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Population, affluence, and environmental impact across development: Evidence from panel cointegration modeling☆

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ABSTRACT

This paper analyzes urban population's and affluence's (GDP per capita's) influence on environmental impact in developed and developing countries by taking as its starting point the STIRPAT framework. In addition to considering environmental impacts particularly influenced by population and affluence (carbon emissions from transport and residential electricity consumption), the paper determines whether and, if so, how those environmental impact relationships vary across development levels by analyzing panels consisting of poor, middle, and rich countries. The development-based panels approach is an improvement on the GDP per capita polynomial model used in the Environmental Kuznets curve and other literature for several reasons: (i) it allows one to determine whether the elasticity of *all variables considered* varies according to development; (ii) it is arguably a more accurate description of the development process; (iii) it avoids potentially spurious regressions involving nonlinear transformations of nonstationary variables (GDP per capita squared); and (iv) unlike the polynomial model, it allows for the possibility that elasticities are significantly different across development levels but still positive—precisely the relationship expected for the environmental impacts considered here. Whether or not the elasticity for affluence was greater than that for population was a function of both the choice of dependent variable and the makeup of the panel (all countries, poor, middle, or rich). Furthermore, the estimated elasticities varied, in a nonlinear fashion, according to the development process: U-shaped, inverted U-shaped, and monotonic patterns were revealed, again, depending on the dependent variable.

1. Introduction

Transport contributes more than one-fifth of global anthropogenic carbon dioxide emissions; the residential sector consumes more than one-quarter of the world's electricity, and transport and residential electricity consumption are increasing in both developed and developing countries. Although there are non-greenhouse gas intensive technologies for generating electricity, two-thirds of electricity is generated from fossil fuels[1] (of which coal is the largest source). Furthermore, many of those alternatives to fossil fuels also have environmental impacts: wind farms affect bird migrations and are considered by some to be unsightly; hydropower often involves massive construction-engineering projects, which contribute their own carbon emissions, and can cause displacements of people, wildlife, and ecosystems (e.g., China's Three Gorges dam); and nuclear power raises safety concerns as well as the threat of non-energy, military uses. Also, as normal goods, transport and residential electricity consumption are unlikely to follow an inverted-U path as countries develop/become richer. Lastly, transport and energy in the home are consumed on the individual, household level, and thus, are much more likely than other environmental impacts to be directly influenced by per capita wealth and population.

Population is less likely to directly impact national, aggregate emissions like carbon dioxide; instead, those emissions should be heavily influenced by the structure and energy intensity of the macro-economy (e.g., the presence and size of sectors like iron and steel and aluminum smelting) and by the technologies used to generate electricity (i.e., coal vs. nuclear). For example, smaller in population (by about a third), but very coal-intensive, Australia uses less than half the energy France uses (France relies substantially on nuclear generated electricity); yet, Australia emits seven percent more carbon than France. However, as noted, the majority of transport and all energy in the home are consumed on an

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[1] US Energy Information Agency projects only a small increase in the share of non-fossil fuels used in electricity generation by 2035 (from 0.32 to 0.35), see http://www.eia.doe.gov/oiaf/ieo/index.html.

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individual, household level, and thus, are much more likely than national, aggregate emissions to be directly influenced by per capita wealth and population.

This paper employs the stochastic version of the IPAT model (or STIRPAT) in order to examine population's—specifically, urban population's—and affluence's (GDP per capita) influence on carbon emissions from transport and residential electricity consumption in both developed and developing countries. Also, the paper determines whether and, if so, how those environmental impact relationships vary across development levels by analyzing development-based panels consisting of poor, middle, and rich countries and by performing difference in means tests. Finally, the paper employs advanced time-series-based techniques like panel cointegration and panel Fully Modified OLS (FMOLS) to estimate variable elasticities (important since STIRPAT variables are stock or stock-related, and thus, likely nonstationary, and at least population and affluence are potentially inter-related).

2. Literature review

2.1. STIRPAT

The IPAT/impact equation of Ehrlich and Holdren (1971) is a common framework to distinguish between population's and GDP's (or income's) environmental impact. Environmental impact (I) is set equal to the product sum of population (P), affluence or consumption per capita (A), and technology or impact per unit of consumption (T). Dietz and Rosa's (1997) STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) framework builds on the IPAT equation by allowing hypothesis testing and by not assuming *a priori* a proportionality in the functional relationships between factors. In general, the STIRPAT model is:

$$I = aP_i^bA_i^cT_i^de_i \tag{1}$$

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. That hypothesis is particularly interesting/important to test: if population's elasticity is one, then population could be removed as an independent variable via division (from Equation (1)), and so the dependent variable would be in per capita terms (the framework used often in non-STIRPAT analyses, like those in the so-called Environmental Kuznets Curve literature).

The studies applying the STIRPAT formulation to carbon emissions typically found that both population and income/affluence are significant drivers. Furthermore, most studies have found that population has a greater impact (i.e., elasticity) than affluence (e.g., Dietz and Rosa, 1997; Shi, 2003; York et al., 2003; Cole and Neumayer, 2004; Martinez-Zarzoso et al., 2007; Liddle and Lung, 2010). However, those studies that sought to determine whether population's elasticity was significantly different from one have produced less consistent results.

For example, Dietz and Rosa (1997), York et al. (2003), and Cole and Neumayer (2004) all found population's elasticity to be statistically indistinguishable from unity (thus, a 1% increase in population causes 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. Similarly, Poumanyvong and Kaneko (2010) estimated population elasticities that ranged from 1.7 to 1.2 to 1.1 for low-income, middle-income, and high-income groups, respectively. Likewise, Martinez-Zarzoso et al. (2007) estimated a statistically insignificant population elasticity for old EU members, but an elasticity of 2.7 for recent EU accession countries. Among the possible reasons for such disparate results are: (i) the different data and methods used (i.e., the time dimension of the data and whether/how the stationarity of the data was considered/addressed); and (ii) whether elasticities were allowed to differ according to development level.

2.1.1. STIRPAT/stock variables, nonstationarity, and endogeneity

Most variables used in STIRPAT analyses are stock (population) or stock-related variables (GDP, emissions, and energy consumption, which are influenced by stocks like population and physical capital); as such, those variables are likely nonstationary—i.e., their mean, variance, and/or covariance with other variables changes over time. When OLS is performed on time-series (or time-series cross-section) variables that are not stationary, then measures like R-squared and t-statistics are unreliable, and there is a serious risk of the estimated relationships being spurious. Yet, few STIRPAT studies that employ annual (or more frequent) times-series cross-section (i.e., panel) data have been concerned with the stationarity issue.

Dietz and Rosa (1997) and York et al. (2003) analyzed single-year cross-sections; whereas, Cole and Neumayer (2004), Martinez-Zarzoso et al. (2007), and Poumanyvong and Kaneko (2010) estimated first-difference models to correct for nonstationarity. (Indeed, Cole and Neumayer, 2004 hypothesized that the much higher elasticity estimated in Shi, 2003 may be spurious because of that paper's use of untreated, nonstationary data.) Although first-differencing often transforms nonstationary variables into stationary ones, first-differencing means that the model is a short-run (rather than a long-run) model and that the estimated coefficients are constants of proportionality between percentage changes in the independent variables and percentage changes in the measure of impact, rather than elasticities.

As an alternative to taking first-differences, one could test for panel-unit roots (or stationarity) and for panel-cointegration (two or more nonstationary variables are said to be cointegrated if some linear combination of them is stationary), and, depending on the outcome of those tests, estimate the equation via methods like FMOLS. (Such tests were originally designed for time-series but have been expanded to cover panel data sets.) Yet, we know of only one STIRPAT paper to employ these alternative methods—Liddle (2011).

Pedroni's (2000) FMOLS estimator is designed for panels of cointegrated variables (finding cointegration among economic or economic-related variables is interpreted as evidence of a long-run, equilibrium relationship), and that estimator produces asymptotically unbiased estimates and standard normal distributions free of nuisance parameters. FMOLS accounts for stationarity and corrects for both residual autocorrelation and endogeneity. Addressing the long-run nature of the relationship (i.e., cointegration) among STIRPAT variables, as well as the likely