CO_2 emissions and income inequality

Part 2: Empirics

Nicole Grünewald, Stephan Klasen, Inmaculada Martínez-Zarzoso and Chris Muris

Georg-August-Universität Göttingen

April 4, 2011

Georg-August-Universität Göttingen

Introduction

1. Document relationship between emissions, GDP, inequality

2. Identify the mechanisms at work

Findings

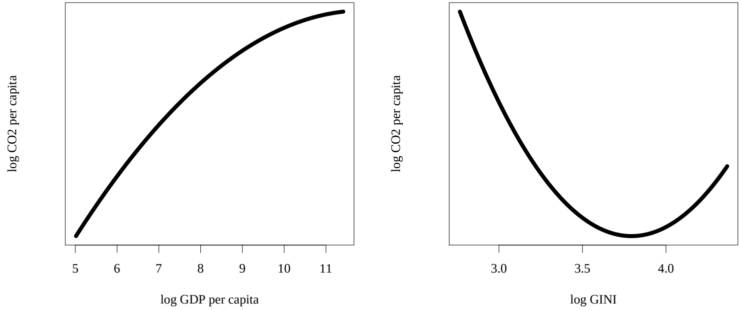

Figure: Relationship between GDP per capita (left), GINI (right) and carbon dioxide emissions

Structure

- Macro panel
- Number of countries: 138
- Time period: 1960–2009
- 3-year averages: 795 observations
- Unbalanced

Inequality

- GINI data from Grün and Klasen (Oxford Economic Papers, 2008)
- GINI data are adjusted for comparability
- Much more extensive than existing literature

Other variables

- GDP: Penn World Tables, real GDP, constant prices
- CO_2 emissions: CDIAC

Specification

- gdp is GDP per capita
- co_2 is CO_2 per capita
- Model: fixed effects (country and year) with

$$\log(\mathrm{co}_2)_{i,t} = \alpha_i + \lambda_t + \beta_1 \log(\mathrm{gdp}_{i,t}) + \beta_2 \log^2(\mathrm{gdp}_{i,t}) + \beta_3 \log(\mathrm{GINI}_{i,t}) + \beta_4 \log^2(\mathrm{GINI}_{i,t}) + \beta_5 \log(\mathrm{GDP}_{i,t}) \log(\mathrm{GINI}_{i,t}) + \varepsilon_{i,t}$$

- Robust standard errors

Coefficients

	EKC	GINI	Preferred
$\log(\mathrm{gdp})$	2.46 (0.24)	2.68 (0.37)	2.17 (0.46)
$\log^2(\mathrm{gdp})$	−0.10 (0.01)	−0.11 (0.02)	−0.11 (0.02)
$\log(\mathrm{GINI})$		−0.21 (0.12)	−6.71 (1.58)
$\log^2(\mathrm{GINI})$			0.74 (0.18)
$\log(\mathrm{gdp}) \cdot \log(\mathrm{GINI})$			0.13 (0.07)

Table: Coefficient estimates (standard errors)

Graphs: GDP

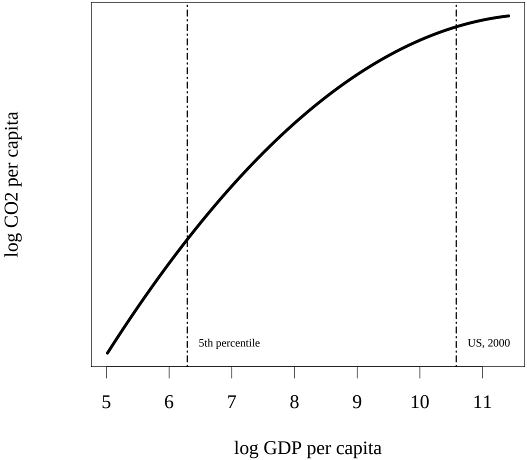

Figure: Relationship GDP per capita and per capita emissions at median GINI

Graphs: GDP

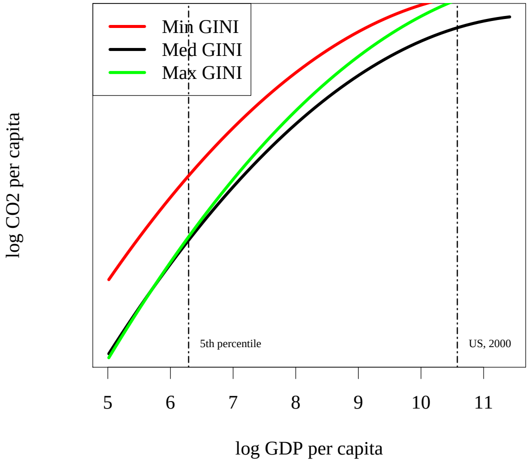

Figure: Relationship GDP per capita and per capita emissions at various values of GINI

Graphs: GINI

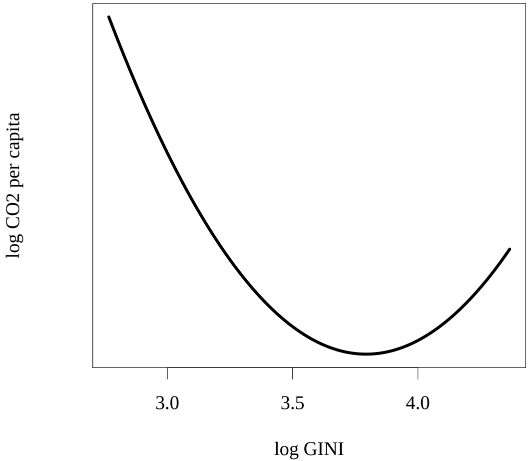

Figure: Relationship GINI and per capita emissions at median GDP

Graphs: GINI

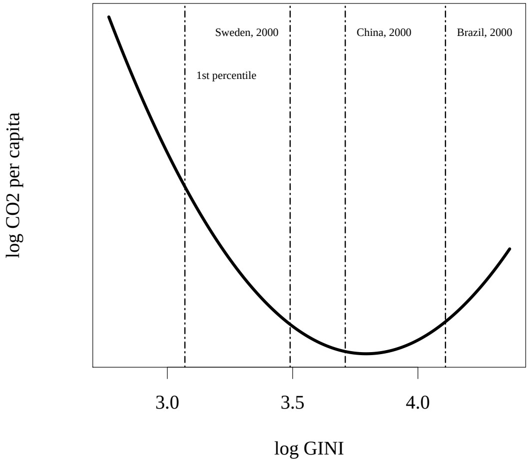

Figure: Relationship GINI and per capita emissions at median GDP

Graphs: GINI

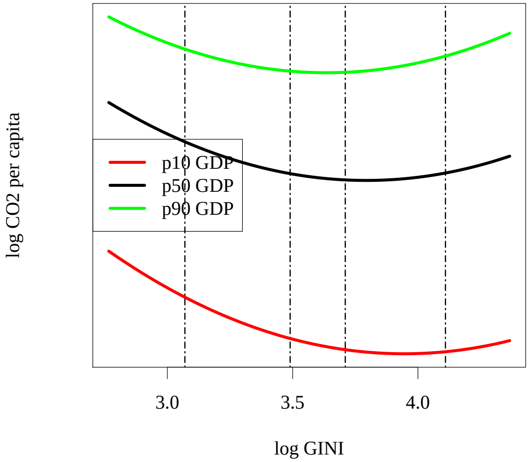

Figure: Relationship GINI and per capita emissions at various values of GDP

Aggregation

	Preferred	Annual	Decadal
$\log(\text{gdp})$	2.17 (0.46)	2.03 (0.33)	1.65 (0.53)
$\log(\text{gdp})^2$	−0.11 (0.02)	−0.11 (0.02)	−0.11 (0.03)
$\log(\text{GINI})$	−6.71 (1.58)	−7.22 (1.29)	−8.62 (3.04)
$\log(\text{GINI})^2$	0.74 (0.18)	0.78 (0.12)	0.83 (0.39)
cross	0.13 (0.07)	0.16 (0.08)	0.28 (0.07)

Table: Coefficient estimates (standard errors)

Robust (2)

	Preferred	1980-	Other GDP
log(gdp)	2.17 (0.46)	2.42 (0.70)	1.44 (0.61)
$\log(\text{gdp})^2$	−0.11 (0.02)	−0.13 (0.04)	−0.08 (0.03)
log(GINI)	−6.71 (1.58)	−9.47 (2.24)	−6.99 (2.25)
$\log(\text{GINI})^2$	0.74 (0.18)	1.08 (0.25)	0.70 (0.26)
cross	0.13 (0.07)	0.15 (0.08)	0.21 (0.08)

Table: Coefficient estimates (standard errors)

Industry share

	Preferred	Industry
$\log(\text{gdp})$	2.17 (0.46)	−0.18 (0.45)
$\log(\text{gdp})^2$	−0.11 (0.02)	−0.01 (0.02)
$\log(\text{GINI})$	−6.71 (1.58)	−6.74 (1.59)
$\log(\text{GINI})^2$	0.74 (0.18)	0.78 (0.19)
cross	0.13 (0.07)	0.11 (0.05)

Table: Coefficient estimates (standard errors)

Summary

- Inequality measure should be included in income-emission relationship
  - Theory
  - Empirical evidence
- U-shaped relationship CO_2 and inequality
- This finding is robust against specification changes

To do

- Homogeneity
  in-sample, complete-sample: offsetting mechanisms
- Mechanism
- Scenarios to evaluate relative size of effects
- Unit roots
- Other inequality measures

Missing data in economics

40% of empirical studies work with missing data

70% of those use a *complete case* estimator

Source: Donald and Abrevaya (2010).

Incomplete observations

- an observation is incomplete not all variables are observed
- incomplete observations can be informative

Examples

- missing instruments
- unbalanced panel data
- no gain: OLS

Generalized method of moments

- We are interested in a parameter $\theta_0 \in \mathbb{R}^p$
- We know that moment condition $E(h(X, \theta_0)) = 0$ holds
  - $X \in \mathbb{R}^d$ is a random vector
  - $h : \mathbb{R}^d \times \mathbb{R}^p \to \mathbb{R}^q$ is a moment function
- A random sample for X is available
- Consider the sample moment $\bar{h}_n(\theta) = \frac{1}{n} \sum_{i=1}^n h(X_i, \theta)$
- GMM estimator minimizes a quadratic form of it

Rodrik example (3)

All data available:

$$h = \begin{pmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \end{pmatrix}, \; S_1 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \qquad \begin{matrix} \textit{constant} \\ \textit{distance to equator} \\ \textit{settler mortality} \\ \textit{trade share constructs} \end{matrix}$$

Rodrik example (3)

No instruments available

$$h = \begin{pmatrix} h_1 \\ h_2 \\ \times \\ \times \end{pmatrix}, \; S_2 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

constant
distance to equator
settler mortality
trade share constructs

Rodrik example (3)

Only trade share constructs available

$$h = \begin{pmatrix} h_1 \\ h_2 \\ \times \\ h_4 \end{pmatrix}, \quad S_3 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

constant
distance to equator
settler mortality
trade share constructs

Rodrik example (3)

Dependent or explanatory variable missing

$$h = \begin{pmatrix} \times \\ \times \\ \times \\ \times \end{pmatrix}, \; S_4 = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

constant
distance to equator
settler mortality
trade share constructs

Semiparametric efficiency

Definition

The semiparametric efficiency bound is a lower bound on the variance of any regular semiparametric estimator

Theorem

The semiparametric efficiency bound for θ_0 is equal to B^{-1}

IV: setup

Linear IV

- Linear IV model with one endogenous variable and two instruments
- No exogenous variables or constant
- $E\begin{pmatrix} Z_1(y - X'\beta) \\ Z_2(y - X'\beta) \end{pmatrix} = 0,$

Two similar, normalized, partially missing instruments

- Same correlation with the endogenous variable
- Each instruments is equally likely to be missing

IV: results

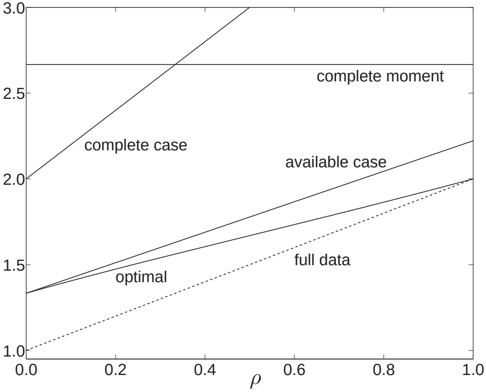

Figure: Asymptotic variance for estimators of β as a function of ρ.

Conclusion

- missing data is a very common problem
- often, incomplete observations are informative
- we show how to efficiently combine all information
- the estimator is easy to implement and computationally cheap
- it extends to inverse probability weighting, continuous updating GMM