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The inequality-emissions nexus in the context of trade and development: A quantile regression approach

Michael Hübler

Leibniz Universität Hannover, Institute for Environmental Economics and World Trade, Königsworther Platz 1, Hannover 30167, Germany

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ABSTRACT

If the emissions attributed to households' consumption rise in their income in a concave way, higher within-country inequality will reduce emissions. To test this negative nexus, the article utilizes simultaneous-quantile regressions with per capita CO_2 emissions (or energy intensities of GDP) as the dependent variable and draws on country-level panel data. Overall, the estimates vary considerably across quantiles. Regressions with pooled data support the negative inequality-emissions (energy) nexus, whereas regressions with fixed-effects question it. International trade and international investments are mostly positively related to emissions (energy).

1. Introduction

During the last decades most countries have become richer, and some of the poorer countries have been able to catch up closer to the richer countries (Khan and Hudson, 2014). At the same time, within-country inequality has increased in many countries and triggered controversies and protests (Chin and Culotta, 2014). Obviously, high inequality is *per se* not desirable: it increases the risk of social tension and incentivises poverty-driven emigration. Notwithstanding, rising within-country inequality may have side effects, for instance in the environmental domain, that have not yet been sufficiently understood.

The Environmental Kuznets Curve (EKC) hypothesis postulates an inverted U-shaped relation between per capita income and per capita emissions and has been frequently studied.[1] The economic appeal of the EKC is the presumed automatism driving down emissions during the course of economic development, possibly supported by international trade and investments.[2] The EKC, however, deals with countries' aggregate income, whereas the connection between income distribution and emissions is hardly researched and controversial. Hence, the following article addresses the inequality-emissions nexus from a conceptual and econometric point of view. Given the urgency of the climate change challenge, the following article relates countries' per capita CO_2 emissions, or alternatively energy intensities, to within-country inequality.[3] Deeper insights in

E-mail address: huebler@iuw.uni-hannover.de (M. Hübler).

[1] The original Kuznets Curve hypothesizes going back to Kuznets (1955) postulates an inverted U-shaped relation between per capita income and inequality. For the EKC version, Selden and Song (1994) (page 147) find four possible explanations: "(i) positive income elasticities for environmental quality; (ii) changes in the consumption of production and consumption; (iii) increasing levels of education and environmental awareness; and (iv) more open political systems."

[2] It is debatable, whether due to declining emissions intensities, total emissions will approach zero in the long-term or keep on growing along with economic growth (Perman et al., 2011 chapter 2).

[3] Energy efficiency improvements are one of the most important measures to reduce CO_2 emissions (cf. Pacala and Socolow, 2004). Hübler and Keller (2010 page 63) note: "Although the EKC is a well-known concept and is regarded as a stylized fact in environmental economics, its existence has recently been challenged on both theoretical and empirical sides (e.g., Stern, 2004; Siebert, 2005). The EKC has traditionally been applied to emissions of local pollutants, but recent studies have also applied this concept to CO_2 emissions (e.g., Mazzanti et al., 2006 [authors' note: more recently published as Musolesi et al., 2010]) as well as energy intensity (Galli, 1998)."

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this nexus can be relevant for policy makers, especially in emerging economies, as well as for climate-economy modellers.[4]

Few scholars have studied the inequality-environment nexus and found contradicting results. Boyce (1994) argues that greater equality of power and income between beneficiaries of and sufferers from environmental degradation reduces environmental degradation. Torras and Boyce (1998) empirically confirm this argument for several pollutants but do not take into account CO_2. Though Scruggs (1998) challenges their findings both on the theoretical and the empirical side. Magnani (2000) finds that higher income equality has a positive effect on public research and development (R&D) expenditures of OECD[5] countries. She argues based on the median voter's preference for environmental amenities and a utility function depending on relative income. Likewise, Baek and Gweisah (2013) find that higher equality reduces CO_2 emissions in the short- and long-term in the United States.

On the opposite, Ravallion et al. (2000) and Heerink et al. (2001) show that higher inequality across households can reduce aggregate environmental degradation. Using cross-country data, Heerink et al. (2001) find that higher inequality indeed significantly reduces CO_2 emissions. Borghesi (2006) confirms Ravallion et al.'s (2000) previous outcome that higher inequality within countries significantly reduces CO_2 emissions in regressions with pooled panel data and shows that this result does not hold in regressions with fixed-effects. Nikodinoska and Schröder (2016) find that higher taxes on German car fuels raise inequality but dampen emissions.

On the conceptual side, the following article draws on Ravallion et al. (2000) and Heerink et al. (2001) by explaining the economic mechanisms that can lead to a concave or convex relation of emissions attributed to households' consumption to their income (technology argument) and by illustrating the connection between the micro- and macro-economic EKC (aggregation argument). It argues accordingly, given a concave (convex) micro-economic relation, rising inequality will ceteris paribus decrease (increase) macro-economic emissions ("rich and efficient" versus "poor and prudent").[6]

On the empirical side, the following article contributes to the literature dealing with the inequality-environment nexus by using a large up-to-date dataset of industrialized as well as developing countries and by including explanatory variables from the context of international trade and Foreign Direct Investment (FDI) (about 150 countries and the years 1985 until 2012 from World Development Indicators, 2014). It uses per capita CO_2 emissions or, as a new indicator in the inequality context, the energy intensity of GDP[7] as the dependent variable.

Whereas a few scholars have applied quantile regressions (Mills and White, 2009, Flores et al., 2014) or semi-parametric methods (Azomahou et al., 2006) to the assessment of the EKC hypothesis, this article applies them to the assessment of the inequality-emissions nexus and the trade/FDI-emissions nexus. In this way, emissions (or energy intensities) and their driving forces can be analyzed at different stages of countries' techno-economic development, represented by different quantiles of the conditional (emissions/energy) distribution.[8] To this end, a semi-parametric simultaneous-quantile regressions approach[9] will be utilized, which allows the direct comparison of the estimates for different quantiles. It also allows the non-parametric assessment of the EKC hypothesis without assuming a quadratic or cubic income-emissions relation (cf. Azomahou et al., 2006).

The results of the simultaneous-quantile regressions with pooled data suggest that *higher inequality reduces per capita CO_2 emissions as well as energy intensities* ("rich and efficient" case). Though panel estimations with country fixed-effects fail to yield a robust, significant inequality-emissions or -energy nexus.

The results underline the relevance of estimating the drivers of energy use and emissions at different quantiles, representing different stages of techno-economic development. The estimated elasticity of per capita CO_2 emissions (energy intensities) with respect to changes in the Gini index increases in the basic regressions from about -0.4 (-0.5) at low quantiles to about -1.2 (-1.5) at high quantiles. The estimated elasticity of per capita CO_2 with respect to GDP decreases from about 1.2 at low quantiles to about 0.9 at high quantiles. This result accords with the first phase of the EKC. For energy intensity as the dependent variable, on the contrary, the corresponding elasticities decrease from -0.1 to -0.4. For per capita CO_2 as a function of the trade intensity (openness), an inverted U-shape is found within the positive domain with statistically significant elasticities of 0.1 to 0.4 and the maximum located at the 60% quantile. A similar pattern is found for energy intensities with the maximum located at the 30% quantile. Evidence for energy or emissions savings via trade or FDI is at best found for the most energy-/emissions-intensive countries.

The article is structured as follows. Section 2 explains the inequality-emissions nexus and the econometric model. Section 3 describes the data, the methodology as well as the results of the different quantile regressions and discusses them. Section 4 concludes.

2. Framework

2.1. Inequality-emissions nexus

This subsection explains how households' income and economy-wide emissions are connected and based on this, in which direction and why higher inequality can affect economy-wide emissions (for a formal setup see the supplementary appendix).[10] We formulate three alternative hypotheses:

Hypothesis (1). *Households' contributions to the economy's emissions are concave in household income*. Equivalently, a household's emissions increase less than proportionally or decrease more than proportionally when the household's income rises ("rich and efficient" case). If inequality increases, i.e., ceteris paribus income is shifted from households with lower to households with higher income, economy-wide (per capita) emissions will decrease. This relation has formally been derived by Ravallion et al. (2000) and Heerink et al. (2001).

(i) Concavity will be supported if firms paying higher wages and returns on capital investments to households are at the same time more energy-/CO_2-efficient. This will be fulfilled when higher total factor productivity also reduces energy inputs. (ii) Concavity will be supported if households' consumption patterns and the resulting *direct CO_2 emissions* change with income in such a way that the induced *technique and composition effects* (cf. Grossman and Krueger, 1993) reduce the CO_2 intensity of the economy. For

[4] The integrated assessment community has recently begun to implement distributional aspects in the welfare functions of climate-economy models (cf. Dennig et al., 2016) while they have not been present in these models so far (e.g. Hübler et al., 2012).

[5] The Organisation for Economic Co-operation and Development.

[6] It is questionable whether the macro-economic EKC also holds at the micro-level. Hübler (2016), for example, identifies no EKC for deforestation activities of rural households in Southest Asia. He shows that not higher household income but education, higher relative affluence, younger age, self-employment and a higher value of assets significantly reduce deforestation.

[7] Gross domestic product.

[8] Section 3.1 (Fig. 3) provides descriptive statistics for selected countries illustrating that the emissions-inequality nexus differs depending on the per capita CO_2 emissions level (quantiles).

[9] This procedure generates a bootstrapped estimate of the variance-covariance matrix with between-quantile blocks (Stata, 2015, pages 2023ff.; Cameron and Trivedi, 2010, chapter 7).

[10] Inequality is measured at the micro-economic level based on households' (annual) income (or consumption) values (cf. World Development Indicators, 2014, the Gini index and its measurement). Wealth inequality is likely higher and not necessarily correlated with income (cf. Wolff and Zacharias, 2009, for the United States).

example, households may demand more eco-products, which are less affordable at lower income levels. (iii) Concavity will also be supported if households' consumption of fossil fuels and the generated *direct CO_2 emissions* are dampened with higher income via the use of more energy-/CO_2-efficient technologies, which are less affordable with lower income, and/or environment-friendly behavior is fostered by higher income.

As a consequence, income redistribution from low to high income levels overall results in an environment-friendly behavioral change and a shift to energy-/CO_2-efficient technologies, which we call the *technology argument*. Note that for Hypothesis 1 to hold it is not relevant whether redistribution occurs around a point at the maximum, within the rising or the falling branch of the EKC.[11]

Fig. 1 summarizes and illustrates the inequality-emissions nexus under the concavity assumption. As an extension of Heerink et al.'s (2001) presentation, the figure describes the relation between income and emissions not only at the household level (subfigure a) but also at the economy-wide level (subfigure b) and derives the connection between both levels (for a more detailed description see the supplementary appendix). It turns out that under the concavity assumption, higher inequality shifts the whole EKC downward.

Hypothesis (2): *Households' contributions to the economy's emissions are convex in household income*. Equivalently, a household's emissions increase more than proportionally or decrease less than proportionally when the household's income rises ("poor and prudent" case). Based on arguments opposite to that of Hypothesis (1), ceteris paribus higher within-country inequality raises a country's emissions intensity and hence (per capita) emissions.

(i) Convexity will be supported if firms paying higher wages and returns on capital investments to households, are at the same time less energy-/CO_2-efficient. This relation may, for example, apply to information technology (IT) firms running huge energy consuming IT equipment. Referring to aspects (ii) and (iii) above, energy-/CO_2-intensive services and goods, such as inter-continental flights or heavy, energy-intensively produced cars with powerful, fuel-consuming engines, are hardly affordable at low income levels, but increasingly demanded by high-income households. As a consequence, an income shift from poor to rich households results in a higher share of energy-/CO_2-intensive goods and services in consumption and hence higher (per capita) emissions of the economy. Under the convexity assumption, higher inequality would shift the whole EKC upward (not shown in Fig. 1).

Hypothesis (3): *Households' contributions to the economy's emissions are proportional to household income*. In contrast to Hypotheses (1) and (2) above, consumption patterns and associated technologies are constant over income levels. As a result, the emissions intensity and economy-wide (per capita) emissions become independent of the income distribution.

Hypotheses (1) and (2) describe two coexisting opposing effects. It is an empirical question, whether one effect dominates so that either Hypothesis (1), (2) or (3) prevails. Moreover, the dominance of a hypothesis can vary with the stage of techno-economic development and hence emissions. In other words, the idealized graph sketched by Fig. 1 (a) can be concave at some stages of development (in some countries) and convex at other stages (in other countries).

[11] It is not relevant, whether marginal household emissions are greater or less than zero. If they are greater than zero, the *scale effect* dominates the technique and composition effect. If they are less than zero, the technique and composition effect dominate. To validate Hypothesis 1, it suffices that the *increase in household emissions* due to higher income is *less than proportional*. Likewise, if households' emissions fall in income, this decrease must be *more than proportional* to validate Hypothesis 1. Via technique and composition effects, consumption driven by higher income can reduce economy-wide (per capita) emissions (negative marginal emissions in the falling branch of the EKC) without waiving consumption.

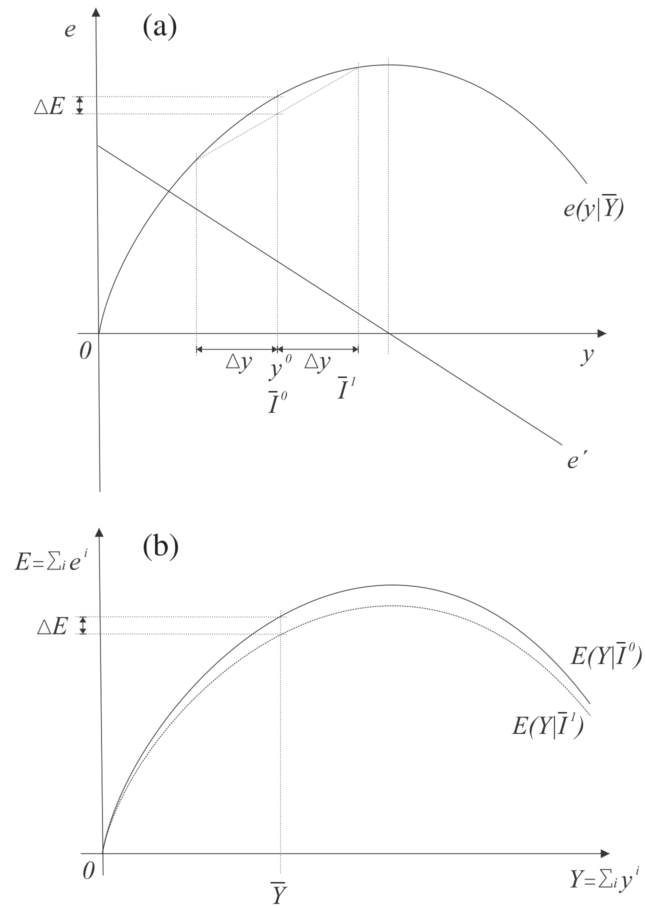

Fig. 1. The inequality-emissions nexus. *Notes:* (a) Illustrates the relation between household i's income, y, and its contribution to economy-wide emissions, e, following Heerink et al. (2001) as well as its marginal emissions, e', given a constant economy-wide income level, $\bar{Y}$. (b) Illustrates the relation between economy-wide income, Y, and economy-wide emissions, E, aggregated over households, i, given a constant inequality level, $\bar{I}$ at the household level (always referring to country c at time t). Δy denotes a redistribution of income which increases inequality from $\bar{I}^0$ to $\bar{I}^1$, and results in a reduction of economy-wide emissions by ΔE.

2.2. Econometric model

To evaluate the hypotheses, we express per capita emissions by assuming a multiplicative exponential (Cobb-Douglas type) relationship:

$$\frac{E_{ct}}{P_{ct}} = \prod_n T_{ctn}^{\beta_{Tn}} \cdot I_{ct}^{\beta_I} \cdot \left(\frac{Y_{ct}}{P_{ct}}\right)^{\beta_Y} \tag{1}$$

E_{ct} represents economy-wide emissions and P_{ct} the population size, defined for each country, c, and year, t. n indicates a number of determinants of the emissions intensity, $\xi_{ct}(\vec{T}_{ct}, I_{ct})$, which is a function of the vector $\vec{T}_{ct}$ of n technology- and industry-related variables, including openness for international trade and international investments, as well as of inequality, I_{ct}. Y_{ct} is a country's GDP in a specific year. The emissions intensity and per capita GDP are multiplied (to obtain a theory-consistent specification, see Eq. 4 in the supplementary appendix); and the n determinants of the emissions intensity are multiplied as well. Accordingly, the determinants are interdependent but neither clear complements nor clear substitutes. As motivated in the previous subsection, the effects of redistribution (changing I_{ct}) depend on the sectoral and technological characteristics of the economy (represented by T_{ctn}). The β-exponents can be interpreted as elasticities with respect to a determinant's impact on the emissions intensity.

Taking natural logarithms, rearranging terms and adding a constant, γ, and an error term, ε_{ct}, leads to the following linear log-log specification with per capita emissions as the dependent variable:

$$\ln\left(\frac{E_{ct}}{P_{ct}}\right) = \beta_I \cdot \ln\left(I_{ct}\right) + \beta_Y \cdot \ln\left(\frac{Y_{ct}}{P_{ct}}\right) + \vec{\beta}_T \cdot \ln\left(\vec{T}_{ct}\right) + \gamma + \varepsilon_{ct} \quad (2)$$

Here the determinants of the emissions intensity, ξ_{ct}, are written as the product of the row-vector of n coefficients, $\vec{\beta}_T$, and the logarithm of a column-vector of n variables, $\vec{T}_{ct}$, which serve as control variables. The β-coefficients and the constant, γ, represent the parameters that will be estimated.

2.3. Explanation of the variables

This subsection explains the macroeconomic variables (indicators) used for the descriptive and econometric analyses and their expected economic effects. Table 1 summarizes the definitions of the variables and their symbols together with the units of measurement.

Per capita emissions, $\frac{E_{ct}}{P_{ct}}$, symbolized by CO2 in the data analysis, are measured as the *CO_2 emissions* generated by firms and households residing *within* country *c* in year *t*, divided by the number of country *c*'s inhabitants. Note that indirect CO_2 emissions embodied in imported goods and services are *not* captured. Emissions embodied in exported goods are not subtracted either. This means, this specification follows the *production-based* approach to emissions accounting.

Inequality, I_{ct}, is measured with the help of the *Gini index*, symbolized by GIN. GIN refers to the consumption or income values (depending on the country-specific data) of households residing in country *c* in year *t* (cf. World Development Indicators, 2014). It takes the value of zero in case of perfect equality (all households enjoy the same income) and one in case of perfect inequality (all income allocated to a single household). The inequality-emissions nexus was explained in Section 2.1.

In the empirical analysis, *per capita GDP*, $\frac{Y_{ct}}{P_{ct}}$, is denoted by GDP. Scholars often use a quadratic GDP term with an expected negative sign to describe the stage-dependent EKC relation (cf. Stern, 2004). The quadratic term is, however, a convenient ad-hoc assumption. We introduce a novel approach to the identification of the EKC. We estimate the impact of GDP on CO2 at different positions of the CO2 distribution. (For further explanations see Section 3.2.) Per capita emissions are in turn related to the stage of techno-economic development and hence GDP. For the first phase of development, as illustrated by Fig. 1 (b), we expect a positive marginal impact of GDP on CO2 represented by a positive estimated elasticity parameter. We expect that this marginal impact decreases with higher CO2, because the slope of the inverted U-shape declines within its left branch. Yet in the second phase, having reached the emissions maximum, the marginal impact is expected to turn negative. Since CO2 is expected to decline in GDP during the second phase, this results in an overlap of the two phases in the CO2 space. If the negative impact in the second phase exceeds the positive impact in the first phase, we will overall measure a negative coefficient of GDP. If not, the negative impact is expected to dampen the positive effect, while the overall impact will be positive. Another possibility is that the data only cover either the first phase *or* the second phase of the EKC so that either a positive or negative effect will emerge.

Table 1
Definition of the variables.

Var.	Definition	Unit
CO2	CO_2 emissions per capita	t/capita
ENI	Energy intensity (of GDP)	kgoe/2011-PPP-$1000
GDP	Gross domestic product per capita	2011-PPP-$/capita
PGA	Local pump price for gasoline	US-$/l
GIN	Gini index (of inequality with 100 ≡ max. ineq.)	%
IND	Industry share (value added in GDP)	%
INV	Domestic investment intensity (of GDP)	%
FDI	Foreign Direct Investment inflow intens. (of GDP)	%
TRD	Trade (export + import values) intensity (of GDP)	%
EDU	Tertiary education (enrollment) rate	%

Data source: According to World Development Indicators (2014).
Notes: Investment refers to gross fixed capital formation.

The analysis includes a number of control variables subsumed under $\vec{T}_{ct}$ in Eq. (2). The variables are related to technical progress, international trade and economic development. One argument for the EKC relation is the transition from an agriculture-based to an industry-based and further to an innovation-based economy. In order to model this transition more explicitly, we include the *share of the industry sector's value added in GDP* and denote it by IND. We expect that especially during the first phase of development a larger industry share results in higher (per capita) emissions (compared to an agriculture-based economy). In the second phase of development after the emissions peak, efficient high-tech industries and products may play a more important role so that a larger industry share brings about emissions savings.[12] As for GDP, the second phase overlaps with the first phase in the CO2 space so that the overall impact can be positive or negative.

The economic transition with an expanding industry share and the utilization of technologies requires *capital investments*. Therefore, we include gross fixed capital formation divided by GDP as a measure for investment and call it INV. Like for IND, one can expect an emissions-increasing effect of investments unless investments involve advanced efficient technologies in later stages of development. Whereas INV refers to domestic investment, FDI refers to *inflows of Foreign Direct Investment*, measured in intensity form relative to the destination country's GDP, too. FDI is more likely to induce technical progress than INV, because it involves activities of innovative international enterprises that likely create technology spillovers (Saggi, 2002), which might diminish emissions (Perkins and Neumayer, 2012). Likewise, *international trade*, TRD, might induce technology spillovers and productivity gains via increased competition and firm selection (Melitz, 2003) that might diminish per capita emissions (Perkins and Neumayer, 2012). We measure trade in intensity form (openness) as the sum of the values of imports and exports divided by GDP. TRD may also indicate the scope of imports and exports of emissions embodied in traded goods and services (consumption-based accounting, leakage and pollution haven; Cole, 2004). The trade intensity does, however, ex ante not indicate whether there is a positive or negative or balanced net import of emissions. Besides, in the context of technical change and technology spillovers, it is widely acknowledged (for example Griffith et al., 2004) that *education* plays a role. To address this aspect, we draw on the enrollment rate in tertiary education, denoted by EDU.

Finally we add the *price for fossil fuels* in the form of the local (domestic) pump price for gasoline, labeled PGA, as an explanatory variable. PGA serves as a control variable that captures country-specific price-driven incentives to use fuels more or less efficiently, created by fuel taxes and subsidies, as well as the development of the oil price.[13] Lower fuel consumption will decrease CO2.

CO_2 emissions are to a large part generated by energy use. Hence, leaving the decarbonization of energy supply aside, energy efficiency-related technical progress can be expected to lower energy use and emissions simultaneously. To study this relation in more

[12] Like Borghesi (2006) or Hübler and Keller (2010) we do not include the shares of the agricultural and the service sector because they are mirror-inverted to the share of the industry sector and likely create collinearity.

[13] Bachmeier & Griffin (2003, page 775) find that "daily regional gasoline prices adjust almost instantaneously and symmetrically to crude-oil price changes."

detail, we use the *energy intensity of GDP*, symbolized by ENI, as a dependent variable alternatively to CO2 and compare the results.

In the absence of energy efficiency improvements, GDP and total energy use grow in parallel during the course of techno-economic development. Consequently, ENI will stay constant. In the presence of energy efficiency improvements, the energy intensity ENI will decline while per capita GDP grows. In other words, ENI captures the composition and technique effect (cf. Cole, 2006, Hübler and Keller, 2010). On the contrary, since CO2 is measured in per capita terms, it will increase while (per capita) GDP and energy use grow simultaneously. In other words, it additionally captures the scale effect.[14] Consequently, albeit energy efficiency-related technical progress is expected to dampen both, CO2 and ENI, their different definitions may affect the estimated relations in an economic and econometric way. For example, from an econometric perspective, GDP fluctuations or shocks will change ENI — with a negative sign because GDP appears in the denominator of ENI — if energy use reacts in a sluggish way. This does not apply to CO2.

We utilize the same regressors for explaining ENI as for CO2. Hübler and Keller (2010) and Hübler and Glas (2014), for example, study the impact of FDI and imports on energy intensities with similar explanatory variables).

A number of positive interdependencies (complementarities) underpin the multiplicative Cobb-Douglas specification in Eq. (1). For example, it is widely acknowledged that the absorptive capacity depends on education and supports technology spillovers via trade and FDI (see, for example, Hübler et al., 2016). Education, trade and FDI contribute to the industrialization of developing countries, represented by the industry share. Industrialization leads to rising GDP per capita following the EKC story, and so forth.[15]

3. Estimation

3.1. Data description

This subsection describes the data which are taken from the World Development Indicators (2014).

In the original dataset the availability of observations for different countries and years varies strongly across the variables. Because GIN is the variable of main interest, in the pooled data, summarized by Table 2 and used in the following regressions, all observations with missing GIN values have been removed.[16] The remaining data go back to the year 1985 (for twelve countries) and reach 2012 (for 25 countries); they cover overall 149 countries, resulting in an unbalanced panel with over 1000 observations. — The weights of all countries in the sample in terms of the number of available years with GIN data per country can be found in Table A1 in the supplementary appendix. — For other variables, however, less observations are available, e.g., 940 for GDP and only 438 for PGA, which reduces the scope of the regressions including these variables.

Figs. 2 and 3 illustrate the inequality-emissions nexus in a descriptive way. Fig. 2 plots the per capita CO_2 emissions of the sample countries[17], for which CO2 and GIN data are available for the year 2010, over their Gini indexes (in %) in 2010. The five highest

Table 2
Descriptive statistics of the pooled data.

Var.	N. obs.	Median	Mean	Std. dev.	Min.	Max.
CO2	1023	2.14	3.94	3.99	0.02	20.21
ENI	825	128.51	157.98	104.63	37.58	886.00
GIN	1072	39.26	40.48	10.36	16.23	74.33
GDP	940	8508.37	11,959.03	11,154.51	484.72	65,780.91
IND	995	29.80	30.46	8.94	7.98	76.63
INV	1026	21.13	22.08	6.96	4.88	67.98
FDI	1026	2.56	4.01	5.79	−16.15	88.10
TRD	1038	71.18	77.79	37.44	12.37	280.36
PGA	438	0.83	0.90	0.43	0.02	2.52
EDU	783	34.01	35.37	22.65	0.34	108.09

Data source: World Development Indicators (2014).
Notes: Numbers without logarithms.

per capita emitters within the sample in 2010[18] were the United States of America (USA), Kazakhstan (KAZ), Canada (CAN), Estonia (EST) and Norway (NOR), whereas the five lowest per capita emitters[19] were Ethiopia (ETH), Malawi (MWI), Mali (MLI), Madagascar (MDG) and Nepal (NPL). The five most unequal countries in 2010 with available data for this year were Zambia (ZMB), Colombia (COL), Lesotho (LSO), Honduras (HND) and Panama (PAN), whereas the five most equal were Ukraine (UKR), Slovenia (SVN), Iceland (ISL), Czech Republic (CZE) and Norway (NOR). The figure also plots a line of fitted values for 2010 generated via an *Ordinary Least Squares (OLS)* regression of CO2 on GIN including a constant. This regression basically follows the approach characterized by Eq. (2) albeit it excludes logarithms and control variables. The simple OLS regression indicates a *negative* relation between inequality and per capita emissions. The following subsection will evaluate this relation in more detail.

Fig. 3 looks at selected countries from a panel perspective. Here, the Gini index (in %) is plotted over per capita CO_2 emissions in order to see which countries are located in low, medium and high areas of the cross-country emissions distribution. This perspective motivates the panel estimation of the effect of GIN on CO2 at various quantiles of the conditional distribution. — Fig. A1 in the supplementary appendix depicts the cumulative distribution of CO2 for the pooled dataset. The graph illustrates that the top say 5% of emitters generate per capita CO_2 emissions far beyond those of the lower say 95% of emitters. — For each of the seven selected countries, Brazil, Cambodia, Canada, China, Germany, Norway and the USA, Fig. 3 plots GIN-CO2-dyads for a number of years, depending on the data availability. — For full descriptive statistics of the seven countries in 2010/11 see Table A2 in the supplementary appendix. — Basically all seven countries were subject to increasing inequality between the mid-1980s and the early 21st century, which underlines the relevance of this research topic. Cambodia exhibits the lowest per capita CO_2 emissions among the seven and medium inequality, which was first rising and then falling between 1994 and 2011. It represents a poor Least Developed Country (LDC) with minor industrial activity and hence low emissions. Similar patterns can be found in African countries, albeit in some cases inequality is higher. Although China and Brazil are major emitters in absolute terms, their per capita emissions are relatively low. China's impressive economic growth was accompanied by strongly increasing inequality between 1987 and 2008 within a range comparable to Cambodia. In 2010 inequality in China started to decline. Furthermore, Brazil is known for its high inequality, which peaked in 1989 and then declined until 2012. Similar patterns can be found for other Latin American

[14] According to the Kaya identity, it is CO2 = EMI · ENI · GDP with EMI symbolizing the CO_2 emissions intensity of energy use and CO2 and GDP measured in per capita terms.

[15] Empirically, these interdependencies must not be pronounced in order to avoid collinearity, which is fulfilled by the data (see the next section and Table A3 in the supplementary appendix).

[16] Whereas missing values occur frequently, negative (for FDI disinvestment) or zero values occur rarely and will drop out when taking logarithms in the econometric analysis.

[17] For a description of all country abbreviations see World Development Indicators (2014).

[18] Qatar, Trinidad and Tobago, Kuwait, Aruba, Luxembourg, Brunei Derussalam, Oman, The United Arab Emirates, Saudi Arabia and Bahrain exhibited the highest CO2 in 2010 according to the data, yet the GIN data are missing. Likewise, other countries might drop out due to missing values.

[19] Burundi, Chad, The Democratic Republic of Congo, Rwanda and The Central African Republic exhibited the lowest CO2 in 2010, yet the GIN data are missing.

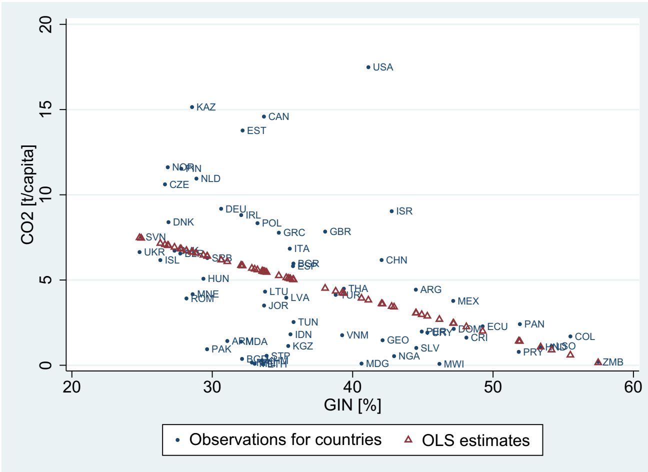

Fig. 2. Countries' per capita CO_2 emissions over their Gini indices in 2010. *Data source:* World Development Indicators (2014). *Notes:* Numbers without logarithms.

countries. While Germany and Norway are among the medium emitters in per capita terms, Norway[20] features low inequality, which is typical for Scandinavian countries. The USA and Canada, on the contrary, are high emitters with medium inequality. Canada exhibits lower CO_2 per capita as well as lower inequality than the USA. The following quantile regressions will reveal whether the location of countries within the conditional distribution indeed matters for the significance and importance of the drivers of emissions.

3.2. Quantile regression approach

In this context, the quantile regressions approach is useful for two reasons.

First, whereas usual regressions refer to the mean, quantile regressions refer to the median, represented by the 50% quantile, or other points in the conditional distribution of the dependent variable, such as the 25% quantile (Cameron and Trivedi, 2010, chapter 7). The regressions describe quantiles of the conditional distribution as linear functions of the explanatory variables (see `qreg` in Stata, 2015, pages 2023ff.). – Table 2 reports the mean as well as the median values of the variables under scrutiny. The differences between the median and the mean are in several cases large, particularly for CO2, ENI and GDP. – Quantile regressions have the advantage to be more robust to outliers than conventional mean regressions (Cameron and Trivedi, 2010, chapter 7).

Second, following the inverted U-shape EKC hypothesis, the level as well as the marginal change in emissions vary during the course of economic development as depicted by Fig. 1 (b). At low stages of techno-economic development (represented by low income or GDP on the left-hand side of the graph) emissions levels are low and emissions increase strongly on the margin. These low stages correspond to (emissions) quantiles between 0 and say 0.5 (50%), i.e., from the lowest emissions in the sample until the median emissions in the sample (compare summary statistics in Table 2). At further stages of development until the emissions maximum in the sample is reached, corresponding to quantiles between say 0.5 and 1, emissions are higher but increase less strongly on the margin. At the maximum, marginal emissions changes are zero in theory. At higher stages of development, emissions are expected to fall more and more rapidly. In terms of emissions quantiles, however, higher stages lead back to lower emissions quantiles, say in the area 1 to 0.5 and thereafter 0.5 to 0.

[20] Norway's inequality declined after a peak in 2004.

In this way, the quantile regressions approach allows us to *examine the Environmental Kuznets Curve (EKC) hypothesis in a new way*. — The resulting overlap of the first and second branch of the EKC, however, is a disadvantage of this approach. — Due to the anticipated stage-dependent behavior of emissions, we also expect different magnitudes and possibly directions of the estimated effects that the explanatory variables exert on CO2. (For further explanations see Section 2.3.) Consequently, the evaluation of the hypotheses derived in Section 2.1 may also vary across quantiles. This view is supported by the descriptive statistics depicted by Fig. 3. The stage dependence may also involve heteroscedasticity, in which case quantile regressions are suitable for dealing with heteroscedastic data (Cameron and Trivedi, 2010, chapter 7).

3.3. Estimators and tests

To take the dependency of the estimated effects on the techno-economic stage of development into account, we have envisaged to perform *simultaneous-quantile regressions* and plot the estimated coefficients as described by Cameron and Trivedi (2010, chapter 7). This semi-parametric approach generates a bootstrapped estimate of the variance-covariance matrix with between-quantile blocks, which takes interdependendies between the estimations for different quantiles into account and allows the direct comparison of the coefficients for different quantiles (see sqreg in Stata, 2015, pages 2023ff.). We carry out 100 bootstrap replications and include all quantiles between 5% and 95% in 5 percentage point steps.

The available unbalanced panel data are, however, subject to a very limited time dimension for a number of countries (see Section 3.1 and Table A1 in the supplementary appendix). This complicates the application of full-fledged panel data techniques. As a consequence of the limited time dimension, in a fixed-effects (FE) estimation with country-specific binary variables, a number of fixed-effects will drop out due to collinearity or leave little remaining variation. This is especially true for the GIN regressor because the country-specific variation of inequality over time is often limited. — Though, *F*-tests indicate that country fixed-effects are preferable to using pooled data. A Hausman test for fixed- versus random-effects (based on standard mean value regressions) clearly rejects the null hypothesis of no systematic difference in the coefficients in all specifications that will be estimated; this outcome is clearly in favor of a fixed-effects specification. — The reduction of the dataset to a balanced panel with a sufficient time dimension, on the contrary, would drastically reduce the number of observations. Panel estimations

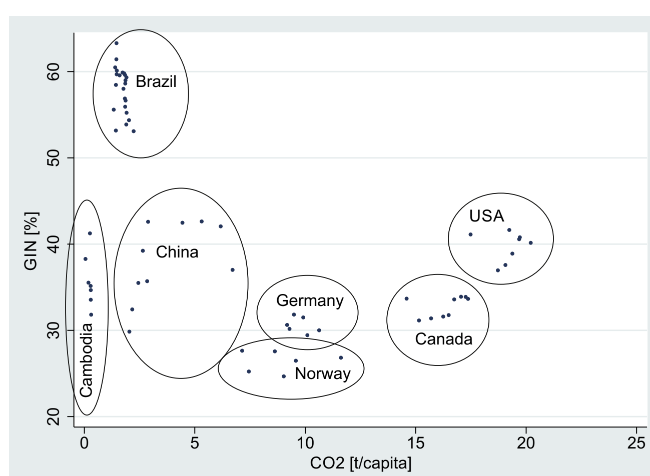

Fig. 3. Countries' Gini indices over per capita CO_2 emissions in the available years. *Data source:* World Development Indicators (2014). *Notes:* Numbers without logarithms.

also impede the application of the semi-parametric simultaneous-quantile approach. Therefore, following the EKC literature, pooled regressions are chosen as the preferable option presented in the following analysis.

Borghesi (2006) referring to Ravallion et al. (2000), however, has shown that, when substituting pooled regressions by fixed-effects panel regressions, the estimated effect of inequality on emissions can become statistically insignificant and even switch its sign. In order to take this into account, we will carry out a *robustness check with country fixed-effects regressions* as well. The robustness check will, however, not make use of the simultaneous-quantile approach but estimate the regressions for different quantiles (0.1, 0.25, 0.5, 0.75, 0.9) independently.

An Augmented-Dickey-Fuller-based Fisher-type test (Choi, 2001) rejects the null hypothesis of all panels containing a unit root. Due to the limited time dimension, autocorrelation is less relevant. Heteroscedasticity and possible outliers are addressed by the bootstrapped quantile regressions approach. Table A3 in the supplementary appendix shows that the correlations across the explanatory variables are relatively low (correlations with the dependent variables, CO2 and ENI, are allowed to be higher). The correlations of 0.45 between PGA and GDP and 0.71 between EDU and GDP are exceptions; therefore the regressions jointly including these variables should be treated with caution. To avoid collinearity and because of the limited number of observations, we restrict the number of simultaneous regressors to four regressors at a time.

3.4. Main results for per capita CO_2 emissions

This subsection describes and interprets the results of the pooled simultaneous-quantile regressions with per capita CO_2 emissions, CO2, as the dependent variable based on Eq. (2). All variables are computed in logarithms. We concentrate on the graphical representation of the results depicted by Figs. 4 to 6. Detailed tables with results for all variables and quantiles are available upon request (120 regressions with in total 600 estimated parameters[21]). Throughout the graphs, the horizontal axis indicates quantiles of the CO2 distribution. Note that in all illustrations the tales (0.05 and 0.95) should be treated with caution, because they can be driven by a small number of extreme values (see grqreg for the Stata software).

Each graph describes the effect of a specific regressor, such as GIN, on CO2. For each (conditional) quantile, the vertical axis plots the estimated coefficients (marginal impacts in the form of log-log elasticities) of the specific regressor. The shaded areas indicate the corresponding 95% confidence intervals. If the confidence interval encompasses the horizontal zero axis, the corresponding estimate is not significantly different from zero. If the curve of estimated coefficients and the surrounding confidence intervals are located within the positive (negative) domain, the regressor represented by this graph has a significantly positive (negative) impact on CO2. The straight dashed lines indicate OLS estimates of Eq. (2) and their corresponding 95% confidence intervals.[22] Thus, the figures contain the full numerical information obtained from the regressions.

Fig. 4 illustrates the drivers of CO_2 emissions measured in per capita form. This estimation makes use of 863 observations. Depending on the quantile, the pseudo R^2 reaches values between 0.35 and 0.69.

Neglecting insignificant border effects at the left and right tales of the distribution, we find (1) that higher within-country inequality represented by GIN *reduces* CO2 (visible in the quantile as well as the OLS regression results), and (2) that the *magnitude* of this effect *increases in* CO2 represented by the quantile-dependence. The elasticity increases from about −0.35 at low quantiles to about −1.20 at high quantiles, whereas the estimates are sometimes insignificant or positive around the lowest quantiles. At the median (50% quantile) the elasticity estimated for the effect of GIN on CO2 is −0.67. These results *support Hypothesis 1* (see Section 2.1).

While the curve of estimated elasticities for the effect of GDP has a falling slope as well, the curve and its surrounding confidence intervals are located in the positive domain, consistent with the first phase of the EKC. The elasticity decreases from about 1.20 at low quantiles to about 0.90 at high quantiles. The estimated median elasticity for the GDP-CO2 nexus reaches 1.05. The magnitudes are in line with the elasticities estimated by Ravallion et al. (2000) ranging from 0.6 to 1.8. They are lower than Heerink et al.'s (2001) estimates of 3.6 to 5.6.[23]

The EKC storyline assumes that the expansion of the industry sector increases per capita emissions during the course of economic development from an agriculture-based to and industry-based economy. Indeed, the estimated elasticity for the effect of IND supports this storyline in accordance wth Borghesi's (2006) finding. Abstracting from border effects, the estimated elasticity is around 0.6 at most quantiles and exceeds 0.8 at high quantiles. The results for INV suggest that the industrial transition is accompanied by domestic investments that mostly attribute to rising emissions with elasticities from 0.28 to 0.48 at quantiles between 15 and 85%. Yet this effect is not significant for low and high quantiles, which might not be merely a border effect (compare the emissions-saving effect of investments found in the robustness check). Intuitively, investment barriers exist in poor low-emissions countries, whereas investments in richer high-emissions countries may bring about technological advancements that reduce, rather than raise, per capita emissions.

Fig. 5 depicts the quantile regression results in the same fashion as before, now including regressors that describe international investments and trade. This estimation includes 869 observations. The pseudo R^2 drops from 0.68 at low quantiles to 0.32 at high quantiles.

The results for the effects of GIN and GDP resemble those in Fig. 4. In other words, rising inequality reduces environmental degradation with a median elasticity of −0.59. Notably, the decline in the magnitude of the GDP impact at high quantiles is more pronounced (falling clearly below 1). This result is in line with the concavity assumption underlying the EKC. When the EKC reaches maximum CO_2 emissions, the slope of the curve flattens, i.e., the impact of changes in per capita GDP on per capita emissions declines.

The estimated coefficients describing the effect of FDI on CO2 are located in the positive domain, though being statistically significant only around the 40% quantile with elasticities of about 0.04. Statistically significant and negative estimates are only found at very high quantiles (−0.13 at the 95% quantile). This result points to the possibility of emissions savings at advanced stages of economic development with high emissions. Perkins and Neumayer (2012) "find that less CO_2-efficient countries and countries with higher institutional quality experience stronger FDI-weighted CO_2-efficiency spillovers, whereas a higher level of human capital increases receptivity to import-weighted international spillovers." Our result can, however, also be a misleading border effect. Our results for the trade intensity, TRD, on the contrary, do not point to any emissions savings via international technology spillovers. They show an inverted U-shaped relation between TRD and CO2 within the positive domain with statistically significant elasticities of 0.10 to 0.36 with the maximum located at the 60% quantile. This result contrasts with Cole's (2004)

[21] (19 quantile results + one OLS result) • (four regressors + a constant) • (three separate estimations) • (two alternative dependent variables, CO2 or ENI).

[22] Whereas OLS represents a mean regression, the 50% quantile regression represents a median regression which is more robust to outliers than the mean regression.

[23] Like many other studies, Ravallion et al. (2000) and Heerink et al.'s (2001) include GDP per capita in squared form so that their results are not exactly comparable.

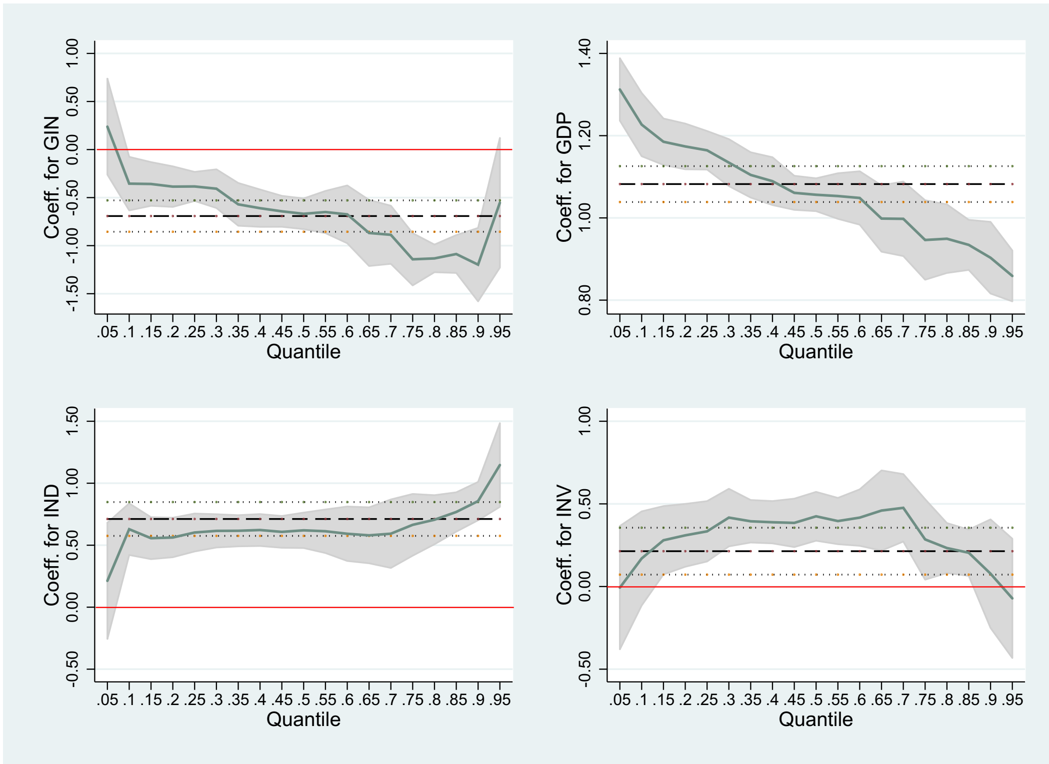

Fig. 4. Drivers of per capita CO_2 emissions, Kuznets curve storyline. *Data source:* Own estimates based on World Development Indicators (2014). *Notes:* Estimated coefficients (marginal impacts in the form of log-log elasticities) from pooled simultaneous-quantile regressions with 863 observations for the four regressors GIN, GDP, IND and INV on CO2 emissions, plotted over quantiles of the CO2 distribution. The shaded areas indicate 95% confidence intervals. The straight dashed lines indicate OLS estimates and their corresponding 95% confidence intervals.

estimated elasticity of −0.004 for the trade intensity with respect to CO_2 emissions.

Fig. 6 focuses on further national aspects that may influence CO2. In these estimations, however, the number of observations drops to 303. The pseudo R^2 declines from 0.78 at low quantiles to 0.43 at high quantiles.

The estimates for GIN and GDP confirm previous findings, albeit the decline in the impact on GDP with increasing quantiles is less pronounced and the median coefficient for GIN reaches −0.91. Tertiary education, EDU, as a national source of knowledge raises emissions with a constant elasticity of around 0.4 over the CO2 quantile space. According to these estimates, education seems to foster emissions-intensive industrial expansion rather than emissions-saving technological progress or environmental consciousness. A higher pump price of gasoline, PGA, reduces CO2 as expected; the estimated price elasticity is between −0.39 and −0.45.

3.5. Alternative results for energy intensities

This subsection describes and interprets the results of the pooled simultaneous-quantile regressions with energy intensity, ENI, as the dependent variable. The inclusion of regressors follows exactly the procedure described in the last subsection. Again, all variables are computed in logarithms. The explanatory power is lower than in the CO2 regressions; the pseudo R^2 drops below 0.1 at low quantiles and exceeds merely 0.25 at higher quantiles.

Figs. A2 to A4 in the supplementary appendix illustrate the results. The outcomes overall resemble those for CO2. In particular, higher inequality, represented by GIN, reduces ENI with elasticities that rise in the ENI quantile space from −0.5 to −1.5. These elasticities are somewhat higher than those for CO2. Notably, the congruence of the results for CO2 and ENI indicates that CO_2 emissions are mainly driven by energy use and only to a small extent by the carbon intensity of energy use or by other sources of CO_2 emissions.

There is, however, one considerable difference. In Figs. A2 to A3 the GDP-ENI nexus exhibits a similar declining trend in the quantile space as previously the GDP-CO2 nexus. Though in all Figs. A2 to A4 the GDP-ENI curve is located in the negative domain (with elasticities between −0.12 and −0.38), i.e., higher per capita GDP decreases the energy intensity. Using ENI as the dependent variable, the environmentally beneficial effect of rising GDP, associated with the second phase of the EKC, seems to dominate. This discrepancy between the results for CO2 and ENI highlights that it matters for the impact of GDP whether the dependent variable is measured in per capita or per GDP form. The specification in per GDP form rules out the scale effect, which previously created the positive GDP-CO2 relation (cf. Cole's, 2006 decomposition).

The previous result of emissions increases via a larger industry share IND is confirmed for energy intensities, yet with smaller elasticities (0.18 to 0.38 at quantiles of at least 45%). As before, the statistical and economic significance rises with higher quantiles. The statistical and economic significance of the positive effect of investments INV on ENI is smaller (0.15 to 0.26) than for CO2 but still detectable at medium quantiles (25 to 70%).

As for CO2, the results caution against energy savings via FDI and trade. This finding is in line with Hübler and Keller (2010) who do not find a significant robust effect of FDI inflows or imports on energy intensities of developing countries. Notwithstanding, Fig. A3 suggests energy savings via FDI at the highest quantiles, i.e., in economically advanced, energy-intensive countries. This result can, however, be subject to border effects. Likewise, the positive elasticities (of 0.15 to 0.22) found for international trade, TRD, are statistically significant at relatively low ENI-related quantiles (10 to 40%) and turn weakly significant and negative at the 90% quantile. The lack of evidence for energy

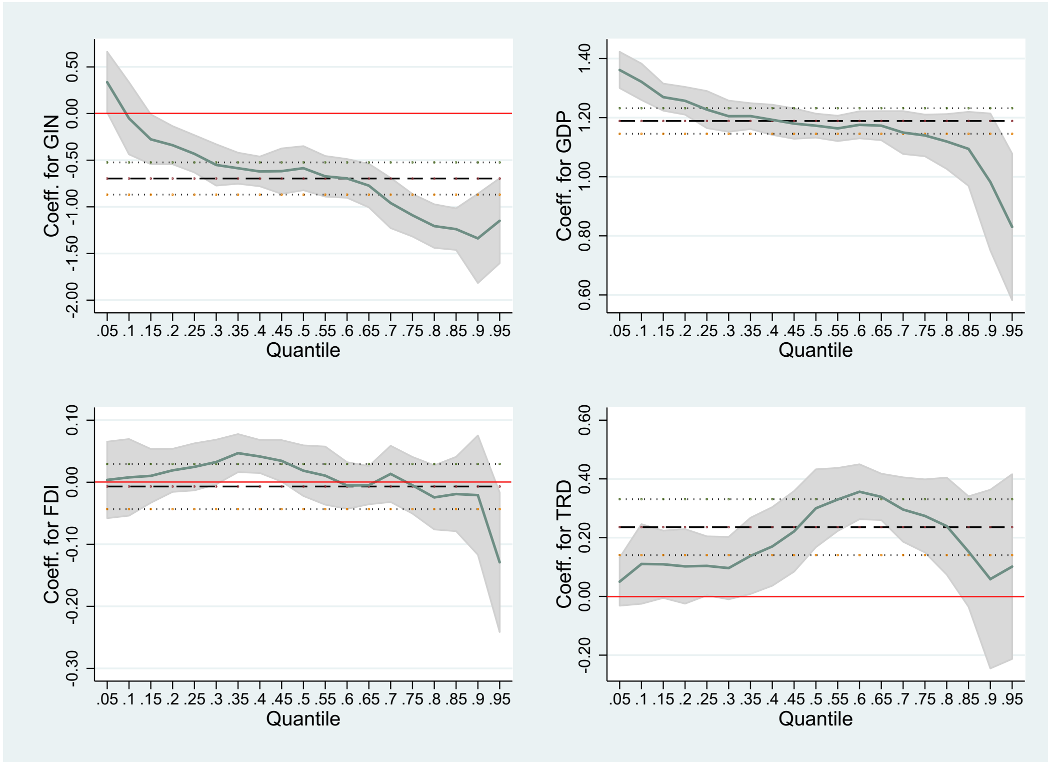

Fig. 5. Drivers of per capita CO_2 emissions, international aspects. *Notes:* Pooled regressions with 869 observations. Analogous to the previous figure.

savings via more intensive trade is in accordance with Cole (2006). It contrasts with Hübler and Glas (2014) who identify improvements of energy intensities at the sectoral level via imports of investment goods. This discrepancy between the findings suggests that specific types of imports in specific sectors generate energy efficiency gains that can hardly be measured at the aggregate macro-level.

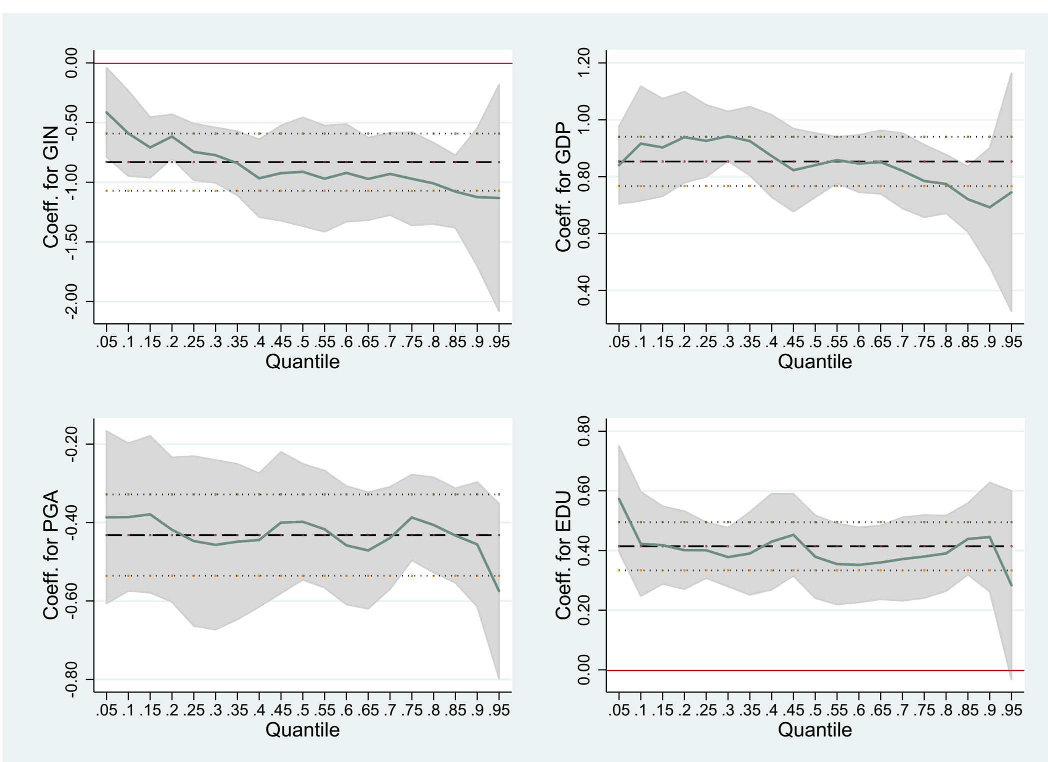

Fig. 6. Drivers of per capita CO_2 emissions, national aspects. *Notes:* Pooled regressions with 303 observations. Analogous to the previous figures.

In the quantiles regressions that address further national aspects displayed by Fig. A4 in the supplementary appendix, the GDP-ENI elasticity varies between −0.23 and −0.33 instead of showing a decreasing trend as in the previous regressions. The pump price for gasoline, PGA, significantly reduces the energy intensity as expected; the estimated price elasticity varies between −0.1 and −0.48. As in the CO2 regressions, tertiary education, EDU, surprisingly increases ENI, but the effect is only significant at low quantiles up to 45% and at the 85% quantile. This outcome might indicate that in developing countries with limited energy availability and unsatisfactory school systems, education fosters energy-intensive production and behavior. In any case, the partly energy-increasing and partly insignificant estimates question a strong role of education in cleaning up production and consumption. They concur with Pritchett's (2001) critical discussion of the role of education in enhancing productivity growth.

3.6. Fixed-effects robustness check results

The results of the panel estimations with country fixed-effects and CO2 (Table A4-A6) or ENI (Table A7-A9) as the dependent variable can be found in the supplementary appendix. The *p*-values in parentheses refer to robust standard errors. Overall, the magnitudes of the estimated effects tend to be slightly smaller than in the pooled regressions, and the statistical significance drops in several cases.

In accordance with Borghesi (2006), the statistical significance of the estimated coefficient for the explanatory variable of main interest, GIN, turns in most cases *insignificant*. This outcome *supports Hypothesis 3*. Whereas the negative sign of the coefficient for GIN with respect to CO2 or ENI is mostly confirmed, its economic significance is often lower than in the pooled regressions. In the median regression including TRD and FDI, the effect of GIN on ENI even switches to weakly significant and positive.

There are at least two possible explanations. First, inequality reflects other country characteristics which are not captured by the available explanatory variables but by the country fixed-effect. In this case, inference with respect to the effects of inequality in the previous subsections is misleading.

Second, the number of observations is overall small compared to the number of parameter values to be estimated; furthermore, for many countries the number of observations over time is small (large N – small T).[24] Additionally, the variation of GIN within time is limited. Especially the regressions including PGA and EDU as explanatory variables restrict the number of observations to about 300 for about 150 parameter values to be estimated. Hence, for CO2 as the dependent variable they do not yield any statistically significant coefficient; even the overall constants are insignificant.

Apart from the regressions with PGA and EDU, the panel estimations mostly corroborate the statistically and economically significant effect of GDP, which increases CO2 (with elasticities between 0.39 and 0.68) but decreases ENI (−0.59 to −0.73) as before. The CO2 and ENI increasing influence of the industry share IND is confirmed in terms of its statistical and economic significance as well (with elasticities between 0.28 to 0.48). The magnitude of this mechanism rises from low to high quantiles; intuitively, emerging economies with a large industry sector are usually energy- and emissions-intensive so that a change in the relative industry size has a large impact on CO2 and ENI. Different to the pooled regressions, the panel estimations do not yield a statistically significant effect of domestic investments, INV, on CO2. In the regressions with ENI as the dependent variable, evidence for the expected negative effect of INV is found; yet the estimate is only at the median statistically significant with a relatively low elasticity of −0.031.

The panel results point to a statistically significant energy-increasing impact of FDI inflows at low quantiles (10 to 25%), though with a small magnitude of about 0.01. A statistically significant impact on CO2 is not detected. Likewise, the trade intensity, TRD, raises energy intensities with a magnitude of about 0.1 at low quantiles (10 to 50%). The previous emissions-increasing effect of TRD is only confirmed for the median, as for energy with an elasticity of about 0.1. Finally, the estimates for PGA and EDU are inconclusive, recalling the small number of observations in these regressions.

3.7. Comparison and discussion

Testing the *EKC hypothesis*, it turned out that higher (emissions) quantiles go along with lower increases in per capita CO_2 emissions driven by GDP growth but not with emissions decreases. The first possible reason is the observation that many high-income economies (such as the USA, Australia and Canada or the Arab oil-rich states) exhibit high emissions as well (except Macao, Singapore, Hong Kong, Switzerland, etc.); this may cause the estimated positive correlation. The second possibility is that the emissions increase during the first phase of the EKC is more pronounced than the expected emissions decrease during the second phase. Following Cole (2006), this implies also that the scale effect of higher income dominates the technique effect (while the role of the composition effect is ambiguous). The third possibility is that the second phase of the EKC lies outside the range covered by the data. This result accords with other findings, for example, by Azomahou et al. (2006).

The negative correlation between *inequality and emissions*, suggested by the pooled regressions, may look surprising, because richer countries have on average lower inequality and higher emissions than poorer countries, while richer households are supposed to consume more energy than poorer households. One discussed explanation for this negative correlation is that due to technique and composition effects, at the micro-economic level, energy and emissions may rise less than proportionally in households' income, which goes along with a negative inequality-emissions nexus at the macroeconomic level. This mechanism could dampen growing energy use and emissions during the course of economic development. The results, however, also indicate that this mechanism vanishes around the lowest quantiles. This could mean, in countries with low income, low emissions and low technology levels, the scope for emissions savings via redistribution is smaller than in countries with higher income, substantial amounts of emissions and better technological capabilities.

Compared to the scarce literature on *inequality and the environment*, this study uses new data including industrialized as well as developing countries at different stages of techno-economic development; it utilizes a quantile regressions approach with an extended set of regressors. Despite these advancements, the results for the inequality-CO_2 emissions nexus corroborate the findings of similar studies by Ravallion et al. (2000), Heerink et al. (2001), Borghesi (2006) and Nikodinoska and Schröder (2016) (microeconometric study of German car fuels). They rebut the results of studies with other indicators by Torras and Boyce (1998) (various pollutants), Magnani (2000) (R&D expenditures for environmental protection) and Baek and Gweisah (2013) for CO_2 emissions in the United States.

Table 3 compares the core results of this analysis with those of other studies on *inequality and CO_2 emissions*. Accordingly, the magnitude of the estimated elasticity from the pooled regression in this study is consistent with other findings in the literature. Taking into consideration the FE estimates of this study and the outcomes of other studies, the literature is overall inconclusive regarding the significance and the sign of the inequality-emissions nexus.

[24] For a technical discussion of quantile regressions for panel data in pooled form, with fixed-effects and the large N – small T problem see Wooldridge (2010), chapter 12.10.3.

Table 3
Comparison with other studies on inequality and CO_2 emissions.

Study	Estimation type	Number of countries/years	Result for $\text{CO2} = \beta_I \cdot \text{GIN}...$
This study	Pooled (median)	149/1985–2012	$\beta_I = -0.67$
	FE (median)		$\beta_I^a = -0.10$
Ravallion et al. (2000)	Pooled	42/1975–1992	$\beta_I = -0.04$
Heerink et al. (2001)	Cross-section	64/1985	$\beta_I = -1.12$
Borghesi (2006)	Pooled	37/1988–1995	$\beta_I^b = -2.42$
	FE		$\beta_I^{bc} = +0.03$
Baek and Gweisah (2013)	Time series (long-run)	1/1967–2008	$\beta_I = +0.76$
	Time series (short-run)		$\beta_I^\Delta = +0.49$

Notes: CO2 and GIN are in general computed in logarithmic form; CO2 is always expressed in per capita form; FE stands for fixed-effects; [a] refers to the statistically significant estimate at the median, whereas the remaining FE estimates for GIN are insignificant; [b] CO2 is computed without logarithms; [c] indicates that the FE results are statistically insignificant; Δ symbolizes a specification in time differences.

As explained in Sections 3.4 to 3.6, the estimated magnitudes of the remaining explanatory variables are consistent with findings of other studies. Nonetheless, the literature is also inconclusive with respect to the relation between trade/FDI and emissions (cf. the literature review by Hübler and Glas, 2014). Against this background, this study highlights three possible reasons for obtaining different or contradicting results in the literature. First, the effects of industrialization, investments, FDI, trade and education on emissions depend on the position in the (conditional) distribution, i.e., on the level of per capita emissions which is related to the stage of techno-economic development. Second, it is crucial for the effect of GDP whether the dependent variable (emissions or energy) is divided by the number of inhabitants or by GDP (cf. Cole, 2006). (For the other regressors, this aspect is less relevant.) Third, it can be decisive whether or not country-specific effects are included in the regressions (cf. Borghesi, 2006).

Furthermore, the scrutinized World Bank data utilize the production-based approach to emissions accounting, which neglects indirectly imported and exported emissions via trade in goods and services and hence leakage and pollution haven effects (cf. Cole, 2004). Teixidó-Figueras et al. (2016) show that consumption-based (footprint) indicators are more unequally distributed across countries than production-based (territorial) indicators. Accordingly, international trade increases inequality of resource use and emissions, and rising income has a stronger impact on consumption- than on production-based indicators. In this sense, our production-based results might underestimate the true consumption-based effects.

4. Conclusion

This article has introduced simultaneous-quantile regressions as a tool for measuring the nexus between income and its distribution on the one hand, and environmental degradation on the other hand, taking into account international trade and FDI. The pooled regressions indicated that higher within-country inequality is attended by countries' lower per capita CO_2 emissions and energy intensities. This result was challenged by the fixed-effects regressions.

Policy recommendations in favor of inequality are, however, precarious. High inequality increases the risk of social tension with severe detrimental social and economic impacts. Nonetheless, policy makers might not be able or willing to reverse the trend of increasing within-country inequality in the near future. If so, the results suggest that rising inequality could at least be accompanied by emissions reductions. This insight can be of particular interest for policy makers in emerging countries like China, India or Brazil. Though, the quantile regressions approach indicated higher possible marginal emissions savings in countries with high per capita emissions like the USA than in less emissions-intensive countries. This aspect dampens possible optimistic expectations of policy makers in developing countries with low or moderate per capita emissions but high inequality.

Besides, the inequality-emissions nexus could be relevant for the integrated assessment community (cf. Dennig et al., 2016), because it deals with a mechanism that can dampen emissions growth (in a growth model like Hübler et al., 2012).

The analysis further demonstrated that the effects of international trade and FDI on emissions and energy use depend on the (emissions/energy) quantiles and hence countries' stages of techno-economic development. This might be one reason for the diversity of the results found by the literature on trade and the environment (cf. Hübler and Glas, 2014).

As in related studies, the estimates lack robustness and clear causality and need to be treated with caution. To improve that, the following amendments can be helpful. First, once a more complete dataset of inequality measures for a larger set of countries with an extended time dimension is available, the additional variation can be exploited. Emissions accounting should preferably be consumption-based. Second, a clear picture of the underlying micro-economic income-emissions nexus will require household data for a larger set of countries.

Acknowledgments

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Appendix A

A supplementary appendix to this article can be found online at http://dx.doi.org/10.1016/j.ecolecon.2016.12.015.

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