

# What Are the Carbon Emissions Elasticities for Income and Population? New Evidence from Panel Estimates Robust to Stationarity and Cross-Sectional Dependence

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## 1. Introduction and background

Ever since the introduction of the so-called IPAT equation in the early 1970s, studies have used it to decompose historical data on environmental impacts (I) into contributions from population growth (P), growth in per capita income or consumption (as measures of affluence, A), and changes in technology (T). Indeed, the IPAT equation was developed for just that purpose, as part of a debate on the relative roles of population growth and technological change in environmental degradation in the U.S. (Ehrlich and Holdren, 1971; Commoner et al., 1971).

A new set of more sophisticated statistical studies has emerged that test whether the effect of population or income growth on environmental impact is proportional by estimating so-called elasticities; they are defined as the percent change in emissions associated with a one percent increase in population (an elasticity of 1.0 indicates a proportional effect). The first study of this kind was by Dietz and Rosa (1997), who coined the term STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) to describe this modeling/estimation framework. In general, the STIRPAT model is:

$$I = aP_i^b A_i^c T_i^d e_i \quad (1)$$

Where the subscript  $i$  denotes cross-sectional units (e.g., countries), the constant  $a$  and exponents  $b$ ,  $c$ , and  $d$  are to be estimated, and  $e$  is the residual error term.

Since Equation 1 is linear in log form, the estimated exponents can be thought of as elasticities (i.e., they reflect how much a percentage change in an independent variable causes a percentage change in the dependent variable.) Furthermore, Equation 1 is no longer an accounting identity whose right and left side dimensions must balance, but a potentially flexible framework for testing hypotheses—such as whether elasticities differ across development levels. In addition to determining whether population or GDP has a greater marginal impact on the environment, another important hypothesis to test is whether population's elasticity is different from unity, i.e., whether population or impact grows faster.

The Dietz and Rosa paper stimulated a number of subsequent studies that employed better estimation techniques, included additional independent variables (intensity or technology variables, represented by  $T$  in Equation 1), and analyzed data taken at different points in time, i.e., time-series cross-section (TSCS) data (a shortcoming of the Dietz and Rosa analysis was

that it relied on cross-sectional data for a single year). Many of these subsequent studies have focused on carbon emissions as the environmental impact because (i) such data is easy to assemble for many countries over long periods of time; and (ii) it is the primary anthropogenic greenhouse gas, and climate change is the most important transnational environmental issue of our time.

Yet, cross-national, inter-temporal STIRPAT studies of carbon emissions have produced a wide range of income and population elasticity estimates—from 0.15 to 2.50 for income and from 0.69 to 2.75 (with several statistically insignificant findings) for population. Also, in answering the question, “is population’s elasticity significantly different from one,” those studies have produced highly inconsistent results. For example, Cole and Neumayer (2004) found population’s elasticity to be statistically indistinguishable from unity (thus, a 1% increase in population caused an approximate 1% increase in emissions). By contrast Shi (2003) estimated a particularly high elasticity for population—between 1.4 and 1.6 for all countries samples; moreover, when Shi separated countries by income groups, the elasticity for high income countries was 0.8, whereas the elasticity for middle and low income countries ranged from 1.4 to 2.0. Among the possible reasons for such disparate results are: (i) the different datasets analyzed and, in particular, whether elasticities were allowed to differ according to development level; (ii) the additional independent variables besides population and income that were considered; and (iii) the various methods used—specifically, the extent of the time dimension of the data and whether/how the stationarity properties of the data were considered/addressed.

This paper performs a robustness exercise using the STIRPAT model to determine what are the carbon emissions elasticities for income and population and whether those elasticities differ across development/income levels. Improved understanding of the elasticities of income and population is important both for climate policy/negotiations and for generating projections of carbon emissions. Indeed, the so-called Kaya Identity—essentially IPAT with energy intensity (energy consumption over GDP) and carbon intensity of energy (carbon emissions over energy consumption) in place of  $T$ —plays a core role in the Intergovernmental Panel on Climate Change estimates of future carbon emissions.

## 2. Data and methods

Because we follow the lead of Liddle and Lung (2010) and consider as intensity/technology variables industrial energy intensity ( $IEI$ ) and the share of primary energy consumption from non-fossil fuels ( $Sh\ nff$ ), we draw data from the International Energy Agency (IEA). Thus, the (unbalanced) dataset consists of observations over 1971-2006 from 26 OECD countries and 45 non-OECD countries. Population ( $P$ ), carbon emissions ( $I$ ), and real GDP per capita ( $A$ , which is converted to USD via purchasing power parities) are also from the IEA. The equation analyzed is:

$$\ln I_{it} = \alpha_i + \beta_t + c \ln P_{it} + d \ln A_{it} + e \ln IEI_{it} + f \ln Shnff_{it} + \varepsilon_{it} \quad (2)$$

Where subscripts  $it$  denote the  $i$ th cross-section and  $t$ th time period. The constants  $\alpha$  and  $\beta$  are the country or cross-section and time fixed effects, respectively.

We estimate elasticities using several common OLS-based methods and two newer methods that were specifically designed to address both stationarity and cross-sectional dependence/correlation in TSCS models. The standard methods are: fixed effects with time

dummies or two-way fixed effects (2FE), fixed effects with time dummies and a (one-period) lagged dependent variable (2FE-LDV), two-way fixed effects with the Prais-Winsten serial correlation correction (FE-Prais), and two-way fixed effects with all terms in first differences (FD-OLS).

The two newer, more advanced methods employed are the Pesaran (2006) common correlated effects mean group estimator (CMG) and augmented mean group (AMG) estimator by Eberhardt and Teal (2010). The CMG estimator accounts for the presence of unobserved common factors by including in the regression cross-section averages of the dependent and independent variables. The AMG estimator accounts for cross-section dependence by including in the regression a common dynamic process—which is extracted from year dummy coefficients of a pooled regression in first differences. (In standard OLS, common time effects, i.e., time dummies, can capture a limited form of cross-sectional dependence.) Lastly, both the CMG and AMG estimators are robust to cointegration among variables, but do not require the pre-testing (neither to determine the existence of cointegration nor to confirm that all variables are of the same order of integration) that both Fully Modified OLS and Dynamic OLS require.

To analyze the robustness of the various methods we run diagnostics tests on the residuals to consider the three most important statistical issues when analyzing TSCS data: (i) serial correlation, (ii) stationarity, and (iii) cross-sectional dependence/correlation.

### 3. Results

Even after correcting for several modelling and methodological short-comings of previous STIRPAT analyses, the population elasticity of carbon emissions is not robust; however, that elasticity is typically not statistically different from one, nor statistically different between developed and developing countries. However, the affluence (or GDP per capita) elasticity of carbon emissions is robust—it is statistically less than one for OECD countries, and statistically smaller for OECD countries than for non-OECD countries (but not statistically different from one for non-OECD countries).

The lack of robustness of the population elasticity over time was not evidence that the elasticity had changed—the sensitivity analysis revealed no evidence that the size, significance, or sign of the population elasticity may have changed over-time (e.g., from 1970-1990 to 1990-2006). Rather, the more extreme estimated values (i.e., particularly large or insignificant estimations) and the larger confidence intervals typically occurred whenever the time span was shortest (e.g., 1971-1990, 1975-1995, 1980-2000, and 1985-2006). Lastly, a robustness analysis on models with all variables in first differences also uncovered substantial instability over time periods for the population estimation (but the coefficient for first differenced income was highly stable).

The CMG and AMG estimators have an additional advantage in that they are heterogeneous (and not pooled) estimators, i.e., they allow all coefficients to vary individually by performing the country specific regressions first. Thus, one can consider nonlinearities in the income and population elasticities with respect to country-specific income and population (size). If the individual country income elasticity is plotted against the country average income for the whole sample period, a U-shaped pattern appears. The income elasticity falls with average income; however, there is no evidence that the income elasticity would become negative within observed

average incomes. By contrast there is no relationship between the population elasticity and average income. Yet, the spread of the individual country population elasticities is much greater for average incomes that are larger than \$13,000 than for countries with average income smaller than that figure. Hence, it seems that as countries get wealthier more variables (or more detailed models) are needed to explain the variance among their carbon emissions because the relationship between their aggregate carbon emissions and their aggregate population is much less similar. Lastly, there was no relationship between the individual population elasticity and average population size.

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