating that an increment of the

population leads to an increase in CO_2 emissions. However, our parametric modelling fails to provide any significant impact of trade openness and financial development on CO_2 emissions in the panel of these Asian countries as the income inequality impact.

[insert Table 4 here]

In addition, we have looked at the impact of income inequality along with the other control variables on CO_2 emissions for each of the 7 countries, using the CCEMG estimator. The results depicted in Table 5 show no strong difference from the finding obtained from the whole panel estimate. Especially, findings show that a 1% increase in income inequality is associated with a 1.96% and 6.63% reduction in CO_2 emissions in Japan and Malaysia respectively. A 1% increase in income inequality leads to an increase in CO_2 emissions by 17.5% in Sri Lanka, while the income inequality impact in India, Korea, Pakistan, and Philippines remains insignificant. We find evidence that trade openness is positively and significantly associated with CO_2 emissions only in Pakistan and the Philippines, while there is no significant impact for the other countries with the exception of Japan, which exhibits a significant negative impact regarding this relationship. Results show that financial development leads to decline in CO_2 emissions in India and Korea, while degrades the environment in Japan and Pakistan. In addition, our results exhibit that EKC does not verified for each country, whereas a normal U-shaped curve does manifests in Japan, Korea and Philippines.

[insert Table 5 here]

It is important to note that a possible shortcoming of the parametric panel estimator is that estimates can be misleading if the model is incorrectly specified (Hailemariam et al., 2019). To overcome this problem, and to grasp the smooth time-varying association between income inequality and CO_2 emissions, we employ local linear estimates of a non-parametric panel data approach.

4.2. Non-parametric specification results

Before providing the results of the LLDVE technique, we apply the M-K trend test to verify whether or not our data exhibits a non-parametric trend. The results of M-K test are shown in Table 6. Table 6 suggests that a significant and positive trend in

CO_2 emissions is evident in all countries except for Philippines. Similarly, the global trend for the selected countries is positive and statically significant at the 1% level of significance. With the exception of the Pakistan, income inequality exhibits a positive trend in India, Japan, and Sri Lanka and a negative trend in Malaysia, Korea and Philippines, while a positive significant global trend at the 5% level of significance. The trends in GDP and in population are positive and significant for each of the countries at the 1% level as well as the global trend for the seven countries. The trade openness shows a significant positive trend in India, Malaysia (at the 1% level) and in Philippines (at the 5% level) with a positive significant global trend at the 5% level for whole panel. Finally, we prove a positive and significant trend for financial development for India, Japan, Korea, Malaysia (at the 1% level) and Sri Lanka (at the 10% level). The global trend is also statistically significant at the 1% level with a positive sign. In overall, the M-K test confirms the existence of trend in our series. Accordingly, we proceed to a rigorous non-parametric analysis using the LLDVE technique (presented in section 2) to estimate the common trend f_t and the time varying coefficients $\beta_{t,j}$.

[insert Table 6 here]

Fig. 2 depicts, therefore, the non-parametric results from the LLDVE method, along with the 90% confidence intervals. The non-parametric panel data estimates, contrarily to parametric point estimates, capture the time-varying association between income inequality and per capita CO_2 emissions. According to Fig. 2, the relationship between income inequality and per capita CO_2 emissions was significant and negative for almost the entire period, except for 1988 to 1997 when it was significant and positive.

[insert Fig. 2 here]

Therefore, based on these results, we suggest that there is a reverse relationship between income inequality and per capita CO_2 emissions for the whole period, except for the period 1988-1997 when it is positive. Whereas, because of the boundary effect

that characterizes the non-parametric estimation method, the results of the coefficient of income inequality for 1971-1975 and post-2010 should be viewed with caution[2].

The reverse relationship between income inequality and per capita CO_2 emissions during the period 1975-1988 is sustained by the income distribution patterns observed at the time. The period 1975 to 1988 was characterized by significant growing of income inequality. However, according to WIR (2018), income inequality has been widening rapidly in Asia since 1980s. Although technological advances, globalization, and market-oriented reforms have been the main drivers of rapid growth in developing Asia over the past two decades, they have also had enormous distributional consequences (Kanbur et al., 2014). A commitment has been made by all Asian countries to become more integrated with the world economy in the decades to come. However, globalisation is considered one of the factors behind the surge of income inequality in the region (Zhuang et al., 2014). For instance, trade integration might affect the relative demand, and therefore the relative wages of skilled and un-skilled workers. It might equally change the distribution of income among capital and labour, since capital and skills frequently have a complementary relationship and often operate together, which depresses the demand for un-skilled labour (Wood, 1997). For its part, financial integration can enhance poor people's access to finance, yet gains are likely to be elite-driven, which means that inequality rises at low income levels and falls with rising income (Choi, 2006; IMF, 2007; Claessens and Perotti, 2007).

Beyond this, fiscal policy weaknesses are another factor driving up inequality in the region in this period (Zhuang, 2018). For the majority of countries in the region, tax systems are heavily skewed toward consumption taxes, which impose a heavy burden on low-income and middle-income groups. Alternatively, the wealth of the upper-income groups is likely to be concentrated under this tax system because taxes are quite favourable to labour income instead of capital earnings and property. Therefore, this leads to falling in MPC from low-income and middle-income groups. For this reason, the opposite relationship between rising of income inequality and decline in per capita CO_2 emission may be explained by the falling of the MPC and also by the fewer emit upper-income earners in the period 1975- 1988.

[2] As Uddin et al. (2020), we consider an insignificant relationship for these periods.

While all the flows that make up globalization can affect income inequality, the most important impact probably comes from flows related to technology and information. Technological change thus affects employment by devaluing and revaluing skills and, indeed, creating entirely new skills and jobs. For many, this relationship between skills and technology is an important factor in increasing income inequality (Goldin and Katz, 2009). However, and according to Hüfner and Koske (2010), the increasing income inequality may improve the marginal propensity to invest for the upper-income households as its inclined MPC. Therefore, through financial deregulation that facilitated corporate borrowing, income inequality has promoted capital accumulation, which has usually been a complement to productivity or productivity enhancement in high income economies (Jones, 2016; Uddin, 2020). At the same time, technology advances have brought about improvements in the energy efficiency of goods bought by upper-income households as well as by lower-income households (Uldin, 2020). Thus, this is another possible way that may explain the reverse relationship between per capita CO_2 emission and the higher income inequality in the selected Asian countries for this period.

Income inequality continued to rise from 1988, but it reversed around the mid-1990s. While the relationship between income inequality and per capita CO_2 emission is significantly positive for the period 1988-1997. One explanation for the environmental degradation exacerbated by the growing income inequality between rich and poor could be that the rich because of their wealth have access to life-styles which are energy intensive, commodity intensive and manufactured goods (UN/ESCAP and ABD, 1995). Some of the most significant changes are the increasing usage of private automobiles and the growing use of a number of other consumer durables including televisions, air conditioners, and washing machines. There has also been a significant increase in the consumption of wood products, particularly paper. For instance, according to UNDP (1998), the number of vehicles in East Asia multiplied by 14 between 1975 and 1993, over seven times the global average growth rate. Consequently, the energy use increased at an average annual rate of about 6% for the period 1980-1998, which is five times faster than other regions (Cleveland, 2001).

The positive relationship between high income inequality and per capita emission is also mainly related to over-exploitation of natural resources in the Asian's region. Meanwhile, within high-income inequality societies, wealthy people have a tendency towards a powerful influence on policy-making. Inequalities in income may cause political instability leading the rich to favour a policy that overexploits natural local resources and exports the proceeds overseas (Boyce, 1994). At the same time, the poor are denied vital resources and are compelled to resort to unsustainable exploitation of the natural resources at their immediate disposal to satisfy their livelihood needs (UN/ESCAP and ABD, 1995). This explains why, around 1990s, it was estimated that the countries of the region were losing between 70 and 90 % of pre-existing natural habitat as a result of agriculture, as well as infrastructure development, deforestation and land deterioration (MacKinnon and MacKinnon, 1986). India, Indonesia, the Philippines, and Sri Lanka were among the countries that recorded the most serious losses. The Philippines, for example, experienced the loss of about 70% of its mangrove forests (AOE, 2001). About 40% of the land capable of supporting closed tropical forests was estimated to have become devoid of forest cover in the period, mainly as a resulting from human actions (Wilson, 1998). Additionally, many countries in the region were confronted pressure on land. About 28% of the region's land area had some degree of land degradation in 1990s, among them about 350 million ha of degraded land are in India, Pakistan, and China (UNEP, 1999). Therefore, the over-exploitation of natural resources, either by rich or poor, will intensify the energy use and hence will generated more CO_2 emissions (Wu et al., 2017). Moreover, with the depletion of natural resources, their role as CO_2 emission sinks will be destroyed.

After reaching a threshold level in the mid-1990s, income inequality shows a declining trend until the mid-2000s. The Asian financial crisis of 1997-1999 is considered to have been a key factor behind this trend. It is common for the rich to face significant capital losses during a crisis, which adversely affecting their incomes (Lopez-Acevedo and Salinas, 2000). In addition, crises lead to greater income damage for employees in non-tradable sectors, including financial services, as well as for those in the top income deciles (Wan and Wang, 2018). However, the decline in income inequality was accompanied by an increase in CO_2 emissions in these Asian countries, particularly between the late 1990s and the mid-2000s, before experiencing

a slow downward tendency after this period. The increase in CO_2 emissions stems from an increase in the consumption of energy-intensive products, especially by low income households. Where, the increase in income equality has contributed to an improvement in the wealth of low income earners, which is reflected in an increase in their MPC more than those with high incomes. So, more consumption of energy-intensive products boosted the MPE and intensified CO_2 emissions.

The mid-to-late 2000s, the relationship between income inequality and per capita CO_2 emissions was negative. Although income inequality shows a slight increasing trend, CO_2 emissions started with a small decreasing trend and then became stable. This result partly reflects both the growing commitment of these Asian countries to environmental challenges from the early 2000s and the nature of income inequalities around that time. Following the growing concern in the 1990s regarding the effects of CO_2 emissions on climate change, countries in the Asian region have already undertaken significant measures to diversify their energy mix and have started to realize substantial socio-economic gains. National renewable energy targets have been set by all countries in the region. For example, in 2003, Japan's government stepped up its involvement in the energy market and introduced its Renewable Portfolio Standard Scheme in which electricity retailers were required to provide a portion of electricity generated from renewable resources to grid users (IEA, 2016; Wang et al., 2016). The growth of non-fossil based energy has been prioritized in Malaysia since 1999 and has been emphasized as the 5th fuel in their energy mix with the target of providing around 5% of its power generation in by 2005 (Siva et al., 2018). Similarly, the renewable energy growth in Korea showed a rapid growth between 1990 and 2013, at about 46% (Boo, 2016). Accordingly, by 2015, investment in renewable energy, excluding large hydropower projects, has reached $160.6 billion in Asia and the Pacific, among them about $103 billion in China and $10 billion in India (McCrone et al., 2015). That points to the significant expansion of the renewable energy sector since the beginning of the century. Subsequently, therefore, using one unit of electricity would necessarily lower, on average, CO_2 emissions. In brief, renewable energy development and deployment has brought about an overall decline in an individual entity's ability to emit. This result is consistent with Zheng et al. (2018) who found that emissions have a downward trend in East Asia during the period 2005-2016. The upward trend in income inequality is mainly related to the

rapid economic growth experienced by the region in the early 2000s (OECD, 2017; Jain-Chandra et al., 2019). Rapid growth has contributed to a rise in income inequality because of rapid income growth among the high-income groups in urban areas (Shi and Sicula, 2014). Therefore, one explanation for the negative relationship between income inequality and per capita CO_2 emissions may be a re-distribution of income in favor of higher incomes that have limited emission capacity, under the assumption that the MPE declines with income.

For the other variables in Fig. 2, the GDPpc plot looks roughly like a normal U-shape, whereby the relationship between GDP and CO_2 emission follows a downward trend from the mid-1980s to the mid-2000s and then starts to increase from that time onward. This result, which is consistent with the parametric estimation findings, does not yet validate the EKC hypothesis for our sample. Since the majority of the countries in our sample are developing countries, a rejection of the conventional EKC hypothesis is not surprising since they may not have reached the expected income-level to capture the inverted U-shaped relationship embodied in the EKC hypothesis. In fact, some existing studies have found the same outcome not only for the same countries but also for the same study period we worked on, such as Kanjilal and Ghosh (2013) and Chandran and Tang (2013) for India and Malaysia, respectively, for the period 1971-2008; Saboori and Sulaiman (2013) for Philippines in the 1971-2009 period. We find that relationship between trade openness and CO_2 emissions are non-linear, despite the small magnitude of the effect. The time-varying coefficient of trade openness was negative for the 1980-87 and 1993-2000 periods, while it was positive for the 1988-92 period. We find that financial development has a non-linear association with CO_2 emissions. The financial development's time-varying coefficient is positive and has an inverted U-shape from 1976 to the late 1980s and becomes stable until 2000 before turning negative in the 2000-2010 period. The findings are coherent with the positive impact on CO_2 emissions during the early stages of financial development, while at later stages, after a certain level, financial development can contribute to the reduction of emissions (Javid and Sharif, 2016; Ben Youssef et al., 2020; Uddin et al., 2020).

4.3. Common and country-specific CO_2 emissions trends

Fig. 3 plots both the country-specific CO_2 emissions trend estimations and the common trend function with 90% confidence intervals. In each box, the dark blue and the dashed red lines represent the common trend function and country-specific CO_2 emission trends, respectively, while the black dashed lines are the wild bootstrapped 90% confidence bands. The blue light lines are the actual CO_2 emissions recorded for the individual economy. The CO_2 emission individual trends for Japan, Korea, and Pakistan are above the common trend, although CO_2 emissions in Pakistan converge towards the common trend until the mid-1990s and then become slightly higher than the common trend. CO_2 emissions in Japan and Korea are very higher than the common trend, while the specific trend of the Korea is increasing considerably and that of Japan seems to have a horizontal shape. The individual trends of CO_2 emissions for India, Malaysia, and Philippines are entirely below the common trend, although India's specific trend closely follows the common trend. Finally, CO_2 emissions in Sri Lanka largely follow the common trend until the early 1980s after which they fell below the current trend.

Overall, although the country-specific trend functions show significant differences in CO2 emissions across the considered Asian countries, they broadly follow the common trend function.

[insert Fig. 3 here]

4.4. Robustness cheek: Su and Ullah (2008) endogeneity test

The endogeneity of income inequality is a potential concern as this variable may be correlated with another omitted variable, exposed to measurement error problems, or co-determined with another explanatory variable in the model. In order to address this issue, we carried out the endogeneity test suggested by Su and Ullah (2008), which is relevant in a non-parametric set-up[3]. To implement this test, we employ the economic freedom as an instrument variable (IV). Economic freedom is generally linked to market oriented institutions and policies, that are supposed to contribute to long run economic development which in turn may reduce income inequality (Acemoglu et al.,

[3] For further details on the procedure of this test, see Hailemariam et al. (2019).

2015), while some believe that higher degrees of economic freedom are also at the cost of rising income inequality (Okun and Summers, 2015)[4]. Accordingly, we believe the existence of strong correlation between economic freedom and income inequality; hence the former can be treated as IV for the latter.

The non-parametric estimator of Su and Ullah (2008) builds on the same idea as the standard two-step least squares, whereas it operates in three steps. The first step consists in performing a non-parametric regression of the variable being endogenous on all regressors that are exogenous. In the second step, a non-parametric regression of the dependent variable will performed on each of the regressors, including the variable being endogenous and the residuals arising from the first step regression. The third, and final, step implies marginal integration to ascertain the validity of the zero mean error term hypothesis.

Following Henderson and Parmeter (2015), we now conduct this endogeneity test involving income inequality as potential endogenous variable and trade openness as control variable[5]. The outcomes of this test are shown in Fig. 4. We compare the results from local linear estimates where endogeneity is ignored (left-hand diagram) with the IV local linear estimates of Su and Ullah (2008) that considers endogeneity (right-hand diagram) by employing economic freedom as IV of income inequality. In Fig. 4, each point on the dark black mid-line correspond to the estimated gradient for each observation, while each point on the outer light blue and light red lines refers respectively to the lower and upper limits of a 95% bootstrapped confidence band for the specific point estimates. When the upper and lower confidence intervals for this estimate both lie in the upper right quadrant, the estimated gradient for an observation is statistically significant with positive sign. If the confidence intervals for the estimated gradient both lie in the lower left quadrant, the given estimate for that observation is statistically significant with negative sign. However, the gradient estimate for an observation appears to be statistically non-significant in cases where the upper or lower confidence intervals overlap the horizontal axis (Henderson et al., 2012).

[4] See Bennett and Nikolaev (2017) for a literature discussion of the impact of economic freedom on income inequality.

[5] We also conducted several other regressions with other control variables and observe no sensitivity in the results when choosing the control variable. Results of these regressions are not reported but are available upon request.

[insert Fig. 4 here]

Based on the results reported in Fig. 4, we observe that the local linear estimate that ignores endogeneity (left panel) and the Su and Ullah IV local linear estimation that take endogeneity into account (right panel) show no significant difference. The statistical significance of the estimated gradients is proven at the 5% level of significance, which means that endogeneity does not bias the estimates. Furthermore, the estimated gradient is broadly distributed in the lower left quadrant, more so than in the upper right quadrant, suggesting that the relationship between income inequality and carbon emissions is mainly negative. This broadly confirms the LLDVE findings obtained in the previous section (Fig. 2).

5. Conclusion and policy implications

We have tested the relationship between income inequality and CO_2 emissions for a panel of seven Asian countries over the 1971-2014 period using a non-parametric procedure. Specifically, we empirically examined the time-varying trend and coefficient functions that govern the income inequality-carbon emissions relationship in these countries employing the local linear data-driven method - LLDVE technique. Carbon emissions, under this approach, are allowed to evolve over time into the form of unknown functional forms along with confidence bands generated by the wild bootstrap method.

Our non-parametric panel estimates reveal a strong non-linear relationship between income inequality and CO_2 emissions which is largely negative. The estimate coefficient of income inequality is negative and statically significant for the periods between 1975 and 1988 and between 1997 and 2010, while positive and statically significant for the period 1988 to 1997. We assign these findings to the main factors of inequality and CO_2 emissions over these different periods. Between 1975 and 1988, income inequality increased mainly due to globalization, which depressed the demand for unskilled labour and promoted financial gains in favour of the rich, consumption taxes that weighed heavily on the poor and technological changes that negatively affected employment. Higher income inequality leads to lower MPC for low- and middle-income households, which in turn leads to weaker MPE. Falling in MPE and improvements in the energy efficiency of goods - bought by upper-income households

- through technology advances are contributing in decline of CO_2 emissions during this period. Between 1988 and 1997, the growing in income inequality is due generally to the same above-mentioned drivers. The rise in CO_2 emissions over this period are induced by the growing consumption of energy-intensive goods by high-income households and the over-exploitation of natural resources by both rich and poor people. Between the end of the 1990s and the mid-2000s, the decline in income inequality is due in particular to the Asian crisis of the 1990s. Greater income equality led to an upsurge in MPE due to an increase in MPC of low-income households. Between the mid to late 2000s, the increase in income inequality is due to the rapid economic growth experienced by the region in the early 2000s. The slight decline in CO_2 emissions during this period highlights the growing commitment to environmental challenges, lower MPEs arising from increased income inequality and improvements in green technologies.

Our findings with regard to the income inequality and CO_2 emissions linkage support the existence of a potential trade-off among them, commonly called the "equity-pollution dilemma" whereby income redistribution induces environmental pollution (Sager, 2019). There are potential implications associated with this dilemma for policies designed to promote redistribution in our selected Asian countries. At first glance, as noted by Sager (2019), the "equity-pollution dilemma" does not necessarily mean that income redistribution is not desirable; rather, the optimal degree of redistributive policy requires an in-depth understanding of welfare economics and will depend on a number of assumptions about market structure, household well-being and desired social outcomes. Another implication is that income redistribution policies in the presence of strict environmental protection policies, such as the promotion of renewable energies, will contribute to improving the quality of the environment. In addition, income redistribution-environmental linkage will provide an important platform for designing appropriate environmental policies that builds on each country's competitive advantage and resource endowments. In this regard, such a relationship suggests that there is a need to synchronize redistributive policies and environmental policies between Asian countries either in national and regional levels (see e.g. Rasiah et al., 2018; Masud et al., 2018).

In conclusion, it noteworthy that our results suggest that the equity-pollution dilemma existed consistently from the mid-1970s to 2010 in the selected Asian countries, however its inexistence afterwards could reflects the boundary conditions involved in this non-parametric analysis. While by observing trends in CO_2 emissions and income inequality from 2010 onwards, its existence is suspected. Therefore, that encourages us to further explore this relationship once aggregate emission data are available after 2014 for these and other countries in the Asian or other continents.

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Appendix A

Table A1 : Summary on recent empirical studies on income inequality-environmental pollution nexus

Authors	Sample countries	Periods of study	Methodology
Ravallion et al. (2000)	42 countries	1975-1992.	Pooled OLS model (POLS) and fixed effects estimate (FEE)
Magnani (2000)	OCDE	1980-1991	Voting model
Baek and Gweisah (2013)	USA	1967-2008	ARDL
Zhang and Zhao (2014)	China	1995-2010	Panel regression analysis
Hao et al. (2016)	China	1995-2012	Generalized Method of Moments (GMM) model
Barra and Zotti (2018)	120 countries	2000-2009	Two step Generalized Method of Moments (GMM) estimator
Knight et al. (2017)	26 developed countries	2000-2010	Two-Way Fixed Effects (2FE) Longitudinal models
Masud et al. (2018)	ASEAN-5 countries	1985–2015	Granger causality and panel regression tests
Zhu et al. (2018)	BRICS countries	1994-2013	Panel Quantile Regression
Demir (2019)	Turkey	1963-2011	Autoregressive distributed lag bounds (ARDL) test
Uzar and Eyuboglus (2019)	Turkey	1984-2014	Autoregressive Distributed Lag Model (ARDL)
Sager (2019)	USA	1996-2009	Environmental Engel curves (EECs)
Chen et al. (2020)	G20 countries	1988-2015	Simultaneous quantile regression
Baloch et al. (2020)	40 Sub-Saharan African countries	2010-2016	Driscoll and Kraay (1998) (DK) standard error method
Hailemariam et al. (2020)	17 OECD countries	1945-2010	CCEMG estimator
Rojas-Vallejos and Lastuka (2020)	68 countries	1961-2010	GMM estimator
Uddin et al. (2020)	G7 countries	1870-2014	Non-parametric panel estimation method with cross-sectional and time-varying coefficients

Table 1

Pesaran (2004) test for cross-sectional correlation

Variable	CD-test	p-value	corr	abs(corr)
$lnCO_2$	23.30*	0.000	0.767	0.767
lnineq	-1.92***	0.055	-0.063	0.655
lngdppc	28.23*	0.000	0.929	0.929
lngdppc_sq	28.25*	0.000	0.929	0.929
lntr	9.62*	0.000	0.317	0.419
lnfd	10.04*	0.000	0.330	0.464
lnpop	29.78*	0.000	0.980	0.980

*and *** indicate the significance at 1% and 10% levels, respectively

Table 2

Pesaran (2007) panel unit root test with CSD:

Variable	Level	First difference
	Intercept & trend	Intercept & trend
$lnCO_2$	-1.936	-6.354*
lnineq	-1.485	-3.825*
lngdppc	-0.798	-5.315*
lngdppc_sq	-0.660	-5.206*
lntr	-1.118	-5.993*
lnfd	-1.240	-5.127*
lnpop	-1.867	-2.912**

*and ** indicate the significance at 1% and 5% levels, respectively

Table 3

Westerlund and Edgerton (2007) panel cointegration test:

Statistic	Value	Robust P-value	Conclusion
G_t	-4.282*	0.000	Cointegration
G_a	-10.778	0.886	No-cointegration
P_t	-11.883**	0.032	Cointegration
P_a	-7.156	0.888	No-cointegration

*and ** indicate the significance at 1% and 5% levels, respectively.

Table 4
CCEMG estimation results

Variables	1	2	3
	$lnCO_2$	$lnCO_2$	$lnCO_2$
lnineq	1.301 (1.685)	0.238 (1.243)	-0.689 (0.533)
lngdppc	-3.819*** (2.118)	-4.915*** (2.979)	-5.940** (2.404)
lngdppc_sq	0.284* (0.100)	0.363** (0.178)	0.407* (0.144)
lnpop	10.565* (3.303)	6.843* (2.517)	6.974* (2.424)
lnfd		-0.064 (0.134)	-0.032 (0.162)
lntr			0.060 (0.148)
Trend	-0.093* (0.0342)	-0.107* (0.037)	-0.069** (0.034)
Constant	-23.216 (33.174)	75.639** (32.932)	-34.654 (30.547)
Observations	308	308	308
Number of groups	7	7	7

(.) represents standard error. *, ** and *** indicate the significance at 1%, 5% and 10% levels, respectively.

Table 5
CCEMG estimation results by country.

	lngdppc	lngdppc_sq	lntr	lnfd	lnpop	lnineq
India						
Coefficient	-4.531	0.357	-0.039	-0.200	6.359	-0.171
St. error	4.214	0.277	0.058	0.073	3.571	0.862
P-value	0.282	0.197	0.502	0.006	0.075	0.842
Japan						
Coefficient	-30.878	1.532	-0.099	0.306	1.375	-1.965
St. error	6.487	0.318	0.048	0.106	0.919	0.434
P-value	0.000	0.000	0.040	0.004	0.135	0.000
Korea						
Coefficient	-3.566	0.226	0.116	-0.214	5.391	0.289
St. error	1.356	0.072	0.090	0.068	1.345	0.407
P-value	0.009	0.002	0.198	0.002	0.000	0.478
Malaysia						
Coefficient	-1.540	0.176	0.135	0.020	1.198	-6.635
St. error	1.767	0.092	0.174	0.070	1.682	1.767
P-value	0.384	0.058	0.425	0.769	0.002	0.001
Pakistan						
Coefficient	0.387	0.017	0.110	0.085	2.230	-0.146
St. error	2.190	0.137	0.033	0.039	0.549	1.001
P-value	0.860	0.900	0.001	0.028	0.000	0.884
Philippines						
Coefficient	-57.707	3.623	0.966	-0.062	5.498	9.653
St. error	29.752	1.816	0.587	0.270	5.280	12.828
P-value	0.052	0.046	0.100	0.921	0.298	0.452
Sri Lanka						
Coefficient	-10.705	0.745	-0.055	-0.049	-2.140	17.520
St. error	7.554	0.456	0.154	0.073	5.025	2.686
P-value	0.156	0.102	0.719	0.502	0.670	0.000

Table 6
Nonparametric country-specific & global trend tests.

Variable	India	japan	Korea	Malysia	Pakistan	Philippines	Sri Lanka	Global
$lnCO_2$	3.6955*	2.0819**	3.6013*	3.3235**	3.4490*	1.1362	2.073**	3.0328*
lnineq	3.3061*	3.1887*	-1.4536	-3.4990*	0.9246	-2.0676**	3.6107*	2.1102**
lngdppc	3.6596*	3.5341*	3.7448*	3.6372*	3.7806*	2.2746**	3.6999*	3.5640*
lntr	3.0052*	-0.6655	0.8314	2.6825*	0.9614	2.5122**	1.6068	2.5062**
lnfd	2.5839*	2.6467*	3.0232*	3.0411*	-0.4728	1.3379	1.7234***	2.8918*
lnpop	3.7941*	3.3459*	3.7941*	3.7941*	3.7941*	3.7941*	3.7941*	3.7441*

*, ** and *** indicate the significance at 1%, 5% and 10% levels, respectively.

Figures

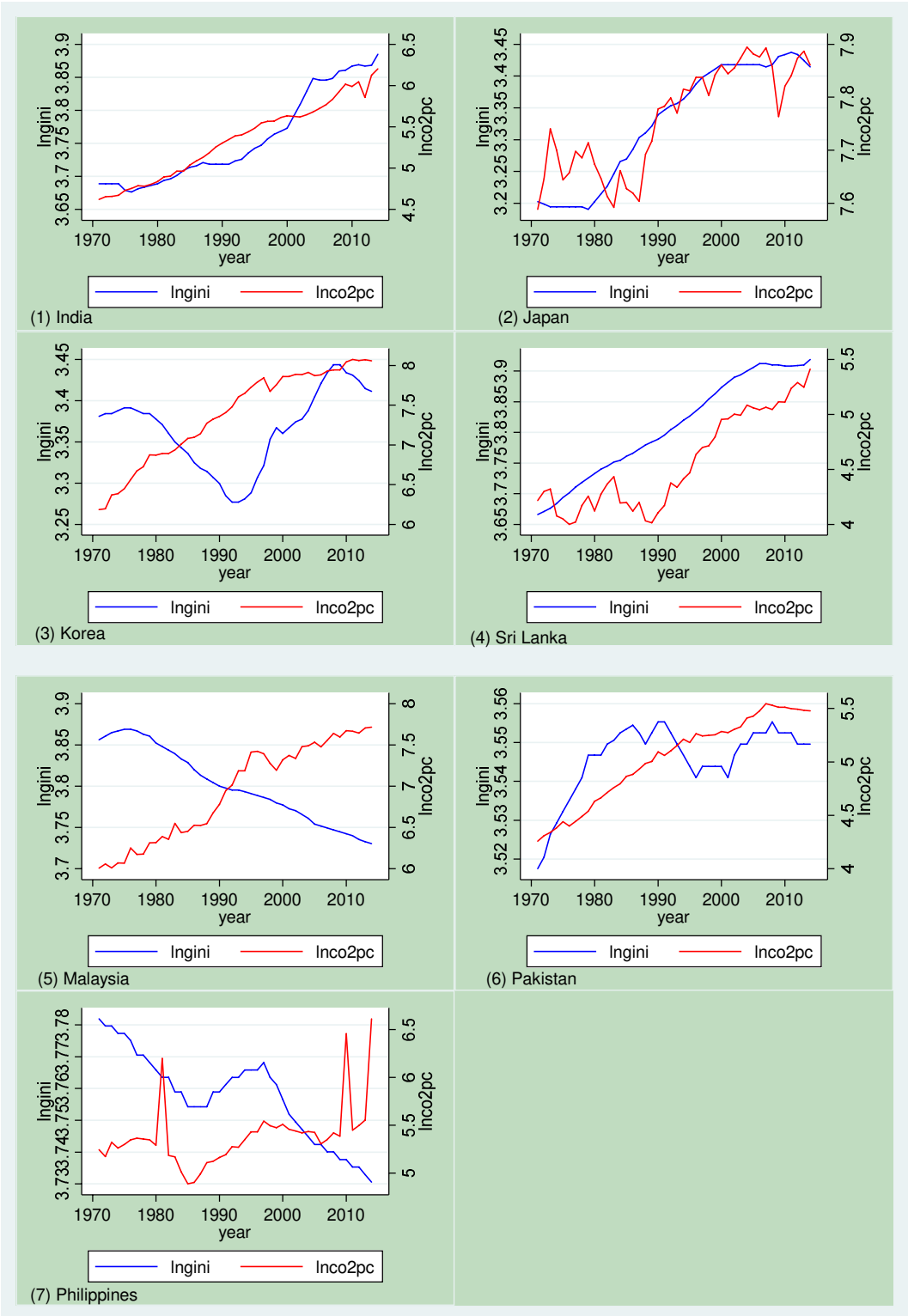

Fig.1. Trends in income inequality (lngini) and per capita CO_2 emissions (lnCO2pc), 1971-2014.

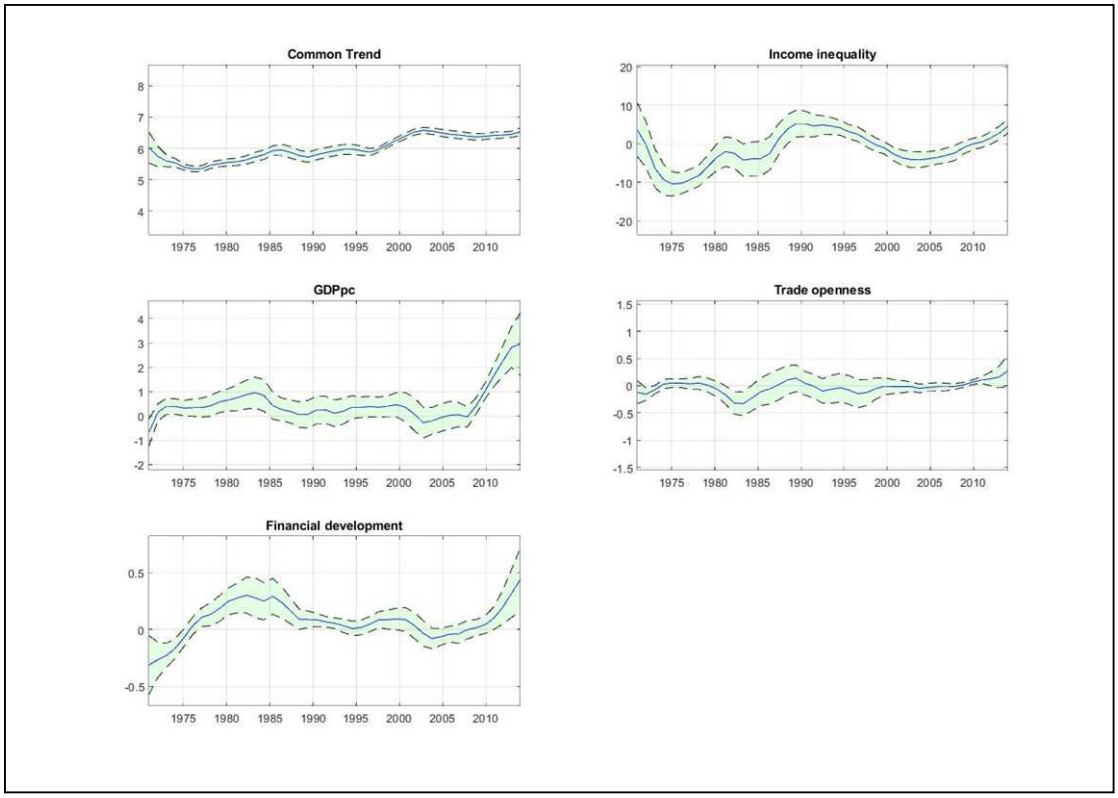

Fig. 2. Non-parametric LLDVE results, 1971-2014.

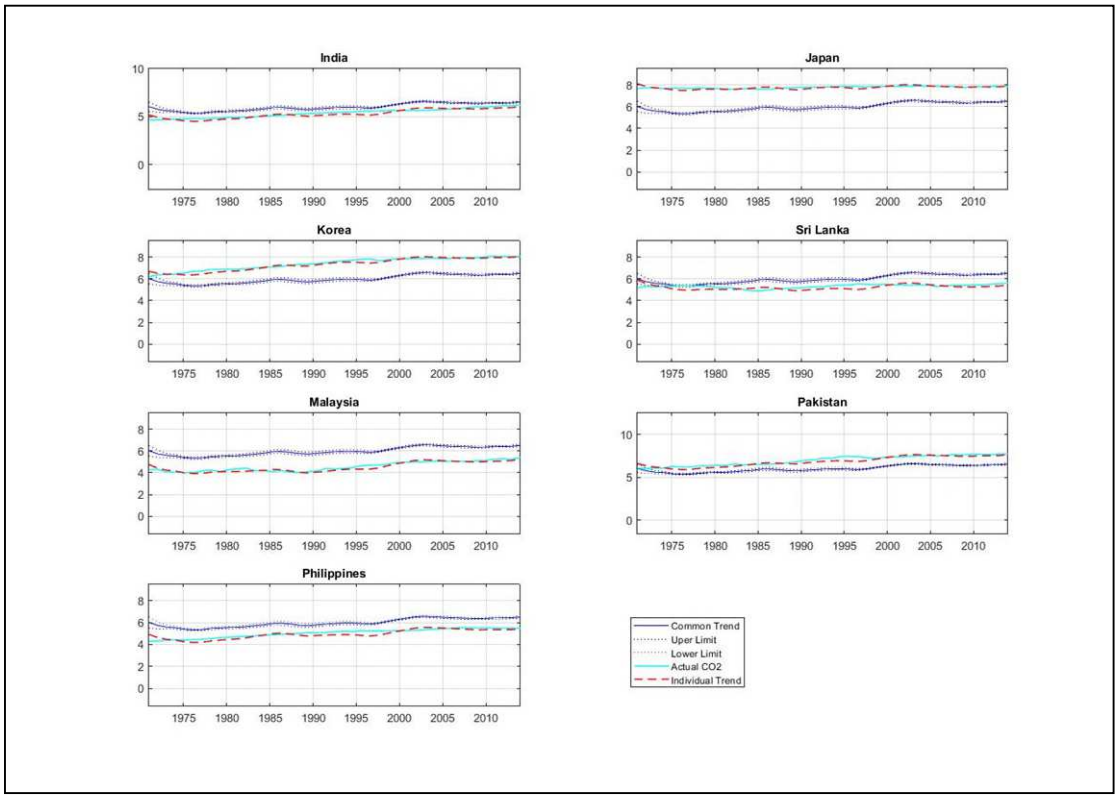

Fig. 3. Country-specific CO_2 emissions trend, 1971-2014.

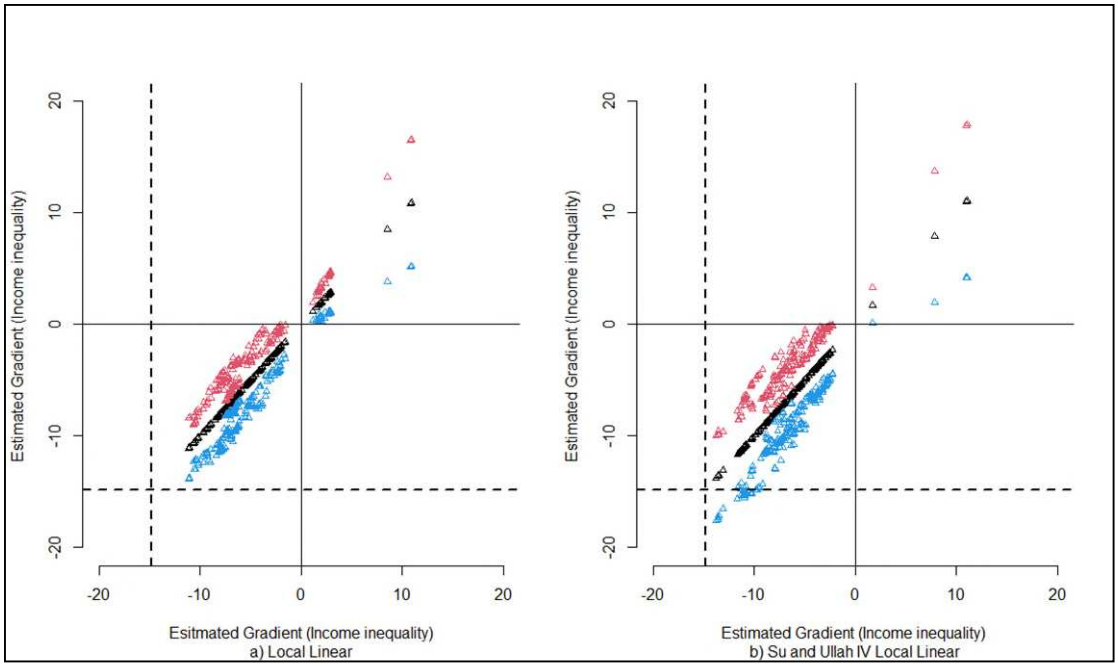

Fig. 4. 45° plot of the estimated gradients (income inequality)

Figures

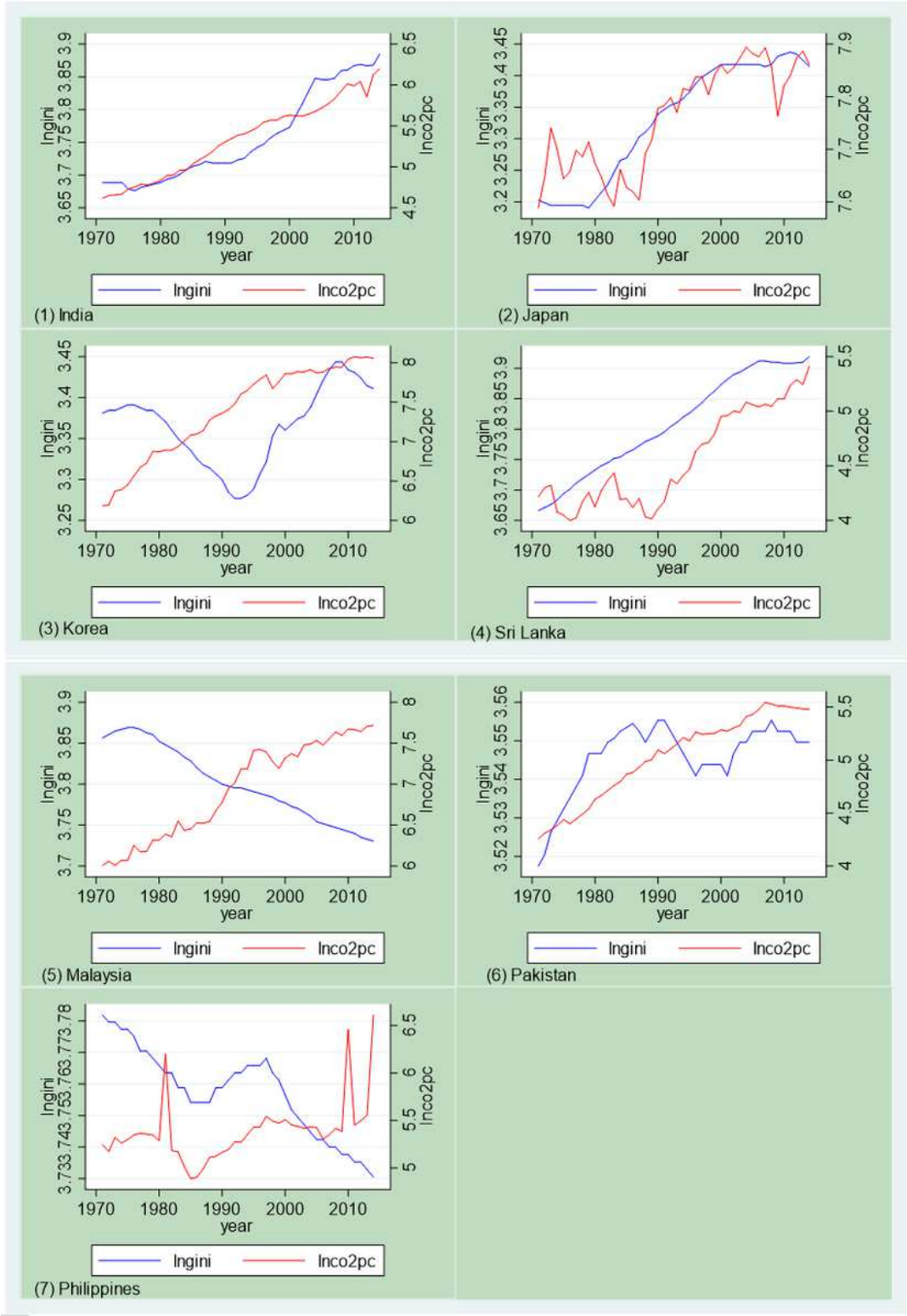

Figure 1

Trends in income inequality (lngini) and per capita CO2 emissions (lnCO2pc), 1971-2014.

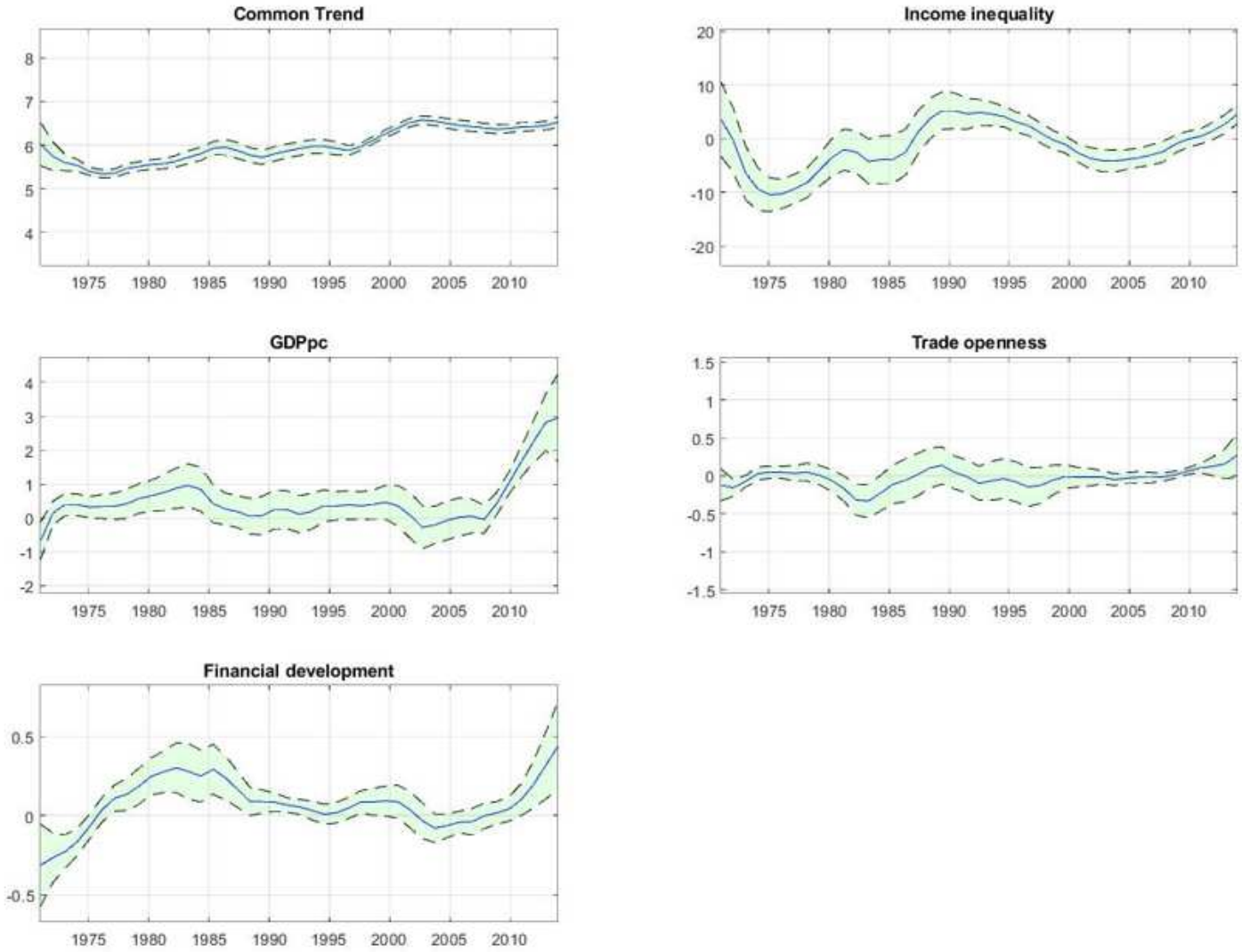

Figure 2

Non-parametric LLDVE results, 1971-2014.

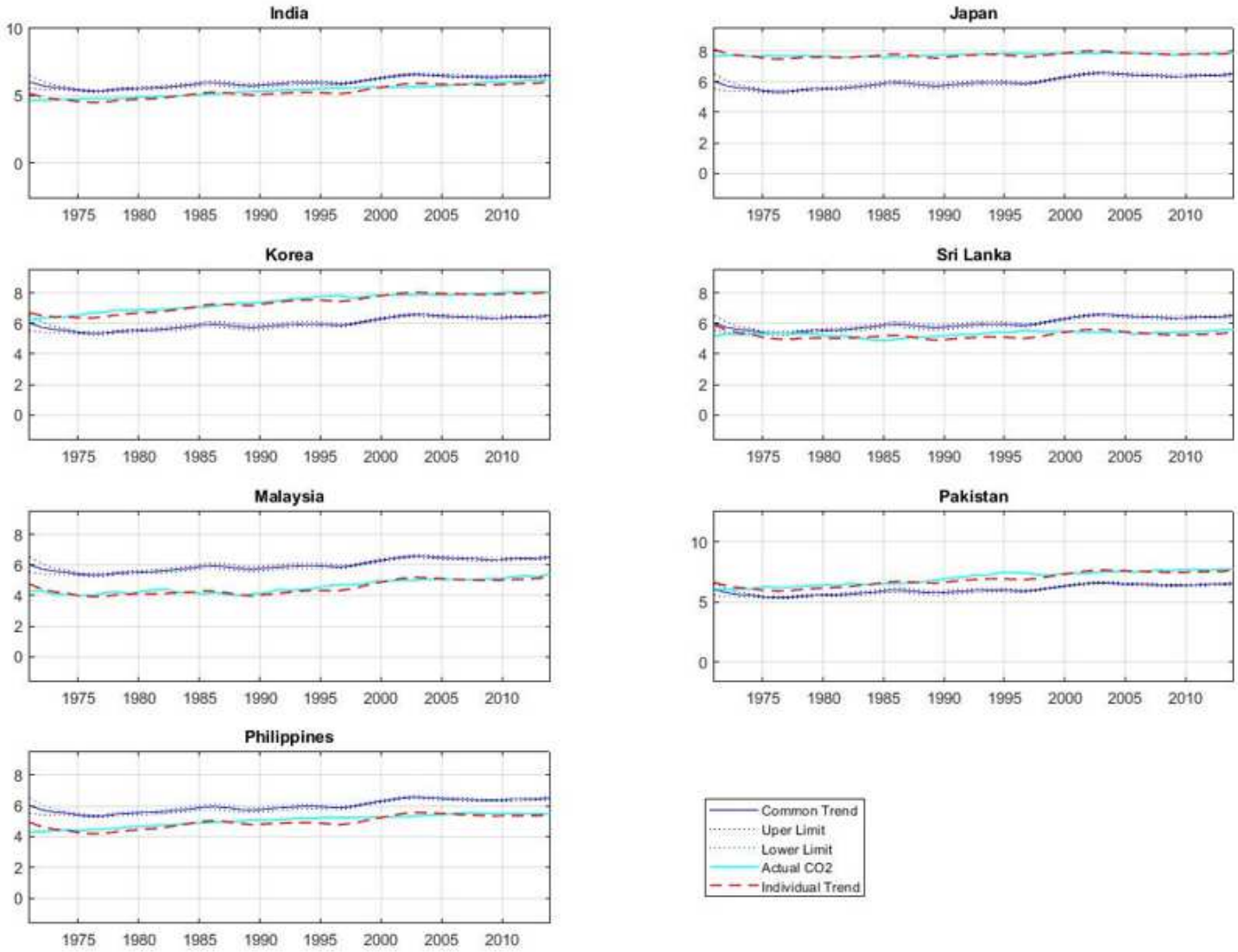

Figure 3

Country-specific CO2 emissions trend, 1971-2014.

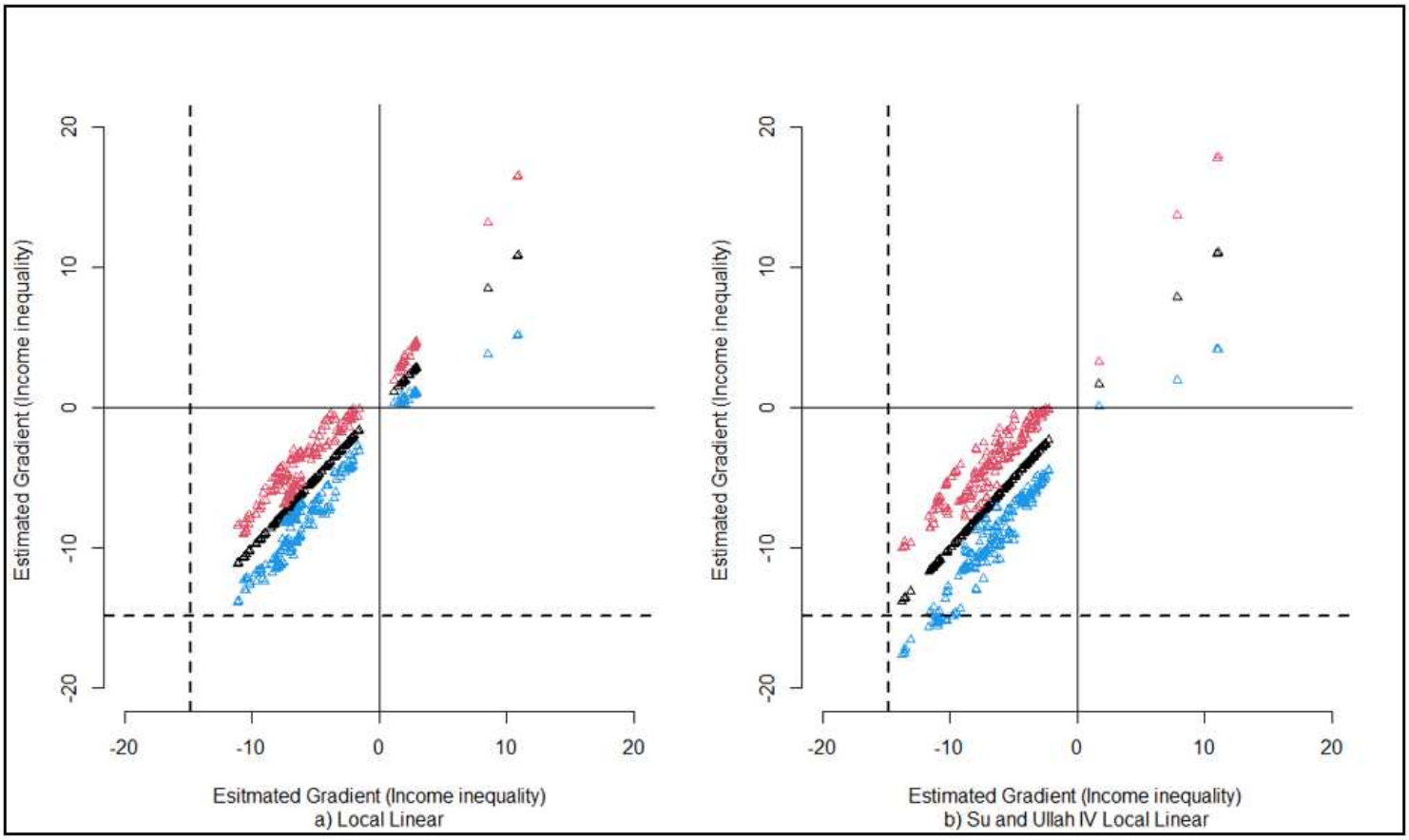

Figure 4

45° plot of the estimated gradients (income inequality)