Consumption-Driven Environmental Impact and Age-Structure Change in OECD Countries: A Cointegration-STIRPAT Analysis

ABSTRACT

This paper examines two types of environmental impact for which population has a substantial demonstrated influence: carbon emissions from transport and residential electricity consumption. It takes as its starting point the stochastic version of the IPAT equation or the STIRPAT framework. The paper advances that framework in two important ways: (1) it disaggregates population into four key age groups: 20-34, 35-49, 50-69, and 70 and older; and (2) it employs advanced time-series-based techniques like panel unit root tests, panel cointegration, and panel Fully Modified OLS. Population has been shown to impact the environment in considerably different ways across age-groups—e.g., young adults typically behave in more environmental intense ways than older ones. The variables typically analyzed in STIRPAT studies are stock (population) or stock-related variables (GDP, emissions, and energy consumption), and thus, are likely nonstationary—i.e., their means change over time. Such data sets should be tested for panel-unit roots and panel-cointegration. Initial results indicate that population has a greater impact than affluence on carbon emissions from transport and residential electricity consumption, that young adults exert a greater influence on the environment than older adults, and that such influence is more pronounced in the transport than in the residential sector.

1. Introduction and literature review

Increases in anthropogenic greenhouse gas (GHG) concentrations are believed to have caused most of the recent increases in global average temperatures, i.e., climate change. The primary anthropogenic GHG is carbon dioxide, which is predominately caused by the combustion of fossil fuels. Yet, many alternatives to carbon-based energy technologies have environmental impacts too: wind farms affect bird migrations and are considered by some to be unsightly; hydro-power 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 and waste disposal issues, as well as the threat of non-energy, military uses. This paper focuses on consumption-driven environmental impact (carbon emissions from transport and residential electricity consumption) and employs the stochastic version of the IPAT model, panel cointegration, and Pedroni's (2000) Fully Modified OLS (FMOLS) estimator to determine the influence of wealth, population, and population age-structure for a panel of OECD countries.

A popular framework used to examine the population-environment relationship at the national level is Dietz and Rosa's (1997) STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology). STIRPAT builds on IPAT/impact equation of Ehrlich and Holdren (1971):

$$I = P \times A \times T \qquad (1)$$

Where I is environmental impact, P is population, A is affluence or consumption per capita, and T is technology or impact per unit of consumption. Two of the criticisms of the Ehrlich-Holdren/IPAT framework are that, as a mathematical or "accounting" identity, it does not permit hypothesis testing, and that it assumes *a priori* a proportionality in the functional relationships between factors. Dietz and Rosa (1997) addressed those two criticisms by proposing a stochastic version of IPAT:

$$I = aP_i^{\,b} A_i^{\,c} T_i^{\,d} e_i \tag{2}$$

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 2 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 2 is no longer an accounting identity whose right and left side dimensions must balance, but a potentially flexible framework for testing hypotheses.

The studies applying the STIRPAT formulation to carbon emissions typically found that both population and income/affluence are significant drivers—with elasticities often near or above unity (thus, e.g., a 1% increase in population caused an approximate 1% increase in emissions). 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; and Liddle and Lung 2010).

This paper advances the population-environment and STIRPAT literature in two important ways. First, it is one of a growing number of national-level studies to examine consumption-driven environmental impacts (like Liddle 2004 and Liddle and Lung 2010) and to consider population structure’s (i.e., household size or age-cohorts) influence on environment (like Cole and Neumayer 2004; Liddle 2004; and Liddle and Lung 2010). Second, it tests the variables analyzed for unit roots (or stationarity) and employs cointegration and FMOLS to estimate elasticities. Although the variables used in STIRPTAT analyses are often highly trending (and thus, likely to be nonstationary), and although cointegration has been used extensively in the energy economics literature to examine relationships among similar variables (e.g., Narayan and Smyth 2008; Lee et al. 2008; Lee and Chang 2008), to our knowledge cointegration has not been used in empirical population-environment studies.

1.1 Consumption-driven impact and population age-structure

Population, and particularly population change, is less likely to directly impact national, aggregate emissions like carbon dioxide, since those emissions should be heavily influenced by the structure and energy intensity of the macro-economy 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 of France (which relies substantially on nuclear generated electricity), yet emits seven percent more carbon than France. However, transport and energy in the home are consumed on the individual, household level, and thus, are much more likely to be directly influenced by per capita wealth and population. Although a few STIRPAT studies have considered aggregate emissions other than carbon dioxide (e.g., Cole and Neumayer 2004 also considered sulphur emissions, and Rosa et al. 2004 considered methane emissions too), only Liddle and Lung (2010) has disaggregated environmental impact by demand or causal sector.

A number of researchers, working with micro-level data, have shown that activities like transport and residential energy consumption vary according to age-structure and household size (e.g., O'Neill and Chen 2002; Liddle 2004; and Prskawetz et al. 2004). A more limited number of studies using macro-level data have shown a similar relationship (specifically, Cole and Neumayer 2004; Liddle 2004; and Liddle and Lung 2010).

In general, age-structure matters because (i) people in different age-cohorts or at different stages of life have different levels of economic activity; and (ii) the age of household head is associated with size of household, and larger households consume more energy in aggregate, but less per person, than smaller households. For example, both residential and transportation energy consumption per capita differ nonlinearly when the age of householder is decomposed at 5-year intervals for US data: transportation follows an inverted-U type shape, whereas residential energy consumption tends to increase with age of householder—but at a non-constant rate (O'Neill and Chen 2002). Liddle (2004), also considering US data, showed that average miles driven per person decline as the number of household members increases, and, at least in small households (one to two people), when controlling for the size of household, 20-30 year-olds drive more per person than other age-groups. In addition, large households (4 people or more) are predominately headed by people in the 35-49 age cohort, and the vast majority of households headed by those aged 50 and older are either single or two-person households (again, from US data). For example, the estimated[1] average household sizes for households headed by persons aged between 20-34, 35-49, 50-64, and 65-75 are 2.7, 3.1, 2.2, and 1.8, respectively.

1.2 Nonstationary variables, cointegration modeling, and FMOLS

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, 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) time-series cross-section (i.e., panel) data have been concerned with the stationarity issue. Two exceptions to this lack of concern were Cole and Neumayer (2004) and Martinez-Zarzoso (2007), both of which recognized this hazard in their data and

[1] This number is estimated because the last household size category supplied in the data is "seven or more" members, i.e., the number of households with exactly eight, nine, etc., members is not explicitly known from the data.

estimated first-difference models to correct for it.[2] However, 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 panel-cointegration, and, depending on the outcome of those tests, estimate the equation via methods like FMOLS.[3] (Such tests were originally designed for time-series but have been expanded to cover panel data sets.) Two or more nonstationary variables are said to be cointegrated if some linear combination of them is stationary. The finding of cointegration among economic or economic-related variables is interpreted as evidence of a long-run, equilibrium relationship. Indeed, the rather large energy consumption-GDP causality literature has shown that (i) variables like GDP per capita, population (or labor force), and emissions/energy consumption are all panel-unit root, and (ii) production-function models—where GDP is a function of energy consumption, labor, and physical capital—are panel-cointegrated for panels of both developed and developing countries (e.g., Narayan and Smyth 2008; Lee et al. 2008; Lee and Chang 2008).

Pedroni's (2000) FMOLS estimator is designed for panels of cointegrated variables and 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 the likely endogeneity among them, is particularly appropriate since such variables are believed to be inter-related and mutually

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[2] Liddle and Lung (2010) observed data at five-year intervals, and thus, stationarity was not an issue in their models.

[3] Another method to estimate coefficients in a cointegrated panel is dynamic OLS; however, there is some evidence that FMOLS is more powerful in small data sets (McCoskey and Koa 1999). Also, FMOLS does not assume a specific form of the nuisance parameters, making it more robust (Pedroni, 2000).

causal according to a number of social science theories. For example, affluence (or GDP per capita) is believed to affect population—through both human capital's influence on birth rates (e.g., Becker et al. 1990) and higher income's ability to lower death rates. Likewise, population has been shown to impact affluence—such as when the size of the working-age population increases faster than the size of the dependent-age population (e.g., Bloom and Williamson 1998); meanwhile, human capital and technology have been recognized as drivers of economic growth (affluence) since Solow (1956).

2. Data, empirical specification, and methods

We use time-series cross-section data from 22 OECD countries spanning 1960-2007. Our panels are not balanced since energy and emissions data start in 1971 for Korea, energy data starts in 1973 for Denmark, and population data starts in 1971 for Greece and in 1976 for Canada (in addition, a few other countries are missing occasional population data points). Table 1 displays the variable names and their sources.

Table 1

We consider as dependent variables two environmental impacts for which population is likely to exert an important influence: carbon emissions from transport (i.e., all transport activity from domestic aviation, domestic navigation, road, rail and pipeline transport) and residential electricity consumption. Furthermore, those two impacts are increasing substantially in developed countries. Figure 1 shows the change since 1971 (data normalized to that year) in per capita consumption of both residential electricity and residential energy and in the per capita emissions of both carbon from transport and carbon from all sources for the OECD as a whole. Electricity consumption is increasing rapidly and linearly (it has more than doubled), and emissions from transport have increased by about 50 percent; however, residential energy consumption has stayed more or less the same, and aggregate carbon emissions have declined some.

Figure 1

2.1 Empirical specification

Following others in the literature, we use real GDP per capita as the measure of affluence. Because we believe age-structure plays an important part in population’s influence on environmental impact, in addition to total population, we consider the population shares of a number of key age groups: 20-34, 35-49, 50-69, and 70 and older. (We do not include the share of those aged 19 and younger since, as primarily dependent children, their impact mostly should be included in their parents’ age group.)

The age groupings are chosen to approximate life-cycle periods that likely correspond to different levels of economic activity (and thus energy consumption) and to various household size memberships. (The age groupings are nearly the same as those used in Liddle and Lung 2010.) In general, the 35-49 age group tends to have the largest households, and thus, should be less energy intensive (i.e., have a negative coefficient); whereas, the oldest age group (70 and older) may stay at home more, and thus, consume more residential electricity. Also, the youngest group (20-34) drives the most per capita, while the oldest age group drives the least.

Since the road sector contributes about 85 percent of transport’s carbon emissions in North America and 93 percent in Europe, two intensity variables that might be related to carbon emissions from transport are urbanization and population density. However, urbanization is probably not a good indication of the spatial density of living in developed countries. For example, over 1960-1990, national levels of urbanization were actually negatively correlated with the population density of inner cities (ρ = -0.33, data from Kenworthy et al. 1999). In addition, Liddle and Lung (2010) ultimately determined that urbanization had no effect on carbon dioxide emissions from transport in their STIRPAT regressions. Also, since national land areas are nonchanging, population density is highly correlated with population (already an independent variable), and differences in area can be captured via country-specific dummy variables. Thus, the equation analyzed for carbon emissions from transport is:

$$\ln I_{it} = \alpha_i + v \ln P_{T,it} + w \ln P_{1,it} + x \ln P_{2,it} + y \ln P_{3,it} + z \ln P_{4,it} + c \ln A_{it} + \varepsilon_{it} \tag{3}$$

Where subscripts *it* denote the *i*th cross section and *t*th time period. The I, P_T, $P_{1\text{-}4}$, and A are the aggregate environmental impact or emissions, total population, the shares of population in the four cohorts defined above, and per capita GDP (or affluence), respectively. The constant α is the country or cross-section fixed effects and ε is the error term.

Urbanization may be correlated to the amount of people who are connected to a country's electricity grid—and thus, positively correlated with residential electricity consumption (indeed, Liddle and Lung 2010, argued this is the case in their regressions). However, urbanization is highly correlated with affluence, and, at least in rich countries, people living in rural areas tend to have access to electricity. A more direct measure of access to a country's electricity grid would be electricity's share of residential energy consumption (a variable that was statistically significant in Liddle and Lung's residential electricity consumption regressions too). Thus, the equation analyzed for residential electricity consumption is:

$$\ln I_{it} = \alpha_i + v \ln P_{T,it} + w \ln P_{1,it} + x \ln P_{2,it} + y \ln P_{3,it} + z \ln P_{4,it} + c \ln A_{it} + d \ln ShE_{it} + \varepsilon_{it} \tag{4}$$

Where *ShE* is electricity's share of residential energy consumption (and subscripts and other variables as in Equation 3).

2.2 Methods

The first step is to determine whether all the variables are integrated of the same order. A variable is said to be integrated of order *d*, written $I(d)$, if it must be differenced *d* times to be made stationary. Thus, a stationary variable is integrated of order zero, i.e., $I(0)$, and a variable that must be differenced once to become stationary is integrated of order one or $I(1)$. A number of panel unit root tests have been developed to determine the order of integration of panel variables; however, these tests sometimes provide conflicting results. Consequently, we employ three of them.

The Breitung (2000) test assumes that there is a common unit root process among the cross-sections, and considers a panel version of the Augmented Dicky-Fuller (ADF) unit root test that proposes a t-test statistic to examine the null hypothesis that the process is non-stationary. (Thus, a statistic that is significantly different from zero is evidence of stationarity.) The Im et al. (2003) test has the advantage over the Breitung test in that it allows for a heterogeneous autoregressive unit root process across cross-sections by testing a statistic that is the average of the individual ADF statistics. Maddala and Wu (1999) proposed a panel unit root test based on Fisher (1932) that, like Im et al., allows for individual unit roots, but improves upon Im et al. by being more general and more appropriate for unbalanced panels. Maddala and Wu's test (ADF-Fisher) is based on combing the p-values of the test-statistic for a unit root in each cross-sectional unit, is non-parametric, and has a chi-square distribution.

If all the variables are integrated of the same order, the next step is to test for cointegration. Engle and Granger (1987) pointed out that a linear combination of two or more nonstationary series may be stationary. If such a stationary linear combination exists, the nonstationary series are said to be cointegrated. The stationary linear combination is called the cointegrating equation and may be interpreted as a long-run equilibrium relationship among the variables.

The Pedroni (1999, 2004) heterogeneous panel cointegration test is an extension to panel data of the Engle-Granger framework. The test involves regressing the variables along with cross-section specific intercepts, and examining whether the residuals are integrated order one (i.e., not cointegrated). Pedroni proposes two sets of test statistics: (i) a panel test based on the within dimension approach (panel cointegration statistics), of which four statistics are calculated: the panel v-, rho-, PP-, and ADF-statistic; and (ii) a group test based on the between dimension approach (group mean panel cointegration statistics), of which three statistics are calculated: the group rho-, PP-, and ADF-statistic. The seven test statistics are not always unanimous, but a consensus among the statistics often is interpreted as evidence in favor of cointegration. (A statistic that is significantly different from zero is evidence of cointegration.) In addition, Pedroni (1999) showed that the panel ADF and group ADF statistics have the best small-sample properties of the seven, and thus, provide the strongest single evidence of cointegration.

If the variables are shown to be cointegrated, then Pedroni's FMOLS estimator produces asymptotically unbiased estimates of the long-run elasticities and efficient, normally distributed standard errors. In addition, the estimations use a semi-parametric correction for endogeneity and residual autocorrelation. The FMOLS estimator is a group mean or between-group estimator that allows for a high degree of heterogeneity in the panel; hence, as well as producing consistent point estimates of the sample means, it allows for the testing of the null hypotheses for all cross-sections—i.e., it provides country specific estimates of all parameters accompanied by efficient standard normal errors.

3. Pre-testing results

As discussed above, in the energy economics literature a number of papers have found variables like GDP per capita—as well as energy consumption and labor force, which should be highly correlated with carbon emissions and population, respectively—to be nonstationary in levels but stationary in first differences for panels of developed countries (e.g., Lee et al. 2008; Apergis and Payne 2010). Thus, we have a strong *a priori* belief that the variables used here that are in levels should be panel $I(1)$ as well. The new variables to be tested in this study are the ones based on shares (population age structure and electricity's share of residential energy consumption).

Table 2 shows the results from the panel unit root tests. As expected all of the variables are determined to be $I(1)$ in at least two of the three tests.[4]

Table 2

Table 3 displays the results of the cointegration tests for both carbon emissions from transport (Equation 3) and residential electricity consumption (Equation 4). There is strong evidence in favor of cointegration among variables both in Equation 3 (carbon emissions from transport) and in Equation 4 (residential electricity consumption) since, in both cases, four of the seven statistics are highly significant, including both panel and group ADF statistics.

Table 3

4. Main estimations and discussion

Table 4 shows the estimated long-run elasticities for both carbon emissions from transport and residential electricity consumption. In both cases the common result from the literature that population is more important than affluence for environmental impact is confirmed. For transport, affluence has an elasticity of slightly greater than one—interesting for a panel of developed countries, most of which have reached saturation in personal transport. This elasticity most likely reflects affluence's contribution to the demand trend of preferring more fuel intensive (lower mileage) and thus more carbon intensive vehicles, rather than its contributing to greater levels of vehicle ownership or miles driven per person.

Age structure's influence on transport emissions is significant and in some cases reasonably large. As expected, young adults (aged 20-34) are environmentally intensive. But the other age cohorts exert a negative effect—implying that population aging will have a

[4] Interestingly, residential *energy* consumption was shown to be stationary in *levels*, i.e., panel $I(0)$ (results not shown). Given the rather flat trajectory of this variables since 1971 for the OECD as a whole, displayed in Figure 1, perhaps that unit root test result is not surprising.

slightly improving environmental effect. However, given the relative sizes of the elasticity coefficients, aging will not likely lead to a reduction of emissions for developed countries in this important end-use sector; instead, real policy efforts to reduce the carbon intensity of transport are needed.

Table 4

The relative importance of population over affluence in terms of the magnitude of their elasticities is much greater for residential electricity consumption than for transport emissions—perhaps surprising since nearly all developed countries have shown an increasing trend in residential electricity consumption (for example, see Figure 7b in Liddle 2009). However, electricity's share of residential energy consumption is significant and positive, and this variable is almost certainly influenced by affluence. Population age-structure's influence on residential electricity consumption has an U-shaped pattern, with the youngest (20-34) and oldest (70 and older) having positive elasticity coefficients and the two middle age groups (35-49 and 50-69) having negative coefficients.

The carbon emissions from transport results reported here provide some contrast to those presented in Liddle and Lung (2010). In their initial carbon emissions from transport regressions (their Models III and IV), they found a greater elasticity for affluence than for population, and not all the coefficients for age structure were statistically significant (they also used a few additional explanatory variables). However, a first difference model (Model VII in Liddle and Lung) produced a greater elasticity for population than for affluence (although the two values were much closer than found here), a positive elasticity for the share of population aged 20-34, and a negative elasticity for the share of population aged 35-64. Their results for residential electricity consumption (Models VI and VIII) are similar to those found here, and their estimated elasticities for affluence, population, and electricity's share of residential energy consumption from a first difference model (Model VIII) are quite similar in magnitude to those reported in Table 4.

Table 5 shows the long-run elasticity estimates for affluence and population by individual countries. For carbon emissions from transport nearly all countries conform to the finding that population has a greater impact than affluence—however, the relative importance of those two factors differ considerably by country (evidence of the importance of pooling countries for the purpose of estimates). A few countries have insignificant elasticity coefficients: Iceland and Norway for affluence and Belgium, Ireland, and the UK for population. Korea and Sweden have surprising and anomalous significant, *negative* coefficients for population. For residential electricity the country specific results are even less uniform—however, when population was statistically significant, it always had a greater impact than affluence. Affluence had an insignificant coefficient for five countries, and population was insignificant for nine countries.

Table 5

5. Projections

To close the analysis, we use the STIRPAT models estimated here to project into the future (to 2050) carbon emissions from transport and residential electricity consumption for the OECD as a whole, and to compare those projections to those made by a simpler STIRPAT model that does not consider the influence of population age structure change. To project population and age structure, we use the United Nations medium variant projections for their classification of more developed regions (which are done on five-year intervals to 2050). Additionally, we assume that real GDP for the OECD will grow by 2.2 percent annually over this time-frame (the same assumption made by the Energy Information Administration in their *Annual Energy Outlook 2009*). Lastly, we assume electricity's share of residential energy consumption, which has increased nearly linearly since 1971 for the

OECD as a whole, will continue to behave in that manner, and we apply a simple, time-trend regression (R-squared value 0.97, result not shown) to estimate its future values. Thus, in the projections, we do not assume that age structure will influence the economic growth rate or that economic growth will further affect electricity's share of residential energy consumption. The primary purpose of the projections is to illustrate the importance of considering age structure change.

As an initial step, we re-estimate the STIRPAT models without the age structure variables; those results are shown in Table 6. The elasticities for affluence and population are now much closer in magnitude, and the elasticities for population are considerably smaller, than when age structure effects were considered.

Table 6

The projections from 2010-2050 for the two models (one that includes age structure effects and one that does not) are displayed in Figure 2a (for carbon emissions from transport) and Figure 2b (for residential electricity consumption). The figures also show the historical values from 1975-2005 as well as the back-cast estimations from the models over that time period. The projection models were calibrated (via a constant term) to the 2005 historical levels.

Figures 2a & 2b

A few generalizations can be made from these simple models. First, population aging in the OECD should have a lowering effect on carbon emissions from transport, but an increasing impact on residential electricity consumption. The model with age structure effects does a better job of "predicting" past (or historical) carbon emissions levels than the model without age structure effects. Both models (with and without age structure effects) are very close for residential electricity consumption (and close to historical levels as well) until around 2030, where the projections from the age structure model begin to rise faster. Perhaps this variation in the difference between the projections with and without age structure effects for the two impacts (carbon emissions from transport and residential energy consumption) is not surprising, given both the expected continued aging of the OECD population and the different magnitudes and signs of the age structure effects reported in Table 4. For carbon emissions from transport the coefficients of all three cohorts beyond 35 are negative, and the four coefficients are negative in sum; whereas, for residential electricity consumption, the coefficients of the four cohorts nearly sum to zero, and the coefficient for the 70 and older cohort is positive.

6. Conclusions

This paper builds upon Liddle and Lung (2010) by also focusing on consumption-based environmental impacts and on the influence of age-structure change in a macro-level empirical setting. It advances the STIRPAT literature by testing for panel unit roots (nonstationarity) and by employing panel cointegration modeling and FMOLS estimations, thus, accounting for the highly inter-related and mutually causal nature of the IPAT variables.

For both carbon emissions from transport and residential electricity consumption, population exerted a greater impact than affluence—confirming a common result in the STIRPAT literature. Population age-structure's influence was significant and varied across cohorts, and its profile was different for two dependent variables. For transport, young adults (20-34) were intensive (i.e., had a positive coefficient), whereas the other cohorts all had negative coefficients (but of different magnitudes). Age-structure had an U-shaped impact on residential electricity consumption since the youngest and oldest (20-34 and 70 and older) had positive coefficients, while the middle cohorts (35-49 and 50-69) had negative coefficients. Individual country elasticity estimates displayed a fair amount of diversity—both in relative magnitudes and statistical significance—arguing for the importance of pooling countries to obtain robust estimates.

Comparing projections from STIRPAT models that included and did not include age structure effects showed that: (i) projections of emissions and energy consumption may be improved by including age structure; and (ii) the expected aging of the OECD population has different influence on different types of environmental impact—aging may lower emissions from transport, but is likely to increase residential electricity consumption. Of course, projections could be further improved by including a system of equations that would consider feedback effects, like population aging's effect on economic growth.

Lastly, the models (both estimations and projections) analyzed here did not allow for the elasticities of affluence or population to change with development or size of population. That question of nonlinear relationships is often answered by including a squared term in regressions (e.g., either GDP per capita or population squared) and testing whether the coefficient for that squared term is negative and statistically significant. However, if the variables of interest are $I(1)$ variables—as the tests conducted here indicated they likely are—then regressions involving nonlinear transformations of such integrated variables could be spurious (Wagner 2008). Thus, a better way to determine whether affluence's or population's environmental impact changes as countries develop may be to compare estimations from panels made up of poor and/or middle-level developing countries to estimations from panels of rich/developed countries.

References

Apergis, N. and Payne, J. 2010. Renewable energy consumption and economic growth: Evidence from a panel of OECD countries. Energy Policy 38, 656-660.

Becker, Gary S & Murphy, Kevin M & Tamura, Robert, 1990. "Human Capital, Fertility, and Economic Growth," Journal of Political Economy, 98(5), S12-37.

Bloom, D. E. and Williamson, J.G. (1998). Demographic Transitions and Economic Miracles in Emerging Asia. The World Bank Economic Review, 12 (3), 419-455.

Breitung, Jörg (2000). "The Local Power of Some Unit Root Tests for Panel Data," in B. Baltagi (ed.), *Advances in Econometrics, Vol. 15: Nonstationary Panels, Panel Cointegration, and Dynamic Panels,* Amsterdam: JAI Press, p. 161–178.

Cole, M. and Neumayer, E. (2004). Examining the impact of demographic factors on air pollution. Population and Environment., 26(1), 5-21.

Dietz, T. and Rosa, E.. (1997). Effects of population and affluence on CO_2 emissions. Proceedings of the National Academy of Sciences of the USA, 94, 175-179.

Ehrlich, P. and Holdren, J. (1971). The Impact of Population Growth. *Science*, 171, 1212-1217.

Engle, R. and Granger, C. 1987. Co-integration and error correction: representation, estimation, and testing. Econometrica 55(2), 251-276.

Fisher, R. A. (1932). Statistical Methods for Research Workers, 4th Edition, Edinburgh: Oliver & Boyd.

Im, K. S., M. H. Pesaran, and Y. Shin (2003). "Testing for Unit Roots in Heterogeneous Panels," *Journal of Econometrics*, 115, 53–74.

Kenworthy, J., Laube, F., and Newman, P. 1999. An International Sourcebook of Automobile Dependence in Cities, 1960-1990. University of Colorado Press, Boulder.

Lee, C. and Chang, C. 2008. "Energy consumption and economic growth in Asian economies: A more comprehensive analysis using panel data," Resource and Energy Economics, 30, 50-65.

Lee, C., Chang, C., and Chen, P. 2008. "Energy-income causality in OECD countries revisited: The key role of capital stock. Energy Economics, 30, 2359-2373.

Liddle, B. (2004). Demographic dynamics and per capita environmental impact: Using panel regressions and household decompositions to examine population and transport. Population and Environment 26(1), 23-39.

Liddle, B. 2009. Electricity intensity convergence in IEA/OECD countries: aggregate and sectoral analysis. Energy Policy, 37, 1470-1478.

Liddle, B. and Lung, S. 2010. Age Structure, Urbanization, and Climate Change in Developed Countries: Revisiting STIRPAT for Disaggregated Population and Consumption-Related Environmental Impacts. Population and Environment, 31, 317-343.

Maddala, G. S. and S. Wu (1999). "A Comparative Study of Unit Root Tests with Panel Data and A New Simple Test," Oxford Bulletin of Economics and Statistics, 61, 631–52.

Martinez-Zarzosos, I., Benochea-Morancho, A., and Morales-Lage, R. (2007). The impact of population on CO_2 emissions: evidence from European countries. Environmental and Resource Economics, 38, 497-512.

McCoskey, S. and Kao, C. 1999. Testing the stability of a production function with urbanization as a shift factor. Oxford Bulletin of Economics and Statistics, 61, 671-689.

Narayan, P. and Smyth, R. 2008. "Energy consumption and real GDP in G7 countries: New evidence from panel cointegration with structural breaks." Energy Economics, 30, 2331-2341.

O'Neill, B. C. and Chen, B. S. (2002). Demographic Determinants of Household Energy Use in the United States. Population and Development Review 28, 53-88.

Pedroni, P. (1999). "Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors," *Oxford Bulletin of Economics and Statistics*, 61, 653–70.

Pedroni, P. 2000. Fully Modified OLS for heterogeneous cointegrated panels. Advances in Econometrics 15: 93-130.

Pedroni, P. (2004). "Panel Cointegration; Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the PPP Hypothesis," *Econometric Theory*, 20, 597–625.

Prskawetz, A., Leiwen J., and O'Neill, B. (2004). "Demographic composition and projections of car use in Austria," *Vienna Yearbook of Population Research*, 2004: 247–326.

Rosa, E., York, R., and Dietz, T. (2004). Tracking the anthropogenic drivers of ecological impacts, Ambio, 33 (8), 509-512.

Shi, A. (2003). The impact of population pressure on global carbon dioxide emissions, 1975-1996: evidence from pooled cross-country data. Ecological Economics, 44, 29-42.

Solow, R. 1956. "A Contribution to the Theory of Economic Growth," Quarterly Journal of Economics, 70: 65-94.

Wagner, Martin. 2008. "The carbon Kuznets curve: A cloudy picture emitted by bad econometrics?" Resource and Energy Economics 30, 3: 388-408.

York, R., Rosa, E., and Dietz, T. (2003). STIRPAT, IPAT, and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. Ecological Economics, 46 351-365.

Table 1. Variables used in the study.

Symbol	Definition	Source
	Dependent variables	
CO2 Transport	Carbon dioxide emissions from transport in metric tons	International Energy Agency
Residential Electricity	Total residential electricity consumption in kilowatt hours	Ibid
	Independent variables	
A	Affluence or real per capita GDP in USD and 2000 constant prices	International Energy Agency.
Sh Electric	Share of residential energy consumption from electricity	Ibid
Population	Total mid-year population	World Bank Development Indicators
Pop2034	Share of population between ages 20-34	Eurostat, OECD.Stat, and national statistical offices
Pop3549	Share of population between ages 35-49	Ibid
Pop5069	Share of population between ages 50-69	Ibid
Pop70+	Share of population age 70 and older	Ibid

Note: All variables in natural log form.

Table 2. Panel unit root tests.

	Breitung t-test		Im et al. W-stat test		ADF-Fisher Chi-square	
Variables	Levels	First differences	Levels	First differences	Levels	First differences
CO2 Transport	5.44	-13.07**	0.10	-21.24**	50.87	423.64**
Residential Electricity	10.74	-10.52**	0.88	-19.52**	56.38	391.89**
Affluence	4.06	-12.08**	-1.42	-18.26**	55.19	351.55**
Population	7.58	0.27	-0.46	-2.33*	60.07	91.79**
Pop 2034	1.19	0.09	-0.05	-2.35*	46.33	70.46*
Pop 3549	4.22	0.98	0.13	-1.86*	43.34	67.10*
Pop 5069	-1.29	-3.31**	0.23	-3.31**	53.82	85.34**
Pop 70+	3.55	-4.36**	1.35	-6.30**	51.54	119.22**
Sh Electric	1.82	-14.69**	0.83	-24.04**	45.62	555.45**

Note: Statistical significance is indicated by: **p <0.001 and * p <0.01.

Table 3. Pedroni panel cointegration tests for the individual models.

Within dimension test statistics		Between dimension test statistics	
CO2 Transport, Affluence, Population, Pop2034, Pop3549, Pop5069, Pop70+			
Panel v-statistic	1.16	Group rho-statistic	6.86
Panel rho-statistic	4.30	Group PP-statistic	-4.89**
Panel PP-statistic	-2.67*	Group ADF-statistic	-8.22**
Panel ADF-statistic	-6.04**		
Residential Electricity, Affluence, Population, Pop2034, Pop3549, Pop5069, Pop70+, Sh Electric			
Panel v-statistic	1.08	Group rho-statistic	1.46
Panel rho-statistic	0.23	Group PP-statistic	-4.48**
Panel PP-statistic	-4.53**	Group ADF-statistic	-4.51 **
Panel ADF-statistic	-3.80**		

Note: Statistical significance is indicated by: ** p <0.001 and * p <0.01.

Table 4. Long-run elasticities from FMOLS.

Dep. variable	CO2 from Transport	Residential Electricity
Affluence	1.055**	0.615**
Population	2.347**	2.686**
Pop2034	0.818**	0.219**
Pop3549	-0.217*	-0.418**
Pop5069	-0.771**	-0.404**
Pop70+	-0.363*	0.552**
Sh Electric		0.259**

Note: Statistical significance is indicated by: ** p <0.001 and * p <0.01.

Table 5. Long-run elasticities for affluence and population by country. FMOLS estimation.

	CO2 from Transport		Residential Electricity	
Country	Affluence	Population	Affluence	Population
Australia	0.525***	0.778**	0.368***	2.336****
Austria	0.680***	4.567****	0.979***	3.042***
Belgium	0.984****	0.314	1.593****	-2.770
Canada	1.888****	5.526****	0.329	2.925****
Denmark	2.120****	6.792*	0.836****	1.027
Finland	0.531**	7.409****	0.062	11.481**
Greece	0.958****	3.127**	0.661****	1.983
Iceland	-0.188	4.137***	0.481***	-0.078
Ireland	1.103****	-0.329	0.798****	1.315
Italy	1.341****	2.637*	1.169****	8.169****
Japan	0.746****	2.621****	0.467***	3.395****
Korea	2.211****	-8.144****	0.796**	11.324****
Luxembourg	0.995***	4.485****	0.708***	-1.135
Netherlands	0.859****	3.379***	0.696**	3.774***
Norway	0.014	4.192***	0.326	-0.309
Portugal	1.497****	1.667*	0.419**	-0.024
Spain	1.461****	2.971****	0.217	1.894***
Sweden	1.301****	-1.209**	0.055	1.550*
Switzerland	1.351****	1.213***	0.446***	1.591****
Turkey	1.234****	1.138****	0.549****	1.152****
United Kingdom	0.731****	-0.026	0.925****	0.136
United States	0.867****	4.386****	0.648***	6.320****

Note: Statistical significance is indicated by: **** p <0.001, *** p <0.01, ** p<0.05, and * p<0.10.

Table 6. Long-run elasticities from models without age structure. FMOLS estimation.

Dep. variable	CO2 from Transport	Residential Electricity
Affluence	0.978*	0.771*
Population	1.342*	1.745*
Sh Electric		0.399*

Note: Statistical significance is indicated by: * p <0.001.

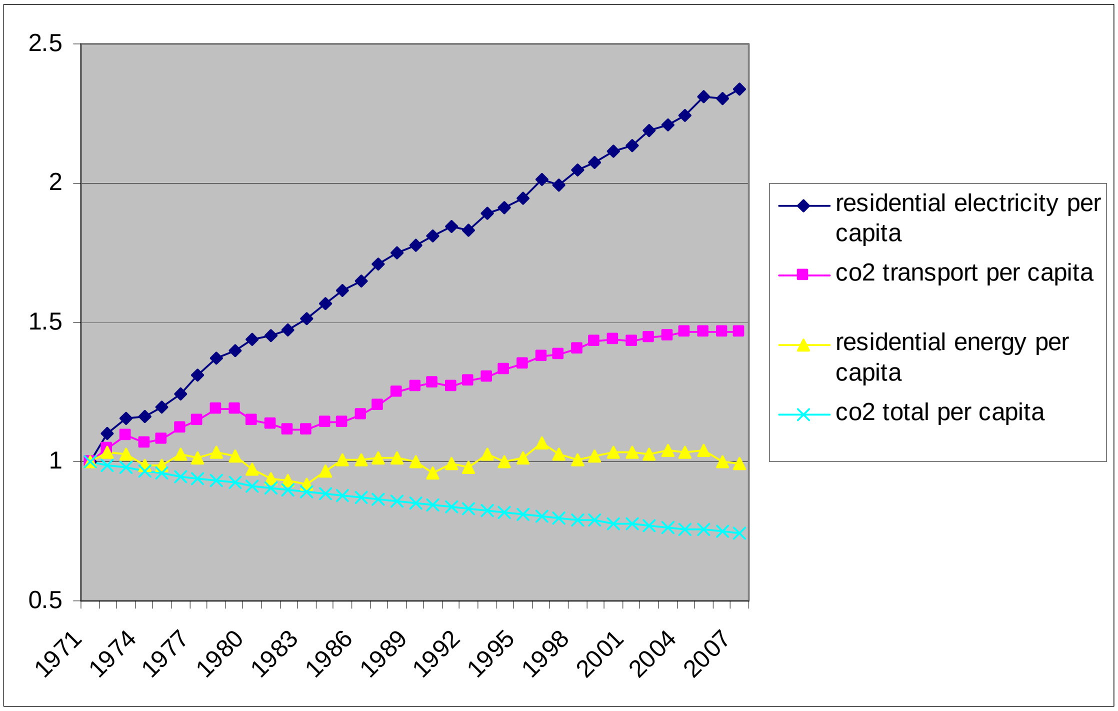

Figure 1. The change in residential electricity consumption per capita, residential energy consumption per capita, CO_2 emissions per capita, and CO_2 emissions from transport per capita since 1971 for the OECD as a whole. (Data has been normalized to its 1971 value.)

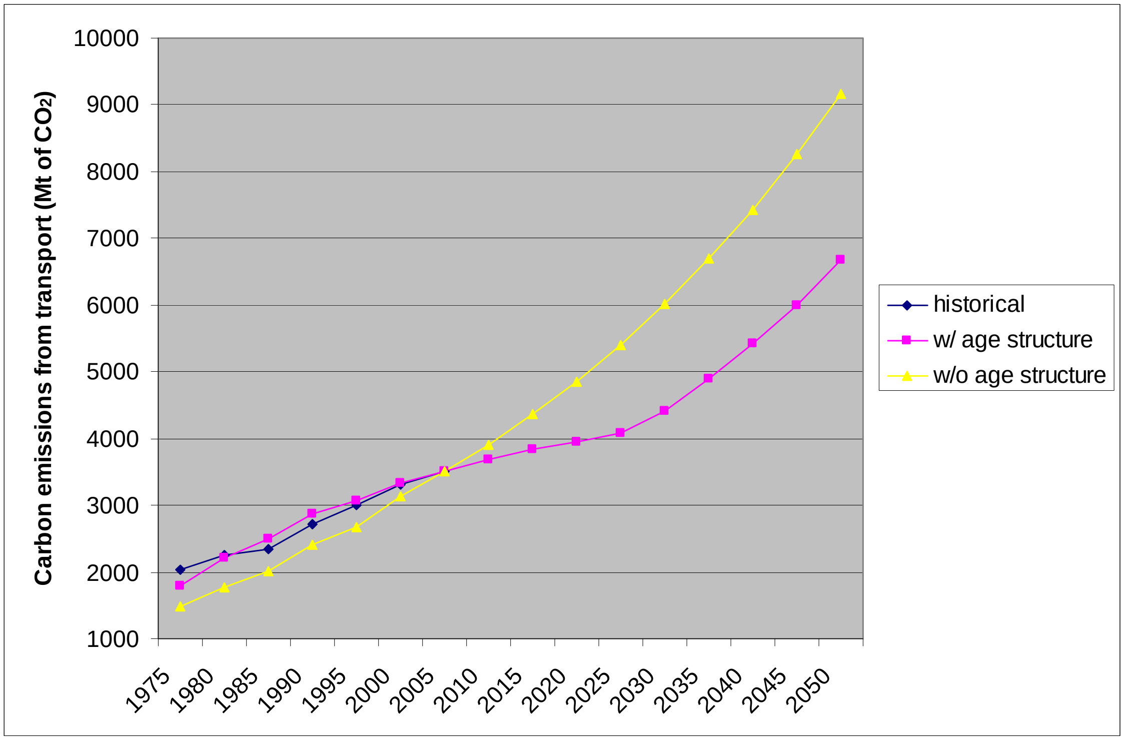

Figure 2a. Projections (from 2010 to 2050 at five-year intervals) of carbon emissions from transport for the OECD as a whole using two STIRPAT models: one that includes age structure variables and one that does not. Historical emissions, as well as model back-casts, from 1975-2005 also are displayed. Projection models have been calibrated to the 2005 historical levels.

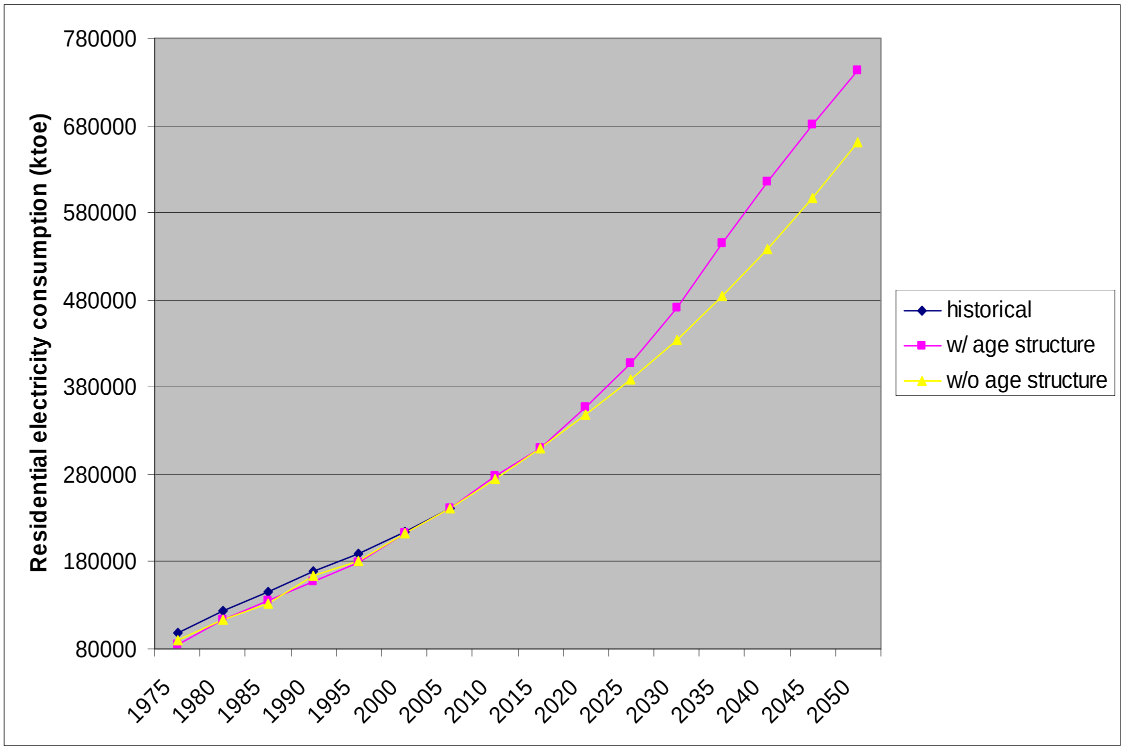

Figure 2b. Projections (from 2010 to 2050 at five-year intervals) of residential electricity consumption for the OECD as a whole using two STIRPAT models: one that includes age structure variables and one that does not. Historical consumption, as well as model back-casts, from 1975-2005 also are displayed. Projection models have been calibrated to the 2005 historical levels.