Different quantile regression models for quantifying the dependence between environmental quality and economic growth

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Abstract

The purpose of this paper is to use different quantile models to quantify the effect of economic growth on environmental quality measured by GHG emissions. For this purpose, panel quantile regression models were used.

This study used data from World Bank for 28 developing countries for the 2003-2019 period. The results shows that the effect of GDP growth on GHG emissions is a positive effect for all quantiles and is significantly lower for the lower quantiles (<0.35) of the conditional distribution of greenhouse gas emissions.

Keywords: GHG emissions, Economic Growth, Energy consumption, Financial development index, Panel quantile models

JEL Codes: Q56, O57, C23, C51

1. Introduction

The literature presents two directions of complementarity between energy consumption, financial development and economic growth in relation to environmental quality. The first focuses on the contribution of economic growth to environmental quality. The second axis of the literature presents the mediating role of financial development in the link between environmental quality and economic growth. The development of the financial system has an impact on economic growth and sustainable development by improving financial services and by facilitating access to credits (financial development debts) and mobilizing savings (Sadorsky, 2010; Zhang, 2011; Shahbaz et al., 2016; Paramati & Huang, 2021; Tahir et al., 2021; Liu & Zhang, 2020). Another point of view addressed in recent studies supports the idea that as financial development intensifies, their ecological use will occupy a greater share in energy production, so that positive effects on the quality of the environment can be expected by reducing polluting emissions (Al Mamun et al., 2018; Gill et al., 2019; Vo & Zaman, 2020; Raghutla & Chittedi, 2020; Mukhtarov et al., 2020).

This study tests the hypothesis of the influence of financial development and energy consumption on the relationship between economic growth and environmental quality (as expressed by the level of greenhouse gas emissions) for a large group of developing countries using non-linear models. We are interested in understanding the heterogeneity of this relationship in addition to the relationship at the mean and median. The research question is how the relationship between economic growth, energy consumption and greenhouse emissions changes for different levels of GHG and financial development index.

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2. Methodology

In this study I use panel quantile regression models. The reasons for selecting these types of models are:

- these models are able to present the effects of the explanatory variables on the dependent variable for the entire distribution of the sample;

- can present unbiased and consistent estimators instead of biased and inconsistent estimators caused by unobserved variables and unobserved heterogeneity effects by including unit fixed effects in the model that do not change over years ;

- can be useful in small samples.

2.1. Conditional quantile regression model (CQR).

In the context of unobserved heteroscedasticity and the assumption of non-normal distribution of variables, linear regression estimators are biased and inconsistent (Koenker and Basset, 1978). Koenker and Basset (1978) introduced the conditional quantile regression model that can describe the changes in the entire distribution of the analyzed variable.

$$Q\tau\left(Y_{i,t}\ /X\right) = \quad \alpha_\tau X_{i,t} \ + \beta_\tau \varphi_{i,t} \tag{5}$$

X represents the vector of explanatory variables included in the model, Φ is the vector of unobservable variables, and τ represents the value of the quantile for which the dependence relationship is investigated. Through the method developed by Koenker (2004), the estimates of the coefficients of the variables are determined by the optimal values (by minimization) of the weighted sum of the absolute deviations of the residuals. The determination of the parameter estimators for each quantile is done by the following minimization:

$$Q\tau(\alpha_\tau) = \min_{\alpha} \sum_{i=1}^{n}(|Y_{i,t} - \alpha_\tau X_{i,t}|) \tag{6}$$

This approach explains how the dependent variable that is ranked above a specified quantile (% τ) changes relative to the change in the characteristics expressed by the explanatory variables. Individual fixed effects, including dummy variables that represent cross-sections, cannot be included in this model without affecting the consistency of the estimate because it creates an incidental problem with the parameters

To solve this problem, Canay (2011) proposed a two-step estimation based on the assumption that the errors are homoscedastic with respect to the individual effects. In the first step, a linear regression model is estimated to obtain an estimate for the individual effects, and in the second step, the conditional quantile regression is estimated for the transformed dependent variable that removes the individual effects. Estimation is done using equation (7) with standard errors obtained by bootstrap resampling methods or the method of moments proposed by Machado and Santos Silva (2019, 2020).

An extended version of the model was developed by Powell (2016):

$$x_{i,t} \ = \sum_{k=1}^{s} D'_{i,t} \ \delta_k(\gamma^*_{i,t}) \tag{7}$$

Where δ_k represent the corresponding estimated parameters for the vector $D_{i,t}$ of the independent variables, the error term $\gamma^*_{i,t}$ including constant and random effects. The quantile regression for each quantile must satisfy the following probability condition (the probability that the predicted values of the analyzed variable are less than the variable itself):

$$P\left(x_{i,t} \le D_{i,t}{}'\delta(\theta) \middle| D_{i,t}\right) = \delta \tag{8}$$

The following constraints are imposed:

$$P\left(x_{i,t} \le D_{i,t}{}'\delta(\theta) \middle| D_i\right) = P\left(x_{i,s} \le D_{i,s}{}'\delta(\theta) \middle| D_i\right) \tag{9}$$

$$P(x_{i,t} \le D_{i,t}{}'\delta(\theta)) = \delta \tag{10}$$

The first of these relationships refers to fixed effects (which do not change over time), and the second corresponds to each observation in the data set.

The coefficients of the explanatory variables and the unobserved variables (θ τ) in the Powell (2016) model can also be estimated by the Markov Chain Monte Carlo (MCMC) method:

$$Q\tau\left(Y_{i,t} \ /X_{i,t}\right) = \theta_\tau = \arg\min[(\vartheta_\tau \ (Y_{\mathrm{i}} - qX_i)] \tag{11}$$

Another method for estimating quantile regression in the presence of fixed effects and heterogeneous effects is the one developed by Machado and Silva (2020) which has an important advantage that it can obtain heterogeneous effects through unitary effects that vary between quantiles. At the same time, this model can provide unbiased estimators in the presence of endogeneity (Machado and Silva, 2019).

Therefore, this method is also included in this study.

2.2. Unconditional quantile regression (UQR) based on the recentered influence function (RIF)

UQR models can identify the effect of the changes in the distribution of independent variables, Z, on the unconditional distribution of the dependent variable, y incorporating fixed effects (which is a problem in QR models).

As shown in our empirical example of the influence of financial development on greenhouse gas emissions, examining the effects for a country over time using QR models has shown conflicting results.

It is possible to include the influence of unobserved individual characteristics that are constant over time (d_i), and an unobservable model error (u_{it}) that is represented by the product of the i.i.d. error term. (v_{it}) and a strictly positive function, sigma(), which depends on the vector of explanatory variables Z and the individual characteristics D. If we consider that the sigma function is a constant, we obtain the homoscedastic version of the model.

The model that describes the relationship is:

$$y_{it}= b_o+b_Z Z_{it}+d_i+u_{it} \tag{12}$$

$$u_{it}=v_{it}\mathrm{sigma}_u(Z, D) \tag{13}$$

$$v_{it}\sim \mathrm{iid}(0,1) \tag{14}$$

As in the usual approach, it is assumed that the unobserved individual characteristics effect d_i is estimated for each i by including dummy variables D_i for each cross-section, and estimating them together with the other coefficients .

According to Machado and Santos Silva (2019), we can describe the sigma function as a linear function of the independent variables and individual unobserved characteristics:

$$\text{sigma}(Z_{it},d_i) = a_o+a_Z Z_{it}+a_d d_i. \qquad (4)$$

The coefficients in relation (1) $b_o(\tau)$, $b_Z(\tau)$, and $b_d(\tau)$ vary depending on the quantile if the model is heteroscedastic with respect to Z or d. If the error is homoscedastic, the coefficients will be identical to the effect from a linear regression model which is the mean effect.

Unconditional quantile regression (UQR) is used to identify the effects of changes in independent variables on the overall or unconditional distribution of the observed dependent variable.

Firpo et al. (2009) proposed a methodology that uses an algorithm to identify unconditional quantile effects that solves the problem of complexity due to the need to use the entire distribution of the dependent variable. This method approximate the marginal effect of small changes in location of the distribution of the independent variables on the unconditional quantile which translates, as described in Rios-Avila (2020a) , through changes in the mean of the independent variables.

It shows how much the observed distribution of the dependent variable change (across individuals and over time), as measured by changing the τ-th quantile of an explanatory variable, on average, holding the rest of the determinants constant. It can be done by estimating the difference between the observed τ-quantile across countries and the predicted quantile.

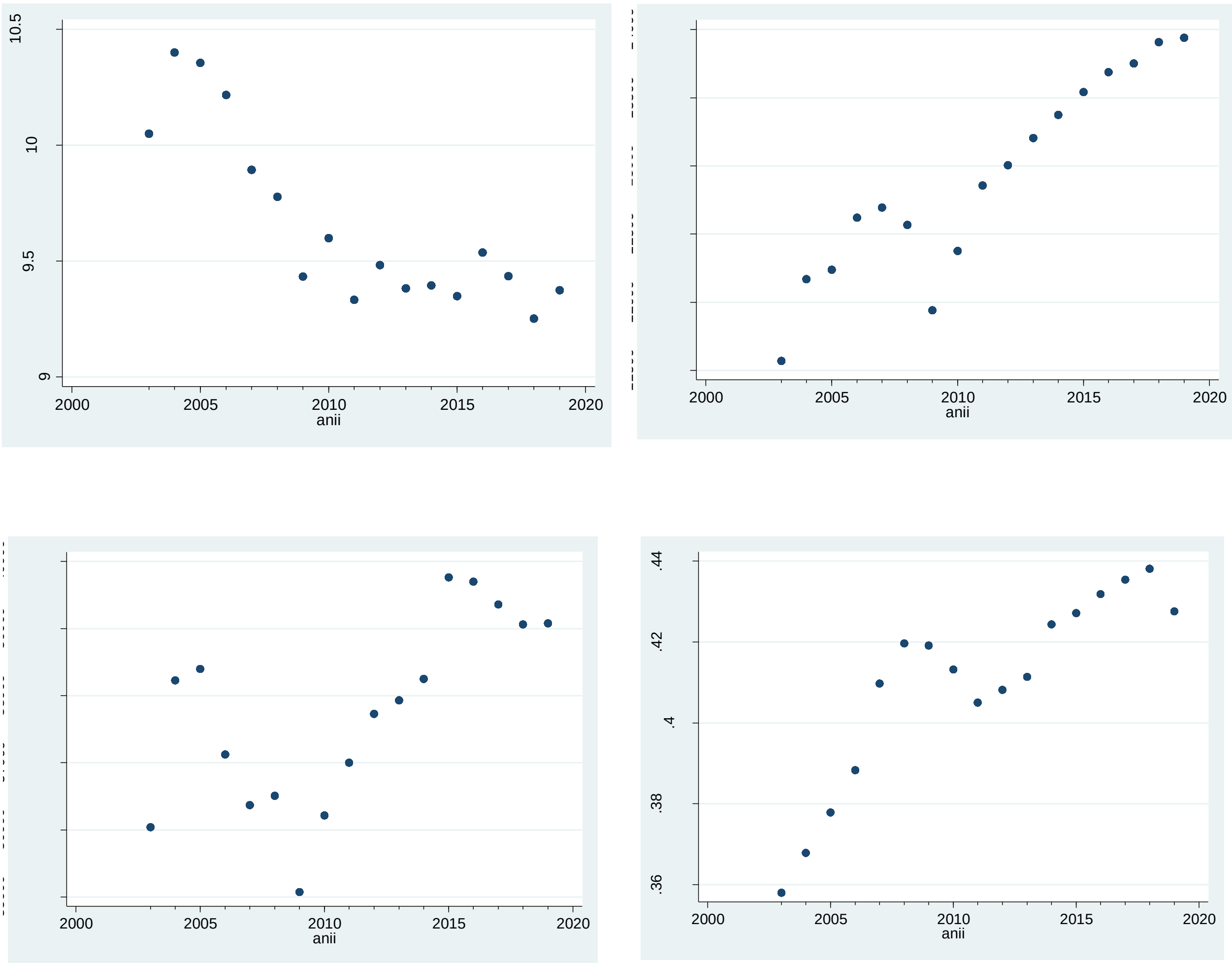
3. Datele

The sample covers the period 2003-2019 and 28 developing countries. Data are obtained from the World Bank World Development Indicators database.

The GDP per capita explains the income-induced environmental policy responses: the increase in income due to economic growth makes public demand for pollution policy tighter over time, which mitigates environmental pollution (Cole, Elliott & Fredriksson, 2006).

Table 1 reports summary statistics and the correlation matrix. Figure 1 displays the scatterplot of average data by country over the period 2003-2019.

Figure 1. Average data by country in the period 2003-2019



The variables used are: ghg = level of GHG emissions; pop = the population; gdppc = GDP per capita; energ= energy consumption; fd = financial development indicator

Table 1. Descriptive statistics

Panel A. Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ghg	476	9.662643	10.95292	0.862	62.035
pop	476	1.52E+08	3.25E+08	681791	1.41E+09
gdppc	476	12908.65	15881.32	707.6051	65129.38
energ	476	37755.6	52857.02	1262.086	261332.7
fd	476	0.4095706	0.1561961	0.0970911	0.7932451
dghg	448	-0.0422344	0.9227428	-7.883	5.934
grpop	475	0.2273007	3.159801	-0.9936939	66.98215
dgdppc	448	148.1622	929.7769	-6174.896	5420.275
denerg	448	189.8029	3581.472	-28449.09	22350.3
fd	476	0.4095706	0.1561961	0.0970911	0.7932451

Panel B. the correlation matrix

	dghg	grpop	dgdppc	denerg	fd
dghg	1				
grpop	-0.4082	1			
dgdppc	0.3504	-0.3257	1		
denerg	0.5141	-0.4213	0.3942	1	
fd	-0.0536	0.0909	0.1509	0.0437	1

Table 2. Unit root test (Pesaran)
for cross-sectional panels and the first mean difference included

		Z(t-bar)	
		Without trend	**With trend**
lghg	level	-1.573	**-2.662****
	1^{st} diff.	-3.746***	-3.922***
lgdppc	level	-1.277	-1.580
	1^{st} diff.	-2.936 ***	-3.558***
lenerg	level	-1.961	-2.000
	1^{st} diff.	-3.165***	-3.394***
fd	level	-2.537***	-2.940***
Critical values at			
	10%	-2.07	-2.58
	5%	-2.15	-2.67
	1%	-2.32	-2.83

*Note. Asterisks indicate significance levels: *p < 0.1, **p < 0.05, ***p < 0.01.*

		Z(t-bar)	
		Without trend	**With trend**
ghg	level	-1.461	-2.260
	1^{st} diff.	-3.341***	-1.573
gdppc	level	-0.740	-1.393
	1^{st} diff.	-2.875***	-3.589***
energ	level	-1.539	-2.376
	1^{st} diff.	-3.166***	-3.364***
fd	level	-2.537***	-2.940***
Critical values at			
	10%	-2.07	-2.58
	5%	-2.15	-2.67
	1%	-2.32	-2.83

4. The quantile models for the panel. Results and Discussion

Panel quantile models are able to show the effects of the explanatory variables on the dependent variable for the entire sample distribution. Most importantly, it can present unbiased and consistent estimators instead of biased and inconsistent estimators caused by unobserved variables and heterogeneity effects by including unit fixed effects in the model that do not change over years and affect reform policies.

4.1. Comparative results for several types of quantile models

Quantile regression with robust and clustered standard errors

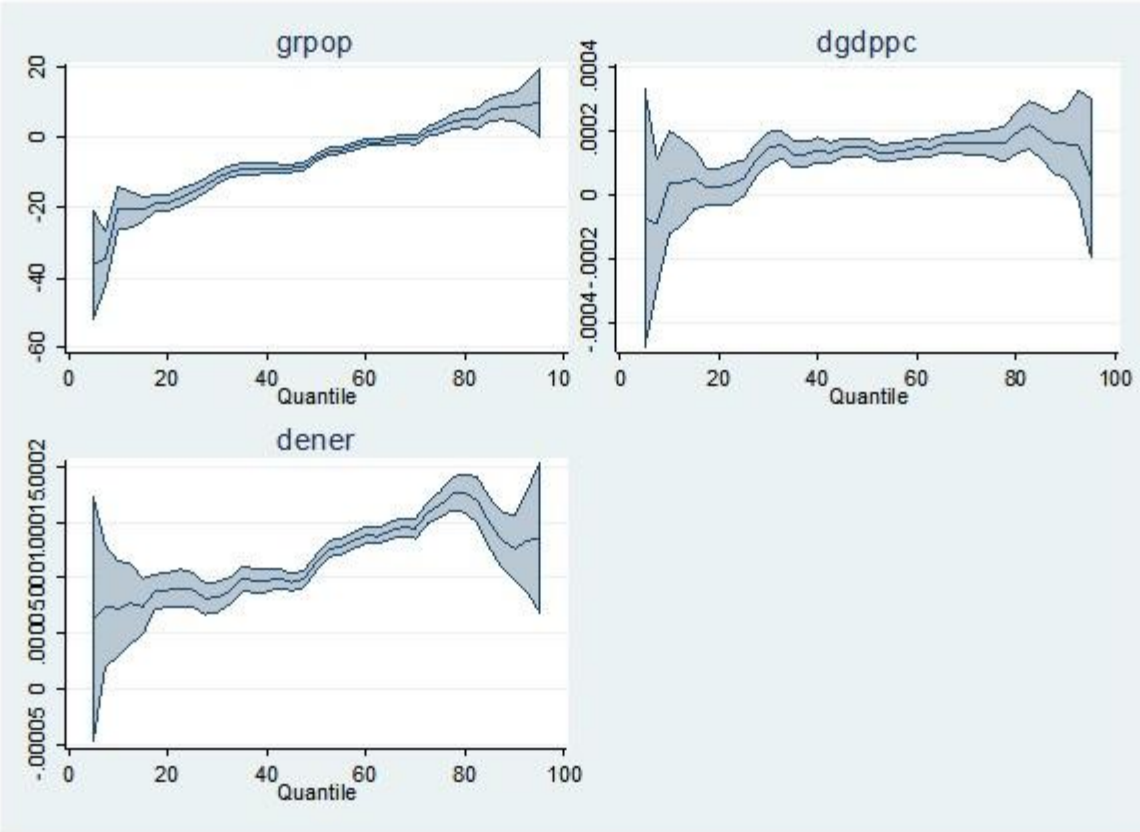
This quantile regression computes asymptotically valid standard errors under heteroskedasticity and misspecification. The Machado-Santos Silva (2000) test for heteroskedasticity, which is a special case of the White test, is performed using the adjusted values of the dependent variable and its squares (Wooldridge, 2009)

Table 2. Quantile regression

dghg	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
grpop	-5.846334	0.5132898	-11.39	0	-6.855113	-4.837554
dgdppc	0.0001494	1.35E-05	11.09	0	0.0001229	0.0001759
denerg	0.000114	3.65E-06	31.24	0	0.0001068	0.0001211
fd				0		
_cons	0.0802055	0.0157221	5.1	0	0.0493065	0.1111045

Note: Median regression Number of obs = 448
Raw sum of deviations 186.245 (about .029)
Min sum of deviations 146.0974 Pseudo R2 = 0.2156

Figure 2. Coefficients for different quartiles



The figure shows the coefficients that result from estimating our baseline specification. The blue lines show the values of $b_X(\tau)$ for different quantiles τ. The gray areas are the 68% confidence intervals.

Table 2. Quantile regression with robust standard errors

dghg	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
grpop	-5.846334	7.228084	-0.81	0.419	-20.05184	8.359173
dgdppc	**0.0001494**	**5.86E-05**	**2.55**	**0.011**	**3.43E-05**	**0.0002646**
denerg	**0.000114**	**4.25E-05**	**2.68**	**0.008**	**3.05E-05**	**0.0001974**
_cons	0.0802055	0.1039913	0.77	0.441	-0.1241708	0.2845818

Note: Median regression

R-squared = .32078217 *Number of obs = 448 Objective function = .16305513*

This quantile regression computes asymptotically valid standard errors under the assumption of heteroscedasticity and misspecification. The Machado-Santos Silva (2000) test for heteroscedasticity, which is a special case of the White test, is run using the adjusted values of the dependent variable and its squares (Wooldridge, 2009).

The Machado-Santos Silva test for studying heteroscedasticity:

Ho: Constant variance

Variables: Fitted values of dghg and its squares chi2(2) = 19.976 Prob > chi2 = 0.000

Figure 3. Coefficients for different quartiles for regression with robust standard errors

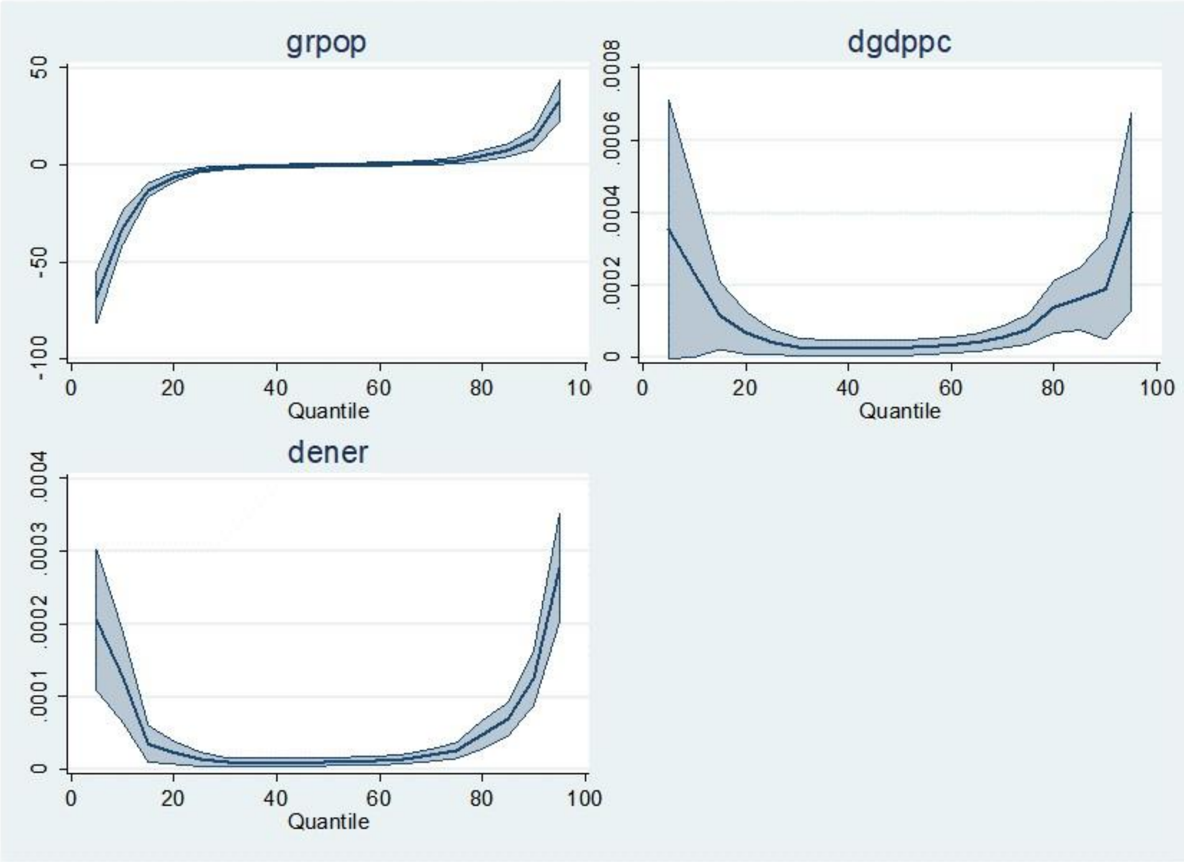
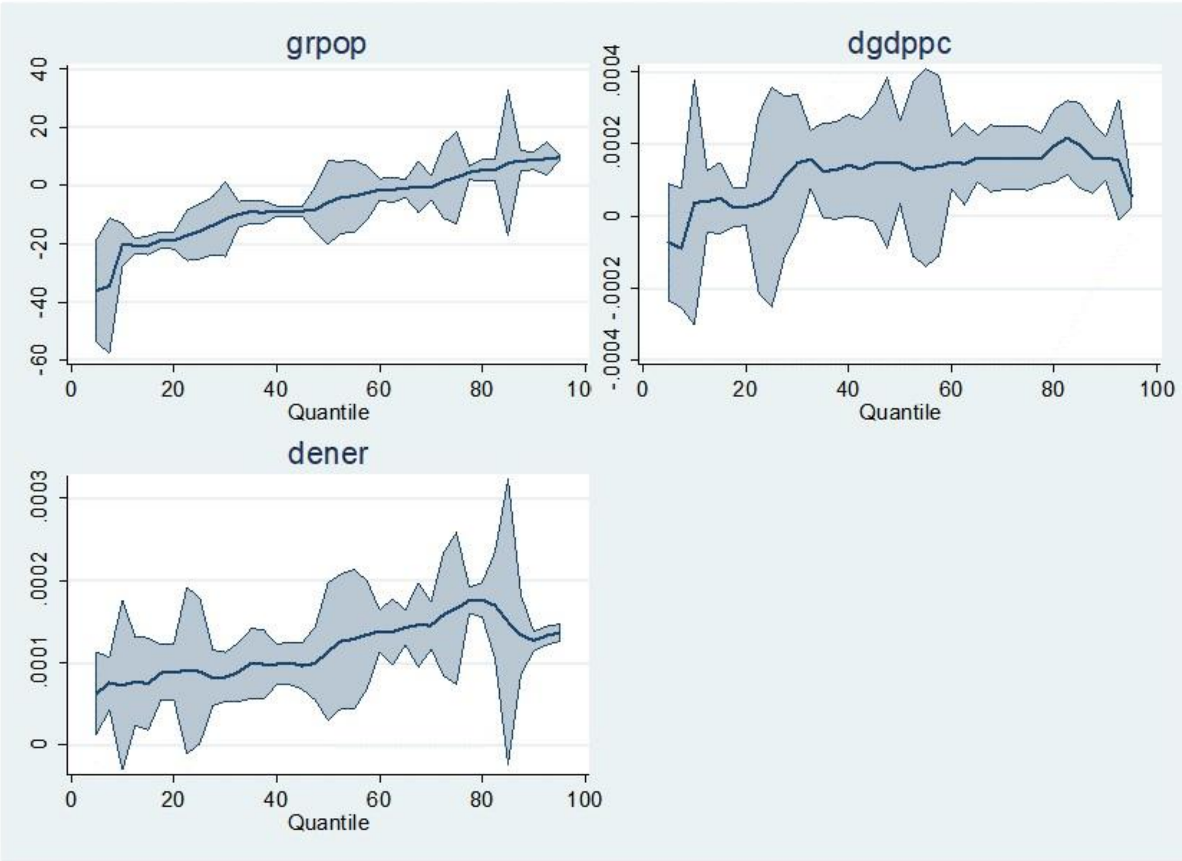


Figure 4. Coefficients for different quartiles for quantile regression with robust standard errors and bootstrap replications



The fact that the effects of the independent variables can vary with the quantiles of the conditional distribution is an important advantage of quantile regression over mean regression.

Table 3. Quantile regression with robust standard errors and bootstrap replications

Bootstrap replications (20)

Simultaneous quantile regression	Number of obs =	448
bootstrap(20) SEs	.10 Pseudo R2 =	0.3646
	.25 Pseudo R2 =	0.27992
	.50 Pseudo R2 =	0.2156
	.60 Pseudo R2 =	0.2192
	.65 Pseudo R2 =	0.2231
	.70 Pseudo R2 =	0.2256
	.75 Pseudo R2 =	0.2300
	.80 Pseudo R2 =	0.2356
	.85 Pseudo R2 =	0.2371
	.90 Pseudo R2 =	0.2474
	.95 Pseudo R2 =	0.2524

	dghg	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
q10							
	grpop	**-20.281970**	**8.336606**	**-2.43**	**0.015**	**-36.66608**	**-3.897859**
	dgdppc	0.000039	0.000107	0.36	0.718	-0.0001711	0.0002481
	denerg	0.000072	0.000059	1.22	0.224	-4.42E-05	0.0001883
	_cons	-0.031377	0.089064	-0.35	0.725	-0.2064165	0.1436634
q25							
	grpop	**-15.690890**	**4.329724**	**-3.62**	**0.000**	**-24.20019**	**-7.18159**
	dgdppc	0.000053	0.000053	0.99	0.322	-5.16E-05	0.0001566
	denerg	**0.000090**	**0.000045**	**2**	**0.046**	**1.47E-06**	**0.0001779**
	_cons	0.100520	0.057790	1.74	0.083	-0.0130551	0.214096
q50							
	grpop	**-5.846334**	**3.827074**	**-1.53**	**0.127**	**-13.36776**	**1.675097**
	dgdppc	**0.000149**	**0.000079**	**1.9**	**0.059**	**-5.52E-06**	**0.0003044**
	denerg	**0.000114**	**0.000030**	**3.75**	**0.000**	**5.42E-05**	**0.0001737**
	_cons	0.080206	0.058490	1.37	0.171	-0.0347459	0.1951568
q60							
	grpop	-1.364475	3.26E+00	-0.42	0.676	-7.777599	5.048649
	dgdppc	**0.000148**	**5.85E-05**	**2.53**	**0.012**	**0.000033**	**0.000263**
	denerg	**0.000139**	**2.29E-05**	**6.04**	**0.000**	**0.000094**	**0.000184**
	_cons	0.034998	5.13E-02	0.68	0.496	-0.065863	0.135858
q65							
	grpop	-0.982066	3.42E+00	-0.29	0.774	-7.709020	5.744889
	dgdppc	**0.000160**	**5.30E-05**	**3.02**	**0.003**	**0.000056**	**0.000264**
	denerg	**0.000143**	**2.39E-05**	**5.97**	**0.000**	**0.000096**	**0.000190**
	_cons	0.042340	5.25E-02	0.81	0.420	-0.060751	0.145430
q70							
	grpop	-0.759791	3.73E+00	-0.2	0.839	-8.093180	6.573598
	dgdppc	**0.000161**	**5.70E-05**	**2.81**	**0.005**	**0.000048**	**0.000273**
	denerg	**0.000145**	**2.62E-05**	**5.53**	**0.000**	**0.000093**	**0.000196**
	_cons	0.054606	5.48E-02	1	0.320	-0.053127	0.162340
q75							
	grpop	2.720287	3.71E+00	0.73	0.463	-4.562530	10.003100
	dgdppc	**0.000160**	**7.66E-05**	**2.09**	**0.037**	**0.000010**	**0.000311**
	denerg	**0.000166**	**2.83E-05**	**5.85**	**0.000**	**0.000110**	**0.000222**

dghg	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
_cons	0.022232	5.15E-02	0.43	0.666	-0.079051	0.123515
q80						
grpop	5.233697	3.70E+00	1.41	0.158	-2.038150	12.505540
dgdppc	**0.000194**	**8.23E-05**	**2.36**	**0.019**	**0.000032**	**0.000356**
denerg	**0.000177**	**2.40E-05**	**7.35**	**0.000**	**0.000129**	**0.000224**
_cons	0.019774	4.61E-02	0.43	0.668	-0.070816	0.110364
q85						
grpop	**7.703370**	**3.79E+00**	**2.03**	**0.043**	**0.260596**	**15.146140**
dgdppc	**0.000196**	**1.04E-04**	**1.89**	**0.059**	**-0.000007**	**0.000400**
denerg	**0.000150**	**2.44E-05**	**6.12**	**0.000**	**0.000102**	**0.000197**
_cons	0.054715	4.56E-02	1.2	0.231	-0.034881	0.144311
q90						
grpop	**8.582169**	**3.46E+00**	**2.48**	**0.014**	**1.776132**	**15.388210**
dgdppc	0.000160	1.18E-04	1.35	0.177	-0.000073	0.000393
denerg	**0.000126**	**2.44E-05**	**5.18**	**0.000**	**0.000078**	**0.000174**
_cons	**0.184415**	**4.70E-02**	**3.92**	**0.000**	**0.092038**	**0.276792**
q95						
grpop	**9.692174**	**4.09E+00**	**2.37**	**0.018**	**1.647695**	**17.736650**
dgdppc	0.000055	1.03E-04	0.53	0.594	-0.000147	0.000257
denerg	**0.000136**	**3.26E-05**	**4.18**	**0.000**	**0.000072**	**0.000200**
_cons	**0.369867**	**9.49E-02**	**3.9**	**0.000**	**0.183435**	**0.556299**

Note: I marked statistically significant values in bold

R^2's specific quantile measures represent a distinctive advantage of quantile regression over more traditional approaches that focus on the conditional mean, and provides an intuitive quantification of the role played by the independent variables in the behavior of the distribution for the dependent variable.

Figure 5. Coefficients for different quartiles for quantile regression

The heterogeneity of the coefficients can verified: The test cannot reject the hypothesis of the equality of the coefficients corresponding to the variable GDP growth per capita (gdppc) for different quantities.

(1) [q25]dgdppc - [q50]dgdppc = 0

(2) [q25]dgdppc - [q75]dgdppc = 0

F(2, 444) = 1.53 Prob > F = 0.2172

Conclusions

The relationship between economic growth and GHG emissions was tested considering the role of population growth and energy consumption. The sample covering the period 2003-2019 and 28 developing countries was analyzed with panel quantile regressions.

The results for the quantile regression show that:

- the population growth rate (grpop) has a positive impact only for the higher quantiles and a greater effect on the higher quantiles than on the lower quantiles of the conditional distribution of greenhouse gas emissions;

- the effect of GDP growth (dgdppc) is a positive effect for all quantiles and is significantly lower for the lower quantiles (<0.35) of the conditional distribution of greenhouse gas emissions;

- the impact of energy consumption on greenhouse gas emissions is positive and significant on all quantiles.

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