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Research Article

Consumption-driven environmental impact and age structure change in OECD countries: A cointegration-STIRPAT analysis

Brantley Liddle

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Brantley Liddle[1]

Abstract

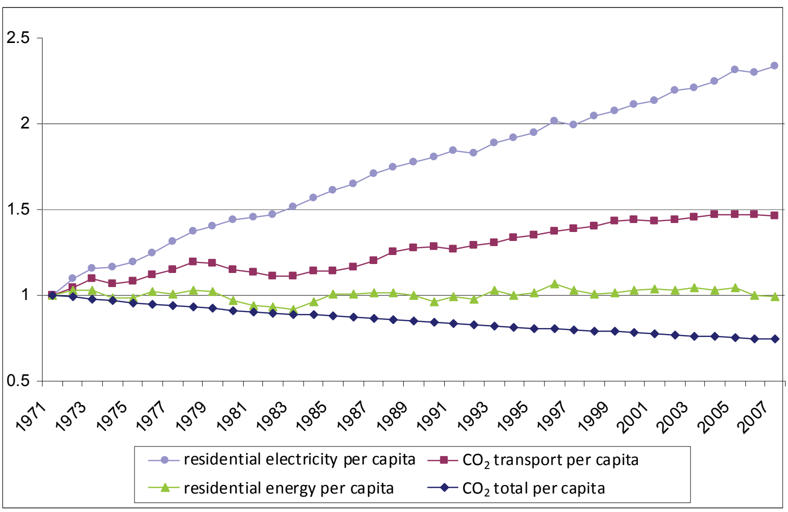
This paper examines two environmental impacts for which population has a substantial demonstrated influence: transport carbon emissions and residential electricity consumption. It takes as its starting point the STIRPAT framework and disaggregates population into four key age groups: 20-34, 35-49, 50-69, and 70 and older. 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, whereas the other cohorts had negative coefficients. For residential electricity consumption, age structure had a U-shaped impact: the youngest and oldest cohorts had positive coefficients, while the middle ones had negative coefficients.

[1] Victoria University. E-mail: btliddle@alum.mit.edu.

1. Introduction and literature review

Transport contributes more than one-fifth of global anthropogenic carbon dioxide emissions and over a quarter of such OECD emissions; the residential sector consumes more than 30% of the OECD's electricity, and both transport and residential electricity consumption are increasing faster than other end-use sectors in OECD countries. Figure 1 shows since 1971 (data normalized to that year) the change in per capita consumption of both residential (final) electricity and residential energy (i.e., consumption by households excluding transport), and in per capita emissions of both carbon from transport (i.e., emissions from the combustion of fuel from all transport activity) and carbon from all sources (i.e., total emissions from all fuel combustion as calculated using the IPCC Tier 1 Sectoral Approach) for the OECD as a whole. Per capita residential electricity consumption is increasing rapidly and linearly (it has more than doubled), and per capita emissions from transport have increased by about 50%. However, per capita residential energy consumption has stayed more or less the same, and per capita carbon emissions from all sources have declined by about 25%.

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



Note: Data has been normalized to its 1971 value.
Source: International Energy Agency.

Although there are non-greenhouse-gas-intensive technologies for generating electricity, even in OECD Europe more than half of electricity is generated from fossil fuels (that share is over 60% for both Japan and Korea, over 70% for the US, and 97% for Australia). Furthermore, many of the alternatives to fossil fuels also have environmental impacts: 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, as well as the threat of non-energy, military uses (e.g., terrorism).

In addition, the majority of transport[2] and all 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. This paper employs the stochastic version of the IPAT model, panel cointegration, and Pedroni's (2000) panel Fully Modified OLS (FMOLS) estimator to determine the influence of wealth, population, and population age structure on those two consumption-driven environmental impacts (carbon emissions from transport and residential electricity consumption) 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 the IPAT/impact equation of Ehrlich and Holdren (1971):

$$I = P \times A \times T \tag{1}$$

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

[2] In the US, approximately 59% of all transport energy consumed is from non-business, household sources (Gardner and Stern 2008).

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 environmental impact (i.e., elasticity) than affluence (e.g., Dietz and Rosa 1997; Shi 2003; York, Rosa, and Dietz 2003; Cole and Neumayer 2004; Martinez-Zarzoso et al. 2007; and Liddle and Lung 2010).[3]

This paper advances the population-environment 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 the influence of population structure (i.e., household size or age cohorts) on environment (e.g., Cole and Neumayer 2004; Liddle 2004; and Liddle and Lung 2010). Second, it tests the variables analyzed for panel unit roots (or stationarity) and employs panel cointegration and panel FMOLS to estimate elasticities. Although the variables used in STIRPTAT analyses are stocks or stock-related and are often highly trending (and thus likely to be nonstationary), and although cointegration and FMOLS have been used extensively in the energy economics literature to examine relationships among similar variables (e.g., Lee, Chang, and Chen 2008; Apergis and Payne 2010), to our knowledge cointegration has not been used in empirical population-environment studies.

As a result of these two innovations, we determine that population age structure's influence was significant and varied across cohorts, and its profile was different for the two dependent variables. For transport, young adults (20-34) were intensive (having a positive coefficient, while other, older cohorts had negative coefficients); whereas, for residential electricity consumption, age structure had a U-shaped impact (the youngest and oldest cohorts had positive coefficients, while the middle cohorts had negative coefficients). The importance of considering age structure was further borne out by comparing projections (of transport emissions and electricity consumption) from STIRPAT models with and without age structure effects.

[3] A few STIRPAT papers (e.g., Dietz and Rosa 1997; York, Rosa, and Dietz 2003) also estimated models with a GDP per capita squared term (which was negative); in some of those regressions, the sum of the elasticities of GDP per capita terms was larger than that for population.

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 (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 7% more carbon than France. However, the majority of transport and all energy in the home are consumed on an 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, York, and Dietz 2004 considered methane emissions too), only Liddle and Lung (2010) 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; Prskawetz, Leiwen, and O'Neill 2004). A more limited number of studies using macro-level data have shown a similar relationship (specifically Cole and Neumayer 2004; Liddle 2004; 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, although less per person, than smaller households. For example, both residential and transportation energy consumption per capita differs nonlinearly when the age of householder is decomposed at five-year intervals for US data: transportation follows an inverted-U 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 (four 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[4] average household sizes for households headed by persons aged 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, FMOLS, and STIRPAT variables

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 to be nonstationary—that is, their mean, variance, and/or covariance with other variables changes over time.[5] 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 estimated first-difference models to correct for it.[6] However, first-differencing means that the model is a short-run (rather than a long-run) model (since some long-run information is lost), 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 panel FMOLS. (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 all have panel

[4] 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).
[5] Several STIRPAT studies—particularly the early ones—were based on cross-sectional data, and thus stationarity properties in the data were not an issue.
[6] Liddle and Lung (2010) observed data at five-year intervals, and thus stationarity was not an issue in their models.

unit roots, and (ii) production-function models—where GDP is a function of energy consumption, labor, and physical capital—are panel-cointegrated for OECD country panels (e.g., Lee, Chang, and Chen 2008; and Apergis and Payne 2010).

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 as the likely endogeneity among them, is particularly appropriate since such variables are believed to be interrelated and mutually 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, Murphy, and Tamura 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).[7]

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 starts 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.

[7] In theory FMOLS accounts for endogeneity among variables implicitly. To more fully and explicitly express the potential mutual feedbacks among the variables would require an approach like multiple structural equation modeling—a discussion of that methodology is beyond the scope of the present paper.

Table 1: Variables used in the study

Symbol	Definition	Source
Dependent variables		
CO_2 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
Pop20-34	Share of population between ages 20-34	Eurostat, OECD.Stat, and national statistical offices
Pop35-49	Share of population between ages 35-49	Ibid
Pop50-69	Share of population between ages 50-69	Ibid
Pop70+	Share of population age 70 and older	Ibid

Note: All variables in natural log form.

2.1 Empirical specification

We consider the environmental impacts of two dependent variables upon which population is likely to exert an important influence: carbon emissions from transport (i.e., emissions from all transport activity, which includes domestic aviation, domestic navigation, road, rail, and pipeline transport) and residential electricity consumption (i.e., household final electricity consumption, except for that which may be used in transport). 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.) Including average household size could help differentiate between the importance of the aging and the household size effects (discussed earlier). Unfortunately, household size data does not have the degree of annual coverage necessary to perform the time-series-derived empirical methods employed here.

The age groupings are chosen to approximate life-cycle periods that most 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 age group (20-34) drives the most per capita, while the oldest age group drives the least.

Since the road sector contributes about 85% of transport's carbon emissions in North America and 93% 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, in the period 1960-1990 national levels of urbanization were actually negatively correlated with the population density of inner cities ($\rho = -0.33$; data from Kenworthy, Laube, and Newman 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 non-changing, population density is highly correlated with population (already an independent variable), and differences in area can be captured via country-specific dummy variables, as can other mostly country-specific and slow-moving factors like public transportation infrastructure and vehicle fuel efficiency standards. Thus the equation analyzed for carbon emissions from transport is:

$$\begin{aligned} \ln I_{it} &= \alpha_i + v \ln P_{T,it} + w \ln ShP_{20-34,it} + x \ln ShP_{35-49,it} \\ &\quad + y \ln ShP_{50-69,it} + z \ln ShP_{70+,it} + c \ln A_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

where subscripts *it* denote the i[th] cross-section and t[th] time period and I, P_T, ShP, and A are the aggregate environmental impact or emissions, population total, share 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 that 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:

$$\begin{aligned} \ln I_{it} &= \alpha_i + v \ln P_{T,it} + w \ln ShP_{20-34,it} + x \ln ShP_{35-49,it} + y \ln ShP_{50-69,it} \\ &\quad + z \ln ShP_{70+,it} + c \ln A_{it} + d \ln ShE_{it} + \varepsilon_{it} \end{aligned} \tag{4}$$

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

Models involving transport demand (which is correlated with carbon emissions from transport) or electricity demand often include price as an explanatory variable. However, to our knowledge, considering price has not been done in the STIRPAT literature. In addition, demand-type models that do have income and price as explanatory variables typically have the dependent variable in per capita terms rather than in aggregate terms, as is the case in the STIRPAT framework. Furthermore, cross-country differences in energy prices primarily reflect differences in taxes, and those differences are fairly constant over time (Dreher and Krieger 2008). Lastly, IEA price data for OECD countries begins only in 1978 and is missing observations for several countries in our panels.

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—that is, $I(0)$—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. These tests typically extend to a panel model, the Augmented Dickey–Fuller (ADF) unit root framework, where the first difference of a series is regressed on the one-period lag of that series and on a selected number of additional lagged first-difference terms to control for autocorrelation. The various tests sometimes provide conflicting results, however, and those results are often dependent on the number of lags selected.[8] Consequently, we employ three different tests that allow for a heterogeneous autoregressive unit root process across cross-sections.

Im, Pesaran, and Shin (2003) developed a test (IPS) that calculates a statistic that is the average of the individual (each cross-sectional unit) ADF statistics. Maddala and Wu (1999) proposed a panel unit root test that, like the IPS test, allows for individual unit roots, but improves upon IPS by being more general. Maddala and Wu's test (ADF–Fisher) is based on Fisher (1932)—that is, it involves combining the *significance levels* of the test statistics rather than combining the *test statistics*, is nonparametric, and has a chi-square distribution (as opposed to a standard normal distribution for the IPS test). Similar to Maddala and Wu, Choi (2001) developed a Fisher-style test (Fisher–

[8] The Schwarz information criterion is used to determine the optimal number of lags.

PP) that assumes individual unit roots too. But the Fisher–PP test, like the Phillips–Perron-type tests (Phillips and Perron 1988) for time series, has the additional advantage of not depending on the lag lengths used in the individual ADF regressions, but instead uses kernel density estimation to control for autocorrelation. All three tests assume the null hypothesis of nonstationarity.

If all the variables are integrated of the same order, the next step is to test for cointegration. Again, if a stationary linear combination of two or more nonstationary series exists, the nonstationary series are said to be cointegrated (Engle and Granger 1987). The stationary linear combination is called the cointegrating equation.

The Pedroni (1999 and 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 statistics; 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 statistics. 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.

Lastly, if the variables are shown to be cointegrated, then the long-run elasticities are calculated from Pedroni's (2000) panel FMOLS estimator. In addition to producing asymptotically unbiased estimates with normally distributed standard errors, FMOLS is a nonparametric approach in which an initial estimation calculates the serial correlation and endogeneity correction terms. Also, 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 panel sample means, it allows for the testing of the null hypotheses for each cross-section—that is, it provides country-specific estimates of all parameters accompanied by efficient standard normal errors.[9]

[9] The reported unit root and cointegration tests were performed in EViews. The FMOLS estimations were made in RATS; however, the cointegration tests when performed in RATS did not differ substantively from those reported.

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 OECD country panels (e.g., Lee, Chang, and Chen 2008; and 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. The tests provide very strong evidence that all of the variables, as expected, are panel $I(1)$ or nonstationary in levels but stationary in first differences; thus OLS regressions with those variables in levels would be inefficient and most likely spurious. The null hypothesis of nonstationarity in levels is never rejected (at least never at a very high level of significance), whereas the null hypothesis of nonstationarity in first differences is rejected by each test at a very high level of significance.

Table 2: Panel unit root tests

	Im et al. W-stat test		ADF–Fisher Chi-square		PP–Fisher Chi-square	
Variables	Levels	First differences	Levels	First differences	Levels	First differences
CO_2 Transport	0.10	-21.24**	50.87	423.64**	57.56	594.68**
Residential Electricity	0.88	-19.52**	56.38	391.89**	64.08	518.92**
Affluence	-1.42	-18.26**	55.19	351.55**	43.98	350.48**
Population	-0.46	-2.33*	60.07	91.79**	42.98	87.66**
Pop20-34	-0.05	-2.35*	46.33	70.46*	19.36	82.02**
Pop35-49	0.13	-1.86*	43.34	67.10*	62.13	161.03**
Pop50-69	0.23	-3.31**	53.82	85.34**	9.56	83.46**
Pop70+	1.35	-6.30**	51.54	119.22**	41.23	400.46**
Sh Electric	0.83	-24.04**	45.62	555.45**	51.56	555.45**

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

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. Thus there is a long-run cointegrating relationship among those environmental impacts, affluence, and the population variables.

Table 3: Pedroni panel cointegration tests for the individual models

Within dimension test statistics		Between dimension test statistics	
CO_2 Transport, Affluence, Population, Pop20-34, Pop35-49, Pop50-69, 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, Pop20-34, Pop35-49, Pop50-69, 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.

4. Main estimations and discussion

Table 4 shows the estimated long-run elasticities for carbon emissions from transport and for residential electricity consumption. In both cases the common result from the literature that environmental impact is more sensitive to changes in population than to changes in affluence is confirmed.[10] 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.[11] But the other age cohorts exert a negative effect—implying that population aging will have a slightly improving environmental effect. However, given the relative sizes of the elasticity coefficients, aging is not likely to lead to a reduction of emissions

[10] It is a common result at least among studies that did not include a GDP per capita squared term.

[11] An anonymous reviewer suggested the possibility that if the young adult population drives economic growth, then such a cohort could lead to higher emissions because they are responsible for creating a larger economy. The idea that young adults substantially drive economic growth and thus transport emissions in developed/OECD countries seems unlikely for several reasons, among them (i) peak individual productivity occurs during ages 35-44 (Skirbekk 2003); and (ii), as mentioned earlier, individual, non-business travel accounts for the majority of transport energy consumption.

for developed countries in this important end-use sector; instead, real policy efforts to reduce the carbon intensity of transport are needed.

Table 4: Long-run elasticities from FMOLS

Dep. variable	CO_2 from Transport	Residential Electricity
Affluence	1.055**	0.615**
Population	2.347**	2.686**
Pop20-34	0.818**	0.219**
Pop35-49	-0.217*	-0.418**
Pop50-69	-0.771**	-0.404**
Pop70+	-0.363*	0.552**
Sh Electric		0.259**

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

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 surprisingly, since nearly all developed countries have shown an increasing trend in residential electricity consumption (see, e.g., 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 a U-shaped pattern, with the youngest (20-34) and oldest (70 and older) age groups having positive elasticity coefficients and the two middle (35-49 and 50-69) ones 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 (Models III and IV), Liddle and Lung 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) 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 differs considerably by country (evidence of the importance of pooling countries to obtain robust 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 surprisingly and anomalously 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: Long-run elasticities for affluence and population by country: FMOLS estimation

	CO_2 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.

5. Projections

To conclude 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 with 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 per capita for the OECD will grow by 2.2% annually over this time frame (the same assumption made by the Energy Information Administration in their *Annual Energy Outlook 2009*). Lastly, we assume that 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; the 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: Long-run elasticities from models without age structure: FMOLS estimation

Dep. variable	CO_2 from Transport	Residential Electricity
Affluence	0.978*	0.771*
Population	1.342*	1.745*
Sh Electric		0.399*

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

The projections from 2010 to 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 to 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. All four projections suggest substantial growth (although not uncharacteristic growth, given the recent historical trends displayed in Figure 1). By contrast, the Energy Information Administration projects transport *energy* consumption to increase by less than 10% and residential electricity consumption to increase by only 34% from 2007 to 2035 for the OECD as a whole.

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 to 2005 also are displayed. Projection models have been calibrated to the 2005 historical levels

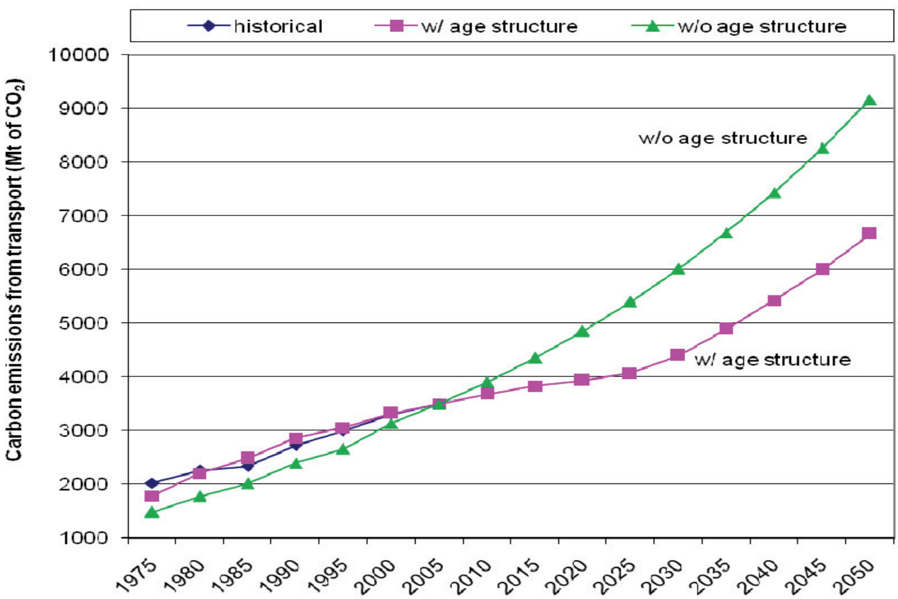
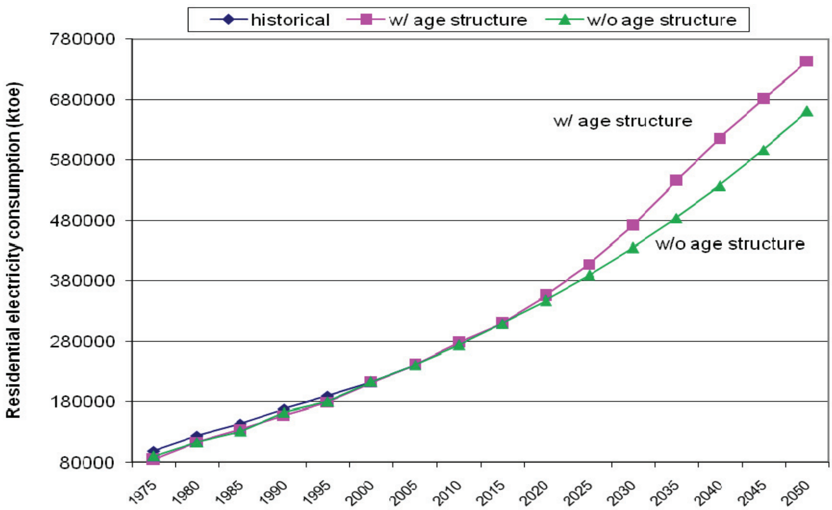


Figure 2b: Projections (from 2010 to 2050 at five-year intervals) of residential electricity consumption for the OECD as a whole using two STIRPAT models: one that includes age structure variables and one that does not. Historical consumption, as well as model back-casts, from 1975 to 2005 also are displayed.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



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. For transport, 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. For residential electricity consumption, both models (with and without age structure effects) are very close to each other (and close to historical levels as well) until around 2030, when 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 20-34 are negative, and the four coefficients are negative in sum; whereas, for residential electricity consumption, the sum of coefficients of the four cohorts is nearly 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 panel FMOLS estimations, thus accounting for the highly interrelated 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 a 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. Again, age structure is important because (i) people at different stages of life have different levels of economic activity; and (ii) the age of household head is associated with household size, and larger households consume less per person than smaller households. Including time-series cross-section data of average household size, if/when available, could help disentangle those two important effects. Individual country elasticity estimates displayed a fair amount of diversity—in both 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 arguably could be improved by including age structure; and (ii) the expected aging of the OECD population has a 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.

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References

Apergis, N. and Payne, J. (2010). Renewable energy consumption and economic growth: Evidence from a panel of OECD countries. *Energy Policy* 38(1): 656-660. doi:10.1016/j.enpol.2009.09.002.

Becker, G., Murphy, K., and Tamura, R. (1990). Human capital, fertility, and economic growth. *Journal of Political Economy* 98(5): 12-37. doi:10.1086/261723.

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.

Choi, I. (2001). Unit root tests for panel data. *Journal of International Money and Finance* 20(2): 249-272. doi:10.1016/S0261-5606(00)00048-6

Cole, M. and Neumayer, E. (2004). Examining the impact of demographic factors on air pollution. *Population and Environment*. 26(1): 5-21. doi:10.1023/B:POEN.0000039950.85422.eb

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(1): 175-179. doi:10.1073/pnas.94.1.175.

Dreher, A. and Krieger, T. (2008). Do prices for petroleum products converge in a unified Europe with non-harmonized tax rates? *The Energy Journal* 29(1): 68-88. doi:10.5547/ISSN0195-6574-EJ-Vol29-No1-4

Ehrlich, P. and Holdren, J. (1971). The impact of population growth. *Science* 171(3977): 1212-1217. doi:10.1126/science.171.3977.1212.

Engle, R. and Granger, C. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica* 55(2): 251-276. doi:10.2307/1913236.

Fisher, R.A. (1932). *Statistical methods for research workers*, 4th Edition. Edinburgh: Oliver & Boyd.

Gardner, G. and Stern, P. (2008). The short list: The most effective actions US households can take to curb climate change. *Environment* 50(5): 13-24. doi:10.3200/ENVT.50.5.12-25.

Im, K.S., Pesaran, M.H., and Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics* 115(1): 53-74. doi:10.1016/S0304-4076(03)00092-7.

Kenworthy, J., Laube, F., and Newman, P. (1999). *An International sourcebook of automobile dependence in cities, 1960-1990*. Boulder: University of Colorado Press.

Lee, C., Chang, C., and Chen, P. (2008). Energy-income causality in OECD countries revisited: The key role of capital stock. *Energy Economics* 30(5): 2359-2373. doi:10.1016/j.eneco.2008.01.005.

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. doi:10.1023/B:POEN.0000039951.37276.f3.

Liddle, B. (2009). Electricity intensity convergence in IEA/OECD countries: aggregate and sectoral analysis. *Energy Policy* 37(4): 1470-1478. doi:10.1016/j.enpol.2008.12.006.

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(5): 317-343. doi:10.1007/s11111-010-0101-5.

Maddala, G.S. and Wu, S. (1999). A Comparative Study of Unit Root Tests with Panel Data and A New Simple Test. *Oxford Bulletin of Economics and Statistics* 61(S1): 631-652. doi:10.1111/1468-0084.0610s1631.

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(4): 497-512. doi:10.1007/s10640-007-9096-5.

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(S1): 653-670. doi:10.1111/1468-0084.0610s1653.

Pedroni, P. (2000). Fully modified OLS for heterogeneous cointegrated panels. *Advances in Econometrics* 15: 93-130. doi:10.1016/S0731-9053(00)15004-2.

Pedroni, P. (2004). Panel cointegration: Asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Econometric Theory* 2004(20): 597-625. doi:10.1017/S0266466604203073.

Phillips, P. and Perron, P. (1988): Testing for a unit Root in time series regression. *Biometrika* 75(2): 335-346. doi:10.1093/biomet/75.2.335.

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(1): 29-42. doi:10.1016/S0921-8009(02)00223-9.

Skirbekk,V. (2003). Age and individual productivity: A literature survey. Rostock: Max Planck Institute for Demographic Research (MPIDR Working Paper; WP-2003-028).

Solow, R. 1956. A contribution to the theory of economic growth. *Quarterly Journal of Economics* 70(1): 65-94. doi:10.2307/1884513.

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(3): 351-365. doi:10.1016/S0921-8009(03)00188-5.