Age-Structure, Urbanization, and Climate Change in Developed Countries: Revisiting STIRPAT for Disaggregated Population and Consumption-Related Environmental Impacts

Liddle, Brantley and Lung, Sidney

2010

Age-Structure, Urbanization, and Climate Change in Developed Countries: Revisiting STIRPAT for Disaggregated Population and Consumption-Related Environmental Impacts

Brant Liddle
Centre for Strategic Economic Studies
Victoria University
btliddle@alum.mit.edu

Sidney Lung
School of Applied Economics
Victoria University

ABSTRACT
We focus on three environmental impacts particularly influenced by population age-structure—carbon emissions from transport and residential energy and electricity consumption—as well as aggregate carbon emissions for a panel of developed countries, and take as our starting point the STIRPAT framework. Among our contributions is to further disaggregate population into three particularly key age groups: 20-34, 35-49, and 50-64, and by doing so demonstrate that population's environmental impact differs considerably across age-groups, with the older age-groups (ones typically associated with larger households) actually exerting a negative influence. Furthermore, those age-specific population influences are different (in absolute and relative terms) for the different environmental impacts we analyze. Also, we find that urbanization, in developed countries, best measures access to a country's power grid, and thus, is positively associated with energy consumption in the residential sector. Lastly, we suggest some modelling and methodological improvements to the STIRPAT framework.

Keywords: STIRPAT; population structural change and environment; carbon dioxide emissions; demography and climate change; panel data.

Published as:
Liddle, B. & 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, Vol. 31, No. 5, pp. 317-343.

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. This paper examines the macro-level links among population change, economic variables, and carbon emissions and energy consumption using country-level data. We base our analysis on the stochastic version of the IPAT model. And we advance the literature associated with the stochastic IPAT model (i) by informing our population variables (the むPめof the equation set out below) with the recent population and environment literature that has emphasized the importance of age-structural change, and (ii) by adding other improved macro-variables to capture the intensity of production and consumption (i.e., the むTめof the equation). Among the insights gleaned from our improved approach is that populationゃenvironmental impact varies across age cohortsみa finding made possible by our further disaggregating population into certain age cohorts.

Much of the work on the population-environment relationship at the national level follows the rather linear reasoning that more people, consuming at the same level, necessarily result in more human impact on the environment. These studies frequently use the framework of Ehrlich and Holdren (1971), also called the IPAT/impact equation:

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

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. Among the criticisms of the Ehrlich-Holdren/IPAT framework are that as a mathematical or むaccountingめidentity it does not permit hypothesis testing, and that it assumes a priori a proportionality in the functional relationships between factors. To address those two deficiencies Dietz and Rosa (1997) proposed a stochastic version of IPAT:

$$I = aP_i^b A_i^c T_i^d e_i \qquad (2)$$

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 also 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. In addition, the T term is now treated more like an intensity of use variable, and the T and P terms are modelled sometimes as a combination of log-linear factors. Dietz and Rosa name Equation 2 and variations of it STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology).

The studies applying the STIRPAT formulation to carbon emissions typically find that both population and income/affluence are significant drivers—with elasticities often near or above unity (thus, e.g., a 1% increase in population causes 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. 2003a; Cole and Neumayer 2004; and Martinez-Zarzoso et al. 2007). This paper strives to further understanding of the influence of population change on some specific anthropogenic environmental impacts and offers some modelling improvements to the STIRPAT framework.

1.1 Population disaggregation

The most common way to disaggregate population is to include (i) the share of working-age population (population aged 15-64) and (ii) the level of urbanization (proportion of population living in urban areas). (Cole and Neumayer 2004 also included the share of population under 15, whereas York 2007 substituted the share of population over 64 for the share of working-age population.) Table 1 lists the STIRPAT studies that disaggregate population and describes their additional population variables, intensity variables, and data sets.

Table 1

Decomposing population in this most common way is clearly an advance on studies that do not disaggregate population at all. However, such population disaggregation is relatively crude, and so fails to capture the richness of age structure and consumption that other studiesみoften using micro-level data and focusing specifically on the impact demographic and household change has on energy consumptionみhave uncovered.[1] For example, Oゃ Neill and Chen (2002) showed how 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みbut at a non-constant rate. To some degree these consumption patterns reflect (i) the association of age of household head with size of household, and (ii) the fact that large households consume more energy in aggregate, but less per person, than smaller households.[2] Figure 1, which shows the breakdown of the number of households of various sizes by age of household head for the US in 2007, illustrates the first point. (The second point will be discussed further below and illustrated in Figure 2 below.) Figure 1 indicates that large households (4 people or more) are predominately headed by people in the 35-49 age cohort, and that the vast majority

[1] Perhaps the level of aggregation encountered in the literature is so popular because it is the level of aggregation in the widely used World Bank data set. The UN does publish (with free access) population data in 5-year age groupings, but the data is only available at 5-year intervals (beginning in 1950), and that data set requires considerably more manipulation by the analyst to compile in a form suitable for regressions. (Web address: http://esa.un.org/unpp.)

[2] The first published population-environment study to consider households as the unit of analysis we know of was MacKellar et al. (1995). However, household size can be a difficult variable to collect for an empirical panel analysis; thus, few other macro-level, cross-country studies have followed MacKellar et al.ゃ leadみtwo exceptions are Cole and Neumayer (2004) and Liddle (2004).

of households headed by those aged 50 and older are either single or two-person (the estimated[3] average household size for the four different household head age groupings shown in the figure are 2.7, 3.1, 2.2, and 1.8, respectively).

Figure 1

Liddle (2004), like O'Neill and Chen considering US data, showed that average miles driven per person decline as the number of household members increases, and, in small households (one to two people) at least, when controlling for the size of household, 20-30 year-olds drive more per person than other age-groups. Prskawetz et al. (2004) demonstrated that similar relationships exist for Austria. Figure 2 shows average vehicle miles traveled (US data from 2001), both per household (left axis) and per person within a household (right axis) for three household types: (i) working adults without children, (ii) households with children, (iii) retired adults without children.[4] The figure also differentiates between urban and rural households. Figure 2 illustrates a number of important generalizations: (i) households with children drive more—because they are larger—but drive less per person than smaller households; (ii) among households without children (typically one or two adults), younger, working-age households drive more; and (iii) keeping household types constant, rural households drive more than urban ones.

Figure 2

1.2 Urbanization

As mentioned above and displayed in Table 1, a number of carbon emissions/energy consumption studies that disaggregate population have included urbanization, and those studies have typically found a positive relationship between urbanization and carbon emissions or energy consumption (e.g., York et al. 2003a; Cole and Neumayer 2004; and

[3] 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.

[4] The working or retired designation is merely to distinguish between two household types that do not include children. The data set used does not otherwise allow for disaggregations by employment status.

York 2007). This finding is not surprising for studies that include developing countries since urbanization is clearly part of the development process. More curious is the comparison between York (2007), who found a positive relationship between urbanization and energy use for 14 EU countries, and Fan et al. (2006), who found a negative and statistically significant relationship between urbanization and carbon emissions for their OLS regressions on a sub-sample of high income countries.

It makes sense that, even in developed countries, certain types of energy consumption might increase with urbanization, for example, residential energy consumption as more people are connected to the electricity grid. On the other hand, if increases in urbanization mean more people living in multiple family and especially high-rise buildings, then less energy should be consumed on a household basis compared to people living in single family, detached housing.[5] Counter-balancing somewhat this last factor is that dwelling area per capita has continued to rise with income (Schipper et al. 2001). A further reason to believe that urbanization may not lead to less residential energy consumption in developed countries is that the definition of urbanization does not necessarily imply high density living in those countries. For example, in highly urban Australia (with the third highest urbanization rate among OECD countries), 83% of people live in single family, detached homes, and only 2% live in apartment blocks of four or more storeys (Australian Social Trends, Australian Bureau of Statistics, 2004).

By contrast, urbanization may lead to less energy consumption in transport since the spatial distribution of population is associated with transport demand (see Badoe and Miller 2000 for a survey of the North American literature); i.e., more dense concentrations of population are associated with greater use of public transport, and thus, negatively associated with transport energy consumption. Indeed, Figure 2 shows, at least in the US, urban

[5] This point was made by an anonymous reviewer.

households drive less than rural ones. And Liddle (2004) found a negative relationship between urbanization and road energy use *per capita* for a panel of 23 IEA countries.

Yet, national-level urbanization rates are a relatively crude measure of spatial density, and thus, perhaps not the most accurate proxy for public transport. For example, Australia, again, a highly urbanized country (with an urbanization rate of over 80 percent in 1960), has a relatively high reliance on personal transport; in contrast, the Netherlands, a country with initially low urbanization (only 60 percent in 1960 and reaching 80 percent only recently)みbut with historically high population densityみhas a relatively low reliance on personal (motorized) transport. Finally, urbanization has a natural limit (100%), which most developed countries have approached. Better measures, although not appropriate for a country-level STIRPAT study, may be population density (also used by Liddle 2004) and population centrality (used by Bento et al. 2003); the latter measure is an urban area-level variable based on the distribution of the cumulative population against the cumulative distance from the central business district of a city.

1.3 Energy intensity

To capture intensity of use (or *T*), for example, a number of studies include measures of economic structure (e.g., Shi 2003; York et al. 2003a; and Cole and Neumayer 2004), like manufacturingやshare of GDP, while others add aggregate energy intensity (Cole and Neumayer 2004; Fan et al. 2006; and Martinez-Zarzoso et al. 2007). However, using *structural shares* of manufacturing or industry activity to explain *aggregate* emissions or energy use is a misspecification. Just because the *share* of economic activity from manufacturing or industry has declined does not mean the *level* of such activity has fallen; and it is the level of activity that should influence the level of emissions. Furthermore, industry is a diverse sector with respect to energy intensity, as it ranges from iron and steel and chemicals to textiles and the manufacturing of computing, medical, precision, and optical instruments. Indeed, as Figure 3 shows, the share of value added from industry has declined over 1971-2005 for the OECD as a whole, but at the same time industrial output has increased rather substantially (variables are indexed to their 1971 value in the figure). Figure 3 also shows a decline in industry energy intensity (industry energy consumption divided by industry output), until around 1990, from where it has been essentially level (again data is for the OECD as a whole).

Figure 3

Aggregate energy intensity is an improvement on economic structural share variables, but as a very macro-level variable it does not capture the importance of diversity/change among/in economic structure. In addition, aggregate energy intensity changes over time at very different rates and for different reasons across countries. Indeed, there is an extensive literature using decomposition methods to uncover the sources of energy intensity change (see Ang and Zhang 2000 for a review).

1.4 This paper's contribution

We advance the current stochastic IPAT/STIRPAT literature in a number of ways. First, and most important, we use a more disaggregated measure of population—decomposed into age cohorts that have a meaningful impact on energy consumption as discussed below (Sec. 3.2). Second, in addition to considering aggregate carbon emissions, we also examine three types of environmental impact for which population has a substantial demonstrated impact or influence, i.e., carbon emissions from transport and residential energy and electricity consumption; no other STIRPAT emissions/energy study has disaggregated environmental impact by demand or causal sector.[6] Third, we employ better intensity factors (share of energy from non-fossil fuels and *industry* energy intensity), and focus more specifically on the role of urbanization by considering end-use environmental

[6] In addition to carbon emissions, Cole and Neumayer (2004) also considered aggregate sulphur emissions, and both York et al. (2003b) and Rosa et al. (2004) considered methane emissions too.

impact. Lastly, we believe, as Cole and Neumayer (2004) did, that we use a data set and econometric techniques that represent an improvement over many previous stochastic IPAT/ STIRPAT analyses. The next section presents a discussion of the empirical methods often employed in macro-level, panel data studies like STIRPAT. The following (third) section covers our data and methods. The fourth section presents and discusses our results, and the fifth section concludes the paper with a summary of our findings and some directions for future research.

2. Macro-level, panel data empirical methods

Empirical studies of macro-level relationships (like STIRPAT) sometimes employ cross-sectional data, i.e., data taken from many countries at one period in time, and ordinary least squares (OLS) estimation. The main statistical concern for such studies is heteroskedasticityみi.e., disturbances do not all have the same variance, e.g., the estimated residuals may be larger for larger values of an independent variable. This problem is typically treated via a transformation developed by White (1980), which is an option on most statistical programs. The disadvantage of cross-sectional data is that dynamics are not directly observed; thus, it is common to collect more time dependent observations and transform the data set into a time-series-cross-section (TSCS) one.

A TSCS data set (which can have more time observations than cross-sections or more cross-sections than time observations) implies more than just a few time observations (more than 2 or 3), and comes in two general varieties: (i) frequent time observations (e.g., every year); or (ii) more infrequent time observations (every five years). In addition to heteroskedasticity, TSCS analysts need to be concerned with serial correlationみi.e., residuals are correlated with their own lagged valuesみbecause of the dynamic nature of their data. Furthermore, in TSCS data sets encompassing yearly or monthly data, series comprised of stock (population) or stock-related variables (GDP, emissions, and energy consumption, which are influenced by stocks like population and physical capital) are likely nonstationary—i.e., their mean, variance, and/or covariance with other variables changes over time. Such data sets should be tested for panel-unit roots[7] and panel-cointegration,[8] and, depending on the outcome of those tests, estimated via time-series (single cross-section)-derived methods like vector error correction models and *dynamic* or *fully modified* ordinary least squares rather than standard OLS. Indeed, the energy consumption-GDP causality literature has shown that GDP, population, and emissions/energy consumption are all panel-unit root and panel-cointegrated for panels consisting of a number of different countries (e.g., Narayan and Smyth 2008; Lee et al. 2008; Lee and Chang 2008).

Beck and Katz (1995 & 1996) argued that a modified version of OLS produces more accurate estimates of standard errors in the presence of serial correlation of the residuals and heteroskedasticity than a number of popular weighted least squares methods (sometimes called feasible generalized least squares). Beck and Katz (1995) recommended that dynamic complications (i.e., serial correlation) be treated first by transforming the data via a common first order autoregressive term (AR(1)) or by adding lagged dependent variables, and that cross-sectional complications (i.e., contemporaneous correlation and panel heteroskedasticity) then be handled via OLS with panel corrected standard errors (PCSE)—a variation of White's method appropriate for TSCS data.[9] In their second paper, Beck and Katz (1996) argued that using lagged dependent variables is better than the AR(1) method because the former method makes the dynamics explicit and can sometimes be justified theoretically, unlike the latter. For TSCS data sets with more infrequent time observations,

---

[7] Unit root tests are used to determine stationarity, and were originally developed for time-series but have been expanded to cover panels.

[8] Two or more nonstationary variables are said to be cointegrated if some linear combination of them is stationary. The finding of cointegration among economic variables is interpreted as evidence of a long-run, equilibrium relationship. Like for unit roots, cointegration tests were originally designed for time-series but have been expanded to cover TSCS data sets.

[9] This variation is now available as an option on most statistical programs too.

nonstationarity of the data usually is not an issue (or at least there are not enough data points to robustly confirm or reject its presence); thus, Beck and Katz's approach may be preferred. Table 2 outlines the types of data sets and recommended methods typical for macro-level empirical studies like STIRPAT.

Table 2

Another choice TSCS modelers face is whether to use fixed effects—cross-section specific and/or time period specific dummy variables—or random effects (a weighting scheme). Some researchers make this decision based on statistical tests; however, theory and the particulars of the data set used can also provide guidance. Fixed effects have the disadvantage of requiring a number of additional coefficients to be estimated; however, cross-section fixed effects are ideal to address country-specific, time-invariant factors (like geographical ones). Also, time-period fixed effects may be able to capture the impact of broadly experienced, short-lived economic shocks like oil price spikes. Random effects may be most appropriate when the cross-sections and/or time periods included can be thought of as being drawn from a larger sample (e.g., a selection of developed and developing countries is used to gain insights into variable relationships believed to apply to all countries).

3. Data and Empirical Specification

We focus our analysis on 17 developed countries for which we were able to collect sufficient data.[10] Our panels span 1960-2005 and include observations at five-year intervals (because we use age-structure disaggregated population data from the United Nations, as discussed below). Table 3 below lists all the variable definitions and sources we use.

3.1 Dependent variables and affluence

We consider total carbon dioxide emissions (from the Carbon Dioxide Information Analysis Center of the Oak Ridge National Laboratory), as do most other studies mentioned

[10] Those countries are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Ireland, Italy, Japan, Netherlands, Portugal, Spain, Sweden, United Kingdom, and United States.

above; we also consider three other climate change related 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 both residential energy and electricity consumption[11] (all from the International Energy Agency). Again, following others in the literature, we use real GDP per capita (from the Penn World Tables) as the measure of affluence.

3.2 Population

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 four potentially key age groups: 20-34, 35-49, 50-64, and 65-79 (data from the United Nations and is only available at five-year intervals).[12] 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 membership (the chosen age groupings are essentially the same as those used in Figure 1). In addition, we must balance the number of independent variables with their costs in degrees of freedom. 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, and we do not include the share of aged 80 and older since such households are few in number and we expect their additional/marginal impact to be small. Hence, we gain in degrees of freedom by having fewer independent variables.

Table 3

[11] Of course, as a secondary energy source, electricity's ultimate greenhouse gas impact depends on the extent to which fossil fuels are used to generate it.

[12] Initially, we planned to use the population *levels* of these age groups, but were deterred because of the multi-colinearity problems such variables created. The size (but not the shares) of population cohorts are very highly correlated.

We expect population age-structure’s effect to be most evident in carbon emissions from transport and in residential energy and residential electricity consumption since those activities are likely to be influenced by household size and levels of individual behavior. Aggregate carbon emissions, by contrast, are likely to be more influenced by macro-economic trends like industrial production and the carbon intensity of all energy sources than by the sum of individual behavior (it would be particularly surprising if the size of the oldest, nonworking-age cohort was significant here). We do not expect all age structure variables to exert a significant impact on all the dependent variables—for some measures of environmental impact, an age cohort’s effect will not be statistically different from that of the population’s as a whole. Again, 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 (65-79) may stay at home more and thus, consume more, residential energy and electricity. Also, the youngest group (20-34) drives the most per capita, while the oldest age group drives the least.

3.3 Technology/intensity variables

We employ technology or intensity variables that are appropriate for the dependent variable (or type of environmental impact) we analyze. For total carbon dioxide emissions we include as variables (i) urbanization (from the World Bank) to facilitate comparisons with other studies, (ii) industrial energy intensity,[13] and (iii) the share of primary energy consumption from non-fossil fuels[14] (both second and third variables from the International Energy Agency); the latter two variables are included since industry is a major end-use

[13] This variable is constructed as follows: industrial energy consumption (from the International Energy Agency—IEA) is divided by industrial output. Industrial output is derived by scaling the IEA’s industrial production index, which is indexed to year-2000, by 2000’s GDP from industry—itself calculated by multiplying total GDP (from Penn World Table) by industry’s share of value added (from the World Bank). A few missing observations in the IEA’s industrial production index are filled from a similar index produced by the International Monetary Fund.

[14] The non-fossil fuel sources considered are: geothermal, nuclear, hydro, and solar/wind.

sector not influenced directly by population age-structure, and since countries that source energy from non-fossil fuels would have lower carbon emissions, all else equal.

Urbanization is included as an intensity variable for residential energy and electricity consumption since, as argued above, it is likely to be correlated to the amount of people who are connected to a country’s power/electricity grid and possibly the level of housing density. Also, since countries differ in the extent to which electricity is used in the residential sector, we include electricity’s share of residential energy consumption. Other intensity variables related to residential electricity consumption are (i) floor area per capita and persons per household, which are influenced by income and population age-structure, and (ii) climate, which is mostly non-changing over our analysis, and thus, potentially could be captured by fixed country effects. Therefore, those two types of intensity variables are not expressly included in the regressions.

For carbon emissions from transport we include the ratio of a country’s rail network to its road network (from the International Road Federation)—a reflection of a country’s priorities in transport mode. Road transport is more carbon intensive than rail, in particular in urbanized areas where rail networks are likely to be for public transit. We also include urbanization; however, urbanization’s impact on transport carbon emissions is difficult to assess. Others have found a positive relationship between urbanization and aggregate emissions; yet, the US data, shown previously, indicated that rural people drive more per capita than urban dwellers.

Another important intensity variable would be the fuel efficiency of the vehicle fleet: since most of the emissions come from the road sector, and since vehicle miles traveled are related to area, income, and population structure, fleet efficiency would be important in explaining differences in fuel consumption. Unfortunately, the limited availability of distance traveled data means it is not possible to assemble a balanced panel that spans the same length of time as our other variables (complete motor fuel consumption data is available for our countries over that time period from the International Energy Agency). Gasoline price is correlated with country level fleet fuel efficiency, but the International Energy Agency's price data starts only in 1978, and so it too would result in a much shorter panel.

About 85 percent of carbon emissions from transport come from the road sector in North America; this share is 93 percent for Europe. One reason for this difference is likely that the size of Canada and the US means more freight travel and more domestic air travel. Thus, area is likely factor in explaining cross-national differences in transport carbon emissions—another factor potentially captured by fixed country effects.

3.4 Methods and specification

Because our mostly balanced[15] panel data occurs at five-year intervals, we follow the advice of Beck and Katz (1996) and (i) treat serial correlation by including a lagged dependent variable among the independent variables[16] and (ii) account for contemporaneous correlation and panel heteroskedasticity by using panel corrected standard errors. It makes sense that emissions and energy consumption would depend on past levels (even 5 years before), even after accounting for affluence, population, and intensity measures, since those emissions and consumption levels depend on physical capital stocks for which we do not account. Adding a lagged dependent variable does impose an information cost, since the first observation (1960) cannot be used for many of our estimations. (Because total carbon dioxide emissions data begins in 1950, those regressions have the full 10 time periods.)

[15] The panels used in the carbon dioxide from transport estimations are missing two observations as described in Table 3.

[16] When including a lagged dependent variable, the Durbin-Watson test for serial correlation is no longer accurate. The recommended test is a Lagrange multiplier (LM) test that involves regressing the residuals from an OLS estimation on the first lag of those residuals as well as all the independent variables (including the lagged dependent variable) used in that OLS estimation. One then performs a LM test on the null hypothesis that the coefficient on the lagged residual term is zero—a rejection of that null is evidence of first-order serial correlation.

Using data at five-year intervals instead of yearly data also exacts an informational cost; however, among the benefits of this frequency of data are that we are not concerned with two statistical problems that have plagued some STIRPAT analyses, and yet we are still able to capture the essence of 45 years of information. As discussed above, in order to correctly (i.e., avoid the possibility of spurious regressions) and fully take advantage of the extra information that yearly data provides, it is necessary to test for nonstationarity in that data. For example, both Cole and Neumayer (2004) and Martinez-Zarzoso (2007) were mindful of this hazard in their data and estimated first-difference (i.e., short-run) models to correct for it. Again, for panel-data at five-year intervals, nonstationarity should not be a concern. Multicolinearity is another common problem since many of the typical independent variables usedみparticularly population and GDP per capitaみare highly correlated (a ρ > 0.9 for population and GDP per capita in some analyses). Both Martinez-Zarzoso (2007) and Fan et al. (2006) recognized this problem existed in their data sets. As displayed in Table 4, high correlations among independent variables are not an issue for the present data set.[17]

Table 4

We estimate our models using OLS with two-way fixed effects (i.e., dummy variables for both cross-sections and for time/periods)みcommon practice for STIRPAT studies employing panel data (e.g. Cole and Neumayer 2004; Martinez-Zarzosos et al. 2007; and York 2007). The cross-section (or country) fixed effects account for the individual cross-section differences that are common for the whole time span. The period fixed effects account for the individual differences that are specific to each period but are common for all

[17] In addition, variance inflation factors were calculated, and all were found to be below 3. Yet, it is nearly impossible for regressions comprised of IPAT variables to avoid completely multicolinearity (mutual association among variables) based on the theories developed to explain how those variables interact. For example, affluence (or GDP per capita) is believed to affect populationみthrough human capitalゃinfluence on birth rates (e.g., Becker et al. 1990) and higher incomeゃability to lower death rates; meanwhile, population has been shown to impact affluenceみwhen the size of the working-age population increases faster than the size of the dependent-age population (e.g., Bloom and Williamson 1998); and human capital and technology have been recognized as drivers of economic growth (affluence) since Solow (1956). The above theories suggest that the best way to perform STIRPAT regressions may be to treat the variables as part of a cointegrated system; however, such analysis requires annual observations and is beyond the scope of the present paper.

the cross-section units. Again, non-changing, cross-section specific geographical factors may influence emissions and energy consumption. Also, commonly felt events like the oil price spike in the 1970s and early 1980s, as well as technological improvements that are diffused over time, might impact emissions and energy consumption in a similar fashion among developed countries.[18]

The general equation we analyze is:

$$\ln I_{it} = \alpha_i + \beta_t + v \ln P_{T,it} + w \ln P_{1,it} + x \ln P_{2,it} + y \ln P_{3,it} + z \ln P_{4,it} + c \ln A_{it} + d \ln T_{it} + f \ln I_{it-1} + \varepsilon_{it} \quad (3)$$

Where subscripts *it* denote the *i*th cross-section and *t*th time period. The constants α and β are the country or cross-section and time fixed effects, respectively. 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 cohorts defined above, and per capita GDP, respectively. The T represents one or more technology or intensity terms that depend on the type of environmental impact represented by I. Again, those specific combinations of intensity terms and dependent variables are: (i) urbanization, industrial energy intensity, and the share of primary energy consumption from non-fossil fuels for aggregate carbon dioxide emissions; (ii) urbanization and the ratio of a country's rail network to its road network for carbon emissions from transport; (iii) urbanization for residential energy consumption; and (iv) urbanization and electricity's share of residential energy consumption for residential electricity consumption. Lastly, I_{it-1} is the one-period lagged dependent variable term, and ε is the error term.

4. Results and discussion

Table 5 shows the results for aggregate carbon dioxide (Models I and II) and carbon dioxide emissions from transport (Models III and IV). For aggregate carbon dioxide the coefficients for affluence and total population are positive, significant, and relatively large.

[18] In addition, tests on the redundancy of the fixed effects were strongly rejected for our models, as were Hausman tests on the consistency and efficiency of a random effects alternative to fixed effects.

As discussed above, in developed countries, it was not clear how urbanization would impact aggregate carbon emissions (or how it would impact carbon emissions from transport as will be discussed later). Model I indicates that, with the two improved intensity variables (share of energy from non-fossil fuels and industry energy intensity) both significant and working in the expected direction, urbanization is non-significant.

Again, we expected the least amount of influence from age-structure on aggregate carbon emissions; however, we might expect the youngest, most active cohort (20-34) to have a positive sign and the other cohorts negative signs because of their lower activity levels (50-64 and 65-79) or larger household sizes (35-49). This is indeed the case; however, only the 20-34 and 50-64 cohorts have statistically significant coefficients, and only marginally so. In case the distinction between the 35-49 and 50-64 cohorts is too fine, the model was run again (Model II) with a larger むmiddle-agedめcohort of 35-64 (the 65-79 cohort was dropped from Model II). Now the 35-64 cohort is statistically significant (p-value is 0.059), although the 20-34 cohort remains significant only at the 10% level.

Table 5

The coefficients for both affluence and total population are positive, significant, and relatively large for carbon dioxide from transport; however, affluenceやimpact is twice that of populationや(Model III). The coefficients for the four age cohorts have the same signs as for Model I, but again they are not uniformly significant. It is not surprising that the 65-79 cohort is not at all significant since they tend to drive the least; yet, it is somewhat puzzling that the youngest (20-34) cohortやimpact is insignificant since transport is an area of environmental impact where population age-structure may have the greatest influence and since the youngest cohort is the most driving intensive. When the two middle cohorts (35-64) are combined (Model IV), their coefficient is negative, significant, and relatively largeみ expected since the larger families associated with this cohort benefit from むcar-poolingめ

however, the 20-34 cohort is still statistically insignificant (as in Model II, the 65-79 cohort was dropped). Perhaps most surprising is urbanization's positive and significant impact on transport emissions. It was believed that higher urbanization would lead to more transit use and thus lower emissions. Again, US household data indicated that people living in urban areas drive less and would therefore emit less carbon from transport than people living in rural areas. (A following sub-section provides more discussion on urbanization as a measure of spatial density.) Having a more rail-intensive rather than road-intensive transport network does lower carbon emissions slightly. Lastly, the country dummy variables (listed in the supplemental table) are correlated with country area (ρ = 0.6)—a factor we hypothesized would be important for aggregate emissions from transport and potentially captured by the fixed effects.

Table 6 displays the results for residential energy and residential electricity consumption (Models V and VI, respectively). For both models the coefficients for affluence and total population are positive, significant, and large—although population has a considerably greater impact than affluence. Population's relatively larger impact than affluence may be surprising for energy consumption in the home—a normal (even luxury) good—but, as discussed above, is a typical result for STIRPAT. Urbanization, as expected, has a significant, positive, and fairly large coefficient in both models—providing evidence that urbanization is a proxy for access to the national (power/electricity) grid. For both Models V and VI, as was the case for the previous models too, the coefficients for the two middle-age cohorts (35-49 and 50-64) are significant and negative (the p-value for the 50-64 cohort in Model VI is 0.07). The coefficient for the 65-79 cohort is positive in both models, as predicted, but is only statistically significant (p-value 0.06) for electricity consumption (Model VI). The coefficient for the 20-34 cohort is not at all distinguishable from zero (it is small and the p-value is 0.63) for energy consumption (Model V), and is positive but statistically insignificant (p-value 0.14) for electricity consumption (Model VI). Yet, since both the 35-49 and 50-64 cohorts are negative and significant, the 20-34 cohort is *relatively* more energy/electricity intensive in the residential sector than those two older cohorts, as may be expected. Lastly, it was argued that country effects might capture temperature differences that could lead to more residential consumption other things being equalみyet, this does not appear to be the case.

Table 6

For all six models (shown in Tables 5 and 6), the addition of a lagged dependent variable solved any apparent serial correlation problems, and all models have very high R-squared values (based on total variance), which is common among panel estimated STIRPAT models not using differencing of the variables (e.g., Shi 2003; Fan et al. 2006; and York 2007). And, for all six models the period effects (shown in the supplemental table) work similarly to a time-trend with the impact factors for all countries becoming less emissions/energy intensive over time. That progression may reflect a diffusion of more energy efficient technology among these highly developed countries.

4.1 Revisiting carbon from transport and residential electricity with first difference models

Although using data at five-year intervals means one cannot convincingly establish a panel unit root (nonstationarity in the data), a number of our data series exhibit high degrees of linear (increasing) trending. This pattern is particularly evident in the dependent variables carbon dioxide from transport and residential electricity consumption, as well as the independent variables affluence and population. Variables not characterized by linear trends include (i) the dependent variables total carbon dioxide emissions and residential energy consumption, for which many countries experienced peaks during the period studied, and (ii) the age structure variables, which are naturally ゐwave-like.めIn addition, the coefficient for lagged electricity consumption (Model VI) was very high (although statistically significantly lower than 0.85); hence, that model is nearing a first difference model. Thus, we ran the models for carbon dioxide from transport and residential electricity consumption (IV and VI, respectively), again with all variables in (logged) first differences. First differencing the variables treats serial correlation without the aid of a lagged dependent variable or AR(1) transformation, and it eliminates any possibility of a (first order)[19] unit root in the data. The logged and differenced model means that the variables are now five-year growth rates, 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. Also, since we believe single events are much less likely to impact percentage changes or growth rates, as opposed to level changes, we include only cross-section (country) fixed effects. (The time component of the variables no longer represents a single year, but a five-year period over which growth rates are calculated.)

Table 7

Table 7 presents the results of the two regressions described in this sub-section. For residential electricity consumption, the results are similar to the previous results (compare Models VIII and VI); however, a number of coefficients (affluence, population, urbanization, and the 35-49 and 50-64 cohorts) are two to three times larger in Model VIII. Also, the 65-79 cohort is not at all statistically significant (p-value 0.81); thus, this cohort affects electricity consumption via level changes (Model VI), but not via growth rate changes (Model VIII). For carbon dioxide from transport (Model VII in Table 7), urbanization's coefficient is no longer significant. It is surprising that the urbanization coefficient is positive and significant in Models III and IV (since a negative relationship was anticipated); it is reasonable that a percentage change in urbanization would not have a proportional effect on the percentage change in transport carbon emissions. Also, the

[19] When economic or demographic variables are nonstationary, they are typically I(1), i.e., if differencing is applied once they become stationary. Orders of integration greater than I(2) are very rare among economic/demographic variables.

coefficient for young adults (aged 20-34) is significant and positive as originally expected; (the coefficient for middle-aged adults (35-64) remained significantみp-value 0.07みand negative as in Model IV). Again, it was believedみmostly because of the associated household sizesみthat people aged 20-34 would drive more per capita and that people aged 35-49 would drive less per capita (or per household member). Lastly, the coefficient for total population is now larger than the coefficient for affluenceみagain, typical for STIRPAT analyses, both in the other models presented here and in the literature.

4.2 Comparisons with other studies

It is hard to compare directly our results with previous work because the other studies considering carbon emissions or energy consumption and employing TSCS data used annual observations (Shi 2003; Cole and Neumayer 2004; Fan et al. 2006; Martinez-Zarzoso et al. 2007; and York 2007). Yet, only Cole and Neumayer (2004) and Martinez-Zarzoso et al. (2007) dealt with the possibility of nonstationarity in their data, and they did so by taking first differences; thus, their coefficient estimates have a slightly different interpretation than most of ours, and the R-squared values of their regressions are (correspondingly) mostly considerably lower (0.06-0.10 and 0.35-0.58, respectively). Also, we added a lagged dependent variable to avoid serial correlationみsomething only Martinez-Zarzoso et al. did too. All studies found population and affluence to be important, with population typically having the higher coefficient, but the relative difference ranged considerably from nearly the same (Cole and Neumayer and Fan et al.) to populationゃcoefficient being about five times as large (York).

Of the studies that considered population age distribution, most used the very large cohort aggregation of 15-64, and their findings ran the gamut from positive (Shi 2003) to insignificant (Cole and Neumayer 2004) to negative (Fan et al. 2006). York (2007) considered the share of population over 65, and found, somewhat surprisingly, a significant, positive (and relatively large) coefficient for that cohort's influence on aggregate commercial energy use. It is not clear why more people over 65 would lead to more energy consumed for that very high economy-wide level of aggregation (i.e., why would industrial energy consumption or consumption in commercial buildings rise with the aged, dependent population?). We hypothesized that a greater percentage of people over 65 could lead to more energy consumed in the residential sector, since that age group may spend more time at home and tend to have smaller households. Indeed, our results uncovered such a relationship; however, the coefficient for the 65-79 cohort was only statistically significant for electricity consumption (Model VI). Yet, since the shares of people aged 35-64 had significant negative coefficients for both residential energy and residential electricity consumption (Models V and VI), all other age groups (0-34 and 65 and over) were *relatively* more energy intensive.

The studies that used aggregate energy intensity (Cole and Neumayer 2004; Fan et al. 2006; and Martinez-Zarzoso et al. 2007) typically found its coefficient to be significant, positive, and relatively larger than our coefficient on industrial energy intensity. It is not surprising that the more *aggregate* energy intensity variable those studies used would be more correlated with *aggregate* carbon emissions than our more specific and disaggregated *industrial* energy intensity variable.[20] Lastly, Cole and Neumayer and Fan et al. found urbanization to be significant, positive, and relatively large in their carbon emissions regressions; by contrast, we found urbanization appropriately to be insignificant in our carbon emissions regressions (Models I and II), we believe, because of our additional included variables (disaggregated population and improved intensity variables). Meanwhile, York (2007) found urbanization to be significant, positive, and of similar magnitude in his

[20] As pointed out by an anonymous reviewer, national, aggregate carbon emissions are calculated from national, aggregate energy consumption; thus, for countries with carbon intensive energy sources, aggregate carbon emissions and *aggregate* energy intensity run the risk of being highly correlated by construction. It can be seen from the correlation matrix (Table 4) that our *industrial* energy intensity variable does not suffer from this problem.

commercial energy regression as we found in our residential energy regressions (Models V and VI), a finding in concert with our idea that urbanization measures access to a country's power grid.

4.3 Urbanization, spatial density, and transit

In the regressions presented here urbanization's coefficient is typically positive, significant, and large (except for aggregate carbon emissions for which it is small and insignificant and for the first difference model of carbon dioxide from transport for which it is also insignificant). Yet, there was a belief that if urbanization is a proxy for the spatial density of living, it might have a negative influence on emissions and energy consumption. Ultimately, the way urbanization is measured and defined, it is a more accurate proxy of sub-urbanization—a process/spatial allocation most people think is rather energy intensive. Indicators of spatial density are probably best measured at a more local level—as opposed to a national-level indicator like urbanization. Hence, two problems for STIRPAT-like analyses are: (i) data on cities tend to be far less frequently collected (than national data); and (ii) city-level data does not lend itself easily to otherwise country-based panels (e.g., how to determine the number of cities per country to include).

Kenworthy et al. (1999) assembled a database that includes 32 cities from 13 developed countries with observations taken at 1960, 1970, 1980, and 1990 for a number of measures of interest here (like population, area, transit and private vehicle travel). Studying their data leads to a couple of conclusions: (i) national measures of urbanization are not accurate indicators of spatial density of living; and (ii) more dense living arrangements indeed are associated with greater use of transit and lessor reliance on personal transport. For example, over 1960-1990, national levels of urbanization were actually negatively correlated with the population density of inner cities (ρ = -0.33). Also, in the cities in their data base, the average population density of *urban* areas actually fell by about one-quarter from 1960-

1990, even though urban populations increased by an average of 40%みbecause urban areas themselves increased in size (or area covered) by an average of 70%, while the inner city areas increased in size by an average of only 20% over that time.

On the other hand the population density of inner city areas (measured by people per hectare) does have the expected correlation with km driven per capita and transit passenger km per capita (ρ = -0.69 and ρ = 0.64, respectively). Figure 4 illustrates these relationships. The Figure shows, for 32 cities and four time periods from the Kenworthy et al. data set, inner city population density (x-axis) and yearly km travelled per capita from driving and transit (y-axis). Driving has a negative relationship with density (R^2=0.47), while transit riding has a positive relationship with density (R^2=0.41).

Figure 4

5. Conclusions and further directions

We have demonstrated the importance, in STIRPAT studies, of both further disaggregating population and considering environmental impactsみwe focused on transport and residential end-usesみwhere population has a more direct influence. Population impacts the environment in considerably different ways across age-groups, and those impacts differ some according to the environmental measure considered. The share of people in the 20-34 age-cohort nearly always had a positive influence on environmental impact, although that impact was not always significant, while the share of people in the 35-64 cohort had a significant, negative influence in all our regressions; and the share of people in the 65-79 cohort exerted a positive effect on residential energy consumption (albeit, statistically significant only for electricity consumption). Thus, it appears people travel an U-shaped life-cycle with respect to (certain types of) energy intensity: they live a relatively energy intensive lifestyle in both early adulthood and as they enter むretirement-ageめor grow older than 65, but intermittingly live a relatively energy nonintensive lifestyle during むmiddle-ageめ

or ages 35-64. Again, these nonlinearities are driven in no small part by the household sizes with which such age groups are typically associatedみlarger households being less energy intensive on a per member basis. Some people working with micro-level, country-specific data already have determined that environmental impact can vary across age-groups; our confirmation of this variable relationship using macro-level, cross-country data provides those researchers with evidence that their findings are generalizable to other developed countries.

For some new measures of environmental impactみcarbon emissions from transport and residential electricity and residential energy consumptionみwe confirmed a consistent finding in the STIRPAT literature; namely, both affluence or GDP per capita and total population are important, but at least for developed countries, population causes a greater impact than affluence. Not surprisingly, countries with higher energy intensity in their industry sectors had higher (aggregate) carbon emissions. Urbanization, again, in developed countries, measures access to a countryや power grid, and thus, is significantly and positively associated with energy consumption in the residential sector. Urbanization had an insignificant impact on aggregate carbon emissions and probably an insignificant impact on carbon emissions from transport (at least it was insignificant in the first difference model, and we cannot think of a theory as to why it would be positively related to transport after controlling for affluence). In developed countries, urbanization is not an accurate proxy for the spatial density of living. (Increasing the spatial density of living almost certainly leads to lower private transport loads.)

Lastly, since the STIRPAT literature traces its origins back to an accounting identityみrather than, say, a set of social-science based theories (e.g., there is no representation of price or measure of equality, etc.)みwe believe it is worthwhile to critique/improve STIRPAT from a technical/methodological point of view. In addition, to further disaggregating population cohorts, we offered two new, important intensity measuresみshare of energy from non-fossil fuels and industry energy intensityみin our aggregate carbon dioxide emissions analysis, and added clarity to the role urbanization plays with the environment in developed countries by including some additional analysis on that relationship and by performing regressions on residential consumption. In terms of methods, we employed data observed at five-year intervals to mitigate two statistical problems encountered in such workみmulticolinearity and nonstationarity in the data, and we discussed another approach to address those concerns, i.e., panel-based cointegration analysis.

An obvious way to move the STIRPAT literature forward would be to explore different/further disaggregation of population and/or environmental impact. Our analysis has been hindered somewhat by data availability; thus, access to improved data could open a number of additional channels of analysis, such as adding developing countries or adding improved intensity measures (like vehicle fleet fuel efficiency, or a related characteristic, like average weight) to transport-focused impact studies. If one could access population data disaggregated by five-year age-cohorts (or at least more disaggregation than 15-64) and issued yearly (rather than in five-year intervals), there might be considerable potential for applying sophisticated time-series techniques like unit root, cointegration, and causality tests, as the expansive GDP-energy literature has already done.

An alternative method to cointegration modeling that also acknowledges the mutual causality among the IPAT variables could involve analyzing a system of multiple equations. As discussed in Footnote 17, a number of social science theories link various combinations of affluence or income, population and population change, environment or energy, and even intensity variables like economic structure and urbanization. Possible additional equations to consider include: affluence as a function of population, energy consumption, and perhaps urbanization; population as a function of affluence and urbanization; and urbanization as a function of affluence and population.

References

Ang, B.W. and F.Q. Zhang. (2000). A survey of index decomposition analysis in energy and environmental studies. Energy, 25, 1149-1176.

Badoe, D. A. and Miller, E. J. (2000). Transportationみland-use interaction: empirical findings in North America, and their implications for modeling. Transportation Research Part D, 5, 235-263.

Baltagi, B. (ed.) 2000. Advances in Econometrics, Vol. 15: Nonstationary Panels, Panel Cointegration, and Dynamic Panels, Amsterdam: JAI Press.

Beck, N. 2008. むTime-SeriesみCross-Section Methods.めIn Oxford Handbook of Political Methodology. Box-Steffensmeier, J., Brady, H., and Collier, D. (eds.). New York: Oxford University Press.

Beck, N. and Katz, J. 1996. むNuisance vs. substance: specifying and estimating time-series-cross-section models,めPolitical Analysis, 6, 1:1-34.

Beck, N. and Katz, J. 1995. むWhat to do (and not to do) with time-series cross-section data,め American Political Science Review, 89, 3: 634-645.

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

Bento, A., Cropper, M, Mobarak, A., and Vinha, K.. (2003). The impact of urban spatial structure on travel demand in the United States. World Bank Policy Research Working Paper no. 3007.

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.

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.

Fan, Y., Liu, L-C., Wu, G., and Wei. Y-M.. (2006). Analyzing impact factors of CO_2 emissions using the STIRPAT model. Environmental Impact Assessment Review, 26, 377-395.

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.

MacKellar, F.L., Lutz, W., Prinz, C., and Goujon, A. (1995). Population, households, and CO_2 emissions. Population and Development Review 21 (4), 849-865.

Maddala, G.S. and Kim, I-M., 2000, Unit Roots, Cointegration, and Structural Change, Cambridge University Press, Cambridge, UK.

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.

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.

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.

Roy, N. (2002). Is adoptive estimation useful for panel models with heteroskedasticity in the individual specific error component? Some Monte Carlo evidence. Econometric Reviews, 21, 189-203.

Schipper, L., Unander, F., Murtishaw, S., Ting, M. (2001). Indicators of energy use and carbon emissions: Explaining the energy economy link. Annual Review of Energy and Environment, 26, 49-81.

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.

White, H. 1980. むA heteroskedasticity-consistent covariance matrix and a direct test for heteroskedasticity,めEconometrica, 48: 817-838.

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

York, R., Rosa, E., and Dietz, T. (2003b). A rift in modernity? Assessing the anthropogenic sources of global climate change with the STIRPAT model, International Journal of Sociology and Social Policy, 23 (10), 31-51.

York, R. (2007). Demographic trends and energy consumption in European Union Nations, 1960-2025. Social Science Research, 36, 855-872.

Table 1. Stochastic IPAT/STIRPAT studies on Carbon emissions/energy consumption using disaggregated population measures

Study	Additional population variables	Intensity variables	Data structure
Shi, 2003	Share of working-age population [a]	Manufacturing share of GDP, Service share of GDP, non-tradeables share of GDP	Unbalanced panel of 93 developed and developing countries, 1975-1996
York et al., 2003a	Share of working-age population, urbanization	Industry share of GDP	Cross-section of 146 developed and developing countries at 1996
Cole and Neumayer, 2004	Share of working-age population, Share of under 15 population, urbanization, average household size	Manufacturing share of GDP, aggregate energy intensity [c]	Balanced panel [b] of 86 developed and developing countries, 1975-1998
Fan et al., 2006	Share of working-age population, urbanization	Aggregate energy intensity	208 Developed and developing countries,[d] 1975-2000
York, 2007 [e]	Share of population over 64, urbanization		14 EU countries, [f] 1960-2000

Notes:
a, working-age population is population aged 15-64, as defined by the World Bank
b, use of average household size means the panel is no longer balanced as about 13 percent of observations are lost
c, total energy use divided by GDP
d, it is not clear from the text whether or not the panel is balanced; but given the number of countries, time span, sole source of data (World Bank), it is likely unbalanced
e, dependent variable is aggregate energy consumption, and no intensity-type variables are used
f, panel is not balance because Germany is included for which data do not begin until 1971; also, German data is the sum of East and West German data prior to reunification
York et al. (2003b) is not materially different from York et al. (2003a) in terms of the dimensions emphasized in the table, and thus, is not included.

Table 2. Common data sets used and empirical methods recommended for macro-level analyses like STIRPAT

	Data structure	Advantages	Drawbacks	Solution	References
‘Pure’ cross-section	Observations taken at one time point for many countries	Simple; main concern heteroskedasticity; can use OLS	Cannot directly observe dynamics;	Add more time observations (then see TSCS) or convert variables to rates of change	Any basic econometrics text
‘Pure’ time series	Frequent observations (yearly, monthly) for one country	Can model short- and long-run relationships	Data likely nonstationary; panelling data from similar countries can improve estimates	Test for unit roots & cointegration; estimate with VECM or DOLS	Maddala & Kim 2000
TSCS w/ frequent time observations	Typically T>N (data observed yearly or monthly) [a]	Many data points (high d.f.); address both cross-sectional & dynamic variation	Some series likely nonstationary; can take first differences to address, but lose ability to model long-run relationship	Test for panel-unit roots & panel-cointegration; estimate with panel-VECM, panel-DOLS, or panel-FMOLS (best if T>N) [c]	Pedroni 1999; Baltagi 2000
TSCS w/ infrequent time observations	Typically N>T (data observed at 5- or 10-yr intervals) [b]	Address both cross-sectional & dynamic variation; stationarity should not be an issue	Can still have serial correlation; heteroskedasticity often present	Transform data with AR(1) or add lagged dependent variables; then use OLS with PCSE	Beck & Katz 1995; Beck & Katz 1996

Notes: a, Most important issue is the times-series properties of the data; not whether T exceeds N.

b, Panel data is sometimes used to describe a data set with many cross-sections but *very* few time observations (say, three). This type of data set is not common for STIRPAT studies since the type of macro-level data they employ is (usually) readily available.

c, Beck & Katz intended their recommendations to be valid for all TSCS data; however, their papers appeared before advances in panel-unit root and panel cointegration testing emerged. A recent paper by Beck (2008) implies he may agree with our categorization of TSCS data and corresponding methods.

Abbreviations: AR (autoregressive function); d.f. (degrees of freedom); DOLS (dynamic ordinary least squares); FMOLS (fully modified ordinary least squares); N (number of cross-sections); OLS (ordinary least squares); PCSE (panel-corrected standard errors); T (number of time periods); TSCS (time-series-cross-section); VECM (vector error correction model).

Table 3. Variables used in the study.

Symbol	Definition	Source
	Dependent variables	
Carbon	Carbon dioxide emissions from fossil fuel combustion and cement manufacture in metric tons of carbon	Marland, G., T.A. Boden, and R.J. Andres. 2007. Global, Regional, and National CO_2 Emissions. In Trends: A Compendium of Data on Global Change. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy.
CarbonT	Carbon dioxide emissions from transport in metric tons	International Energy Agency
Electric [a]	Total residential electricity consumption in kilowatt hours	Ibid
ResEnrg [a]	Total residential energy consumption in metric tons oil equivalent	Ibid
	Independent variables	
A	Real per capita GDP in USD and 2000 constant prices	A. Heston, R. Summers and B. Aten, Penn World Table Version 6.2, Center for International Comparisons, University of Pennsylvania.
Pop2034	Share of mid-year population between ages 20-34	Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat, World Population Prospects: The 2006 Revision and World Urbanization Prospects.
Pop3549	Share of mid--year population between ages 35-49	Ibid
Pop5064	Share of mid--year population between ages 50-64	Ibid
Pop6579	Share of mid--year population between ages 65-79	Ibid
Poptot	Total mid-year population	Ibid
Urban	Share of population living in urban areas	World Bank
NonFF	Share of total primary energy supply generated from non-fossil fuels	International Energy Agency
ShElec	Share of residential energy consumption from electricity	Ibid
RailRoad [b]	Ratio of total rail network (in km) to total road network (in km)	International Road Federation
EI	Industrial energy consumption divided by industrial output in ton oil equivalent over one-thousand USD in 2000 constant prices	Penn World Table, International Energy Agency, International Monetary Fund

Notes: a, missing data for Denmark;
b, missing single data points for Portugal (1985) and Sweden (2000);
All series begin in 1960 except for Carbon, A, and the UN population data, which all begin in 1950.

Table 4. Correlation matrix for all variables.

Independent Variables	A	Poptot	Pop2034	Pop3549	Pop5064	Pop6579	ShElec	Urban	EI	Rail Road	NonFF
						Independent Variables					
A	1.000										
Poptot	0.303	1.000									
Pop2034	0.112	0.116	1.000								
Pop3549	0.621	0.079	-0.096	1.000							
Pop5064	0.293	-0.105	-0.414	0.296	1.000						
Pop6579	0.444	-0.143	-0.201	0.340	0.678	1.000					
ShElec	0.502	0.274	0.179	0.397	0.029	0.109	1.000				
Urban	0.541	0.080	-0.033	0.239	0.221	0.361	0.249	1.000			
EI	-0.304	-0.014	-0.148	-0.312	-0.182	-0.301	-0.175	-0.015	1.000		
RailRoad	-0.259	-0.180	0.071	-0.191	-0.196	-0.303	-0.189	-0.080	0.331	1.000	1.000
NonFF	0.343	0.016	-0.039	0.270	0.191	0.318	0.333	0.229	0.057	0.124	
						Dependent Variables					
Carbon	0.357	0.949	0.094	0.053	-0.137	-0.137		0.136	0.083		-0.027
CarbonT	0.388	0.921	0.104	0.074	-0.143	-0.125		0.136		-0.120	
Electric	0.452	0.897	0.104	0.139	-0.088	-0.071	0.317	0.153			
ResEnrg	0.374	0.932	0.067	0.046	-0.120	-0.106		0.171			

Note: Dependent variable correlation coefficients are only shown for those independent variables that appear in the same model.

Table 5. Estimation results for aggregate carbon dioxide emissions and carbon dioxide from transport from OLS with two-way (cross-section and time) fixed effects.

Dep. variable	Aggregate Carbon dioxide		Carbon dioxide from Transport	
	I	II	III	IV
A	0.568****	0.570****	0.608****	0.607****
	(0.091)	(0.100)	(0.098)	(0.096)
Poptot	0.695****	0.693****	0.282**	0.297**
	(0.137)	(0.164)	(0.139)	(0.140)
Pop2034	0.173*	0.205*	0.074	0.064
	(0.096)	(0.118)	(0.113)	(0.107)
Pop3549	-0.188		-0.312**	
	(0.127)		(0.141)	
Pop5064	-0.202*		-0.192	
	(0.116)		(0.131)	
Pop6579	-0.058		-0.011	
	(0.083)		(0.093)	
Pop3564		-0.359*		-0.531**
		(0.188)		(0.236)
NonFF	-0.020****	-0.020****		
	(0.005)	(0.006)		
EI	0.193****	0.186****		
	(0.040)	(0.050)		
Urban	0.064	0.038	0.344**	0.352**
	(0.141)	(0.138)	(0.157)	(0.157)
Carbon (-1)	0.687****	0.673****		
	(0.037)	(0.037)		
RailRoad			-0.064***	-0.065***
			(0.024)	(0.024)
CarbonT (-1)			0.622****	0.626****
			(0.067)	(0.060)
R^2	0.9975	0.9975	0.9976	0.9976
Adjusted R^2	0.9968	0.997	0.9969	0.9970
LM test for serial correlation	0.170	0.273	0.303	0.337
	(0.680)	(0.602)	(0.762) [a]	(0.737) [a]
x-sections	17	17	17	17
observations	170	170	151	151

Notes: Standard errors, panel-corrected for cross-section heteroskedasticity and contemporaneous correlation, are in parentheses. Coefficients for the fixed effects (country and time) and intercept are not shown. All variables are in natural logarithmic form. Probabilities for the LM test are shown in parentheses.

a, because the panels for carbon dioxide from transport are unbalanced, a T-test had to be used instead of the LM test. However, if the two series with a missing observation were removed, a LM test rejected serial correlation, and the regression coefficients were not substantially different.

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

Table 6. Estimation results for residential energy and electricity consumption from OLS with two-way (cross-section and time) fixed effects.

Dep. variable	Residential energy consumption	Residential electricity consumption
	V	VI
A	0.650****	0.347****
	(0.144)	(0.085)
Poptot	1.038****	0.619****
	(0.277)	(0.161)
Pop2034	-0.087	0.175
	(0.182)	(0.118)
Pop3549	-0.915****	-0.303*
	(0.243)	(0.166)
Pop5064	-0.503 **	-0.285**
	(0.213)	(0.137)
Pop6579	0.178	0.174*
	(0.145)	(0.093)
Urban	0.611**	0.450***
	(0.301)	(0.159)
ShElec		0.143***
		(0.036)
ResEnrg (-1)	0.602****	
	(0.051)	
Electric (-1)		0.754****
		(0.038)
R^2	0.9909	0.9975
Adjusted R^2	0.9884	0.9969
LM test for serial correlation	0.885	0.616
	(0.347)	(0.433)
x-sections	16	16
observations	144	144

Notes: Standard errors, panel-corrected for cross-section heteroskedasticity and contemporaneous correlation, are in parentheses. Coefficients for the fixed effects (country and time) and intercept are not shown. All variables are in natural logarithmic form. Probabilities for the LM test are shown in parentheses. Statistical significance is indicated by: **** p <0.001, *** p <0.01, ** p<0.05, and * p<0.10.

Table 7. Estimation results for rates of change in carbon dioxide from transport and residential electricity consumption from OLS with cross-section fixed effects (all variables in logged differences).

Dep. variable	Δ Carbon dioxide from Transport	Δ Residential electricity consumption
	VII	VIII
Δ A	0.789****	0.766****
	(0.098)	(0.124)
Δ Poptot	1.341***	2.240****
	(0.506)	(0.559)
Δ Pop2034	0.304**	0.187
	(0.136)	(0.174)
Δ Pop3549		-0.665***
		(0.204)
Δ Pop5064		-0.671***
		(0.233)
Δ Pop3564	-0.484*	
	(0.267)	
Δ Pop6579		0.061
		(0.254)
Δ Urban	0.482	1.916****
	(0.328)	(0.438)
Δ ShElec		0.243****
		(0.049)
R^2	0.5957	0.7126
Adjusted R^2	0.5308	0.6575
DW d test	1.962	2.155
x-sections	17	16
observations	153	144

Notes: All variables are in natural logarithmic form. Δ denotes first difference. Standard errors, panel-corrected for cross-section heteroskedasticity and contemporaneous correlation, are in parentheses. Coefficients for country fixed effects and intercept are not shown. Statistical significance is indicated by: **** p <0.001, *** p <0.01, ** p<0.05, and * p<0.10.

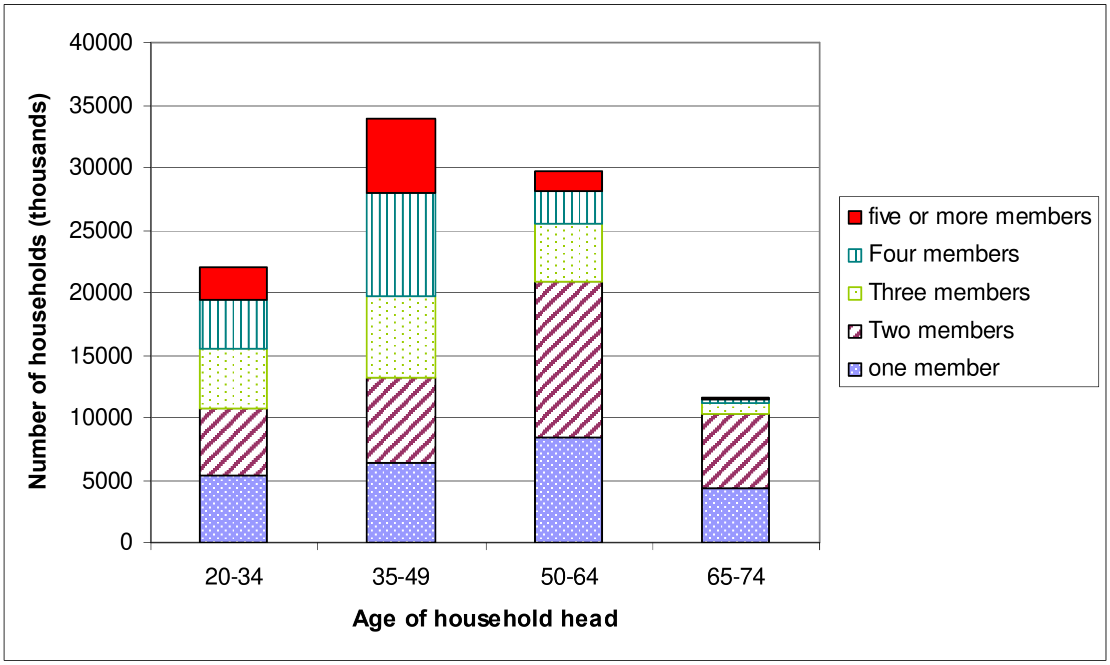

Figure 1. The number of households in five different household-size groups by age of household head for the US in 2007. Data from the US Census Bureau.

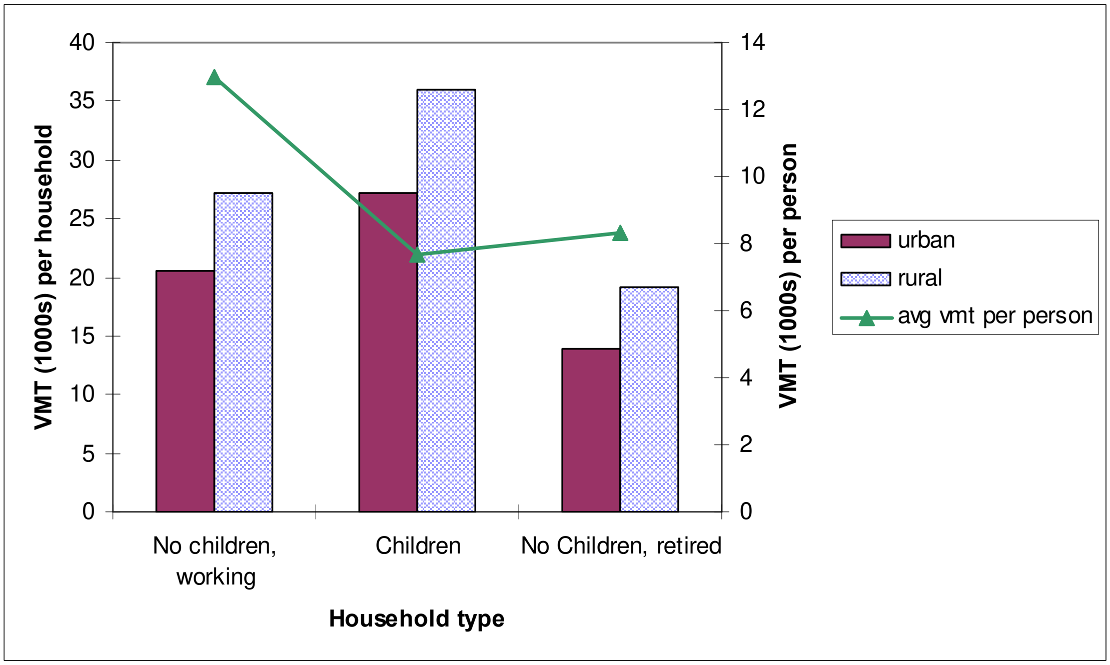

Figure 2. Vehicle miles travelled (VMT) for three household types: (1) those working but without children, (2) those with children, and (3) those retired and without children. The left axis shows VMT (in thousands) *per household* and also differentiates between urban and rural households (VMT per urban/rural household is indicated by the bars). The right axis shows VMT (again in thousands) *per person* for the three household types (VMT per person is indicated by the line). Data are from US Department of Energy, Energy Information Agency, 2001.

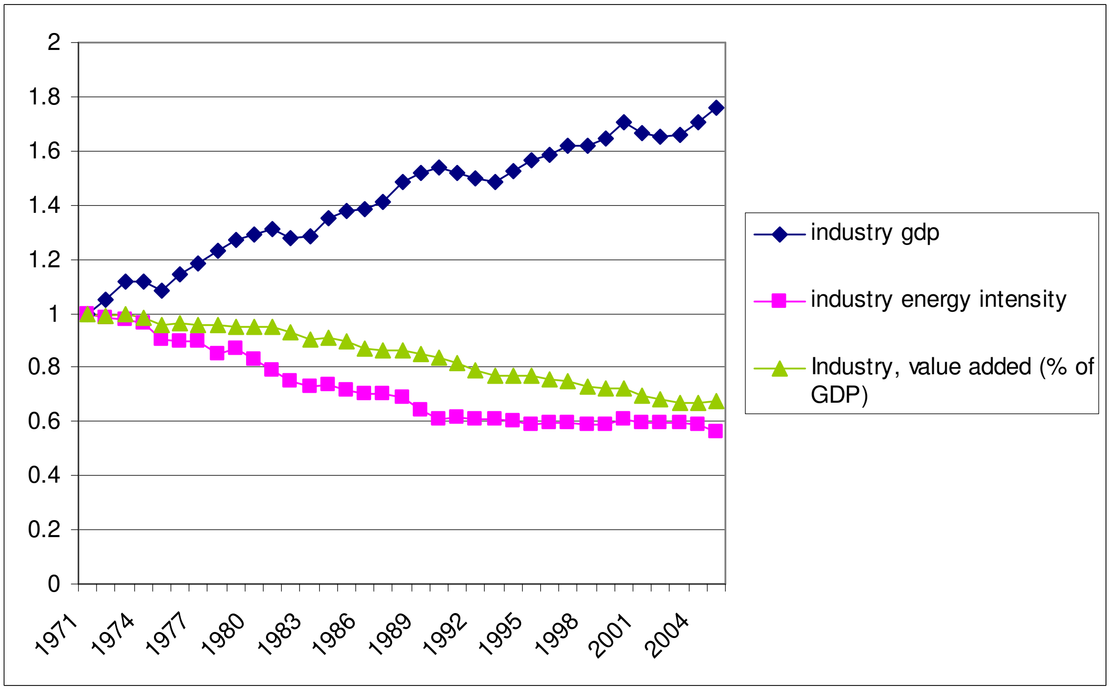

Figure 3. The intertemporal paths (data normalized to the 1971 value) of industry output (in GDP terms), industry energy intensity (energy consumption/output), and industry value added (as a percent of GDP) for OECD as a whole, 1971-2005. Industry output and energy intensity are derived from the International Energy Agency's *Energy Balances of OECD Countries*, 2008 edition. Industry's share of value added is from the World Bank.

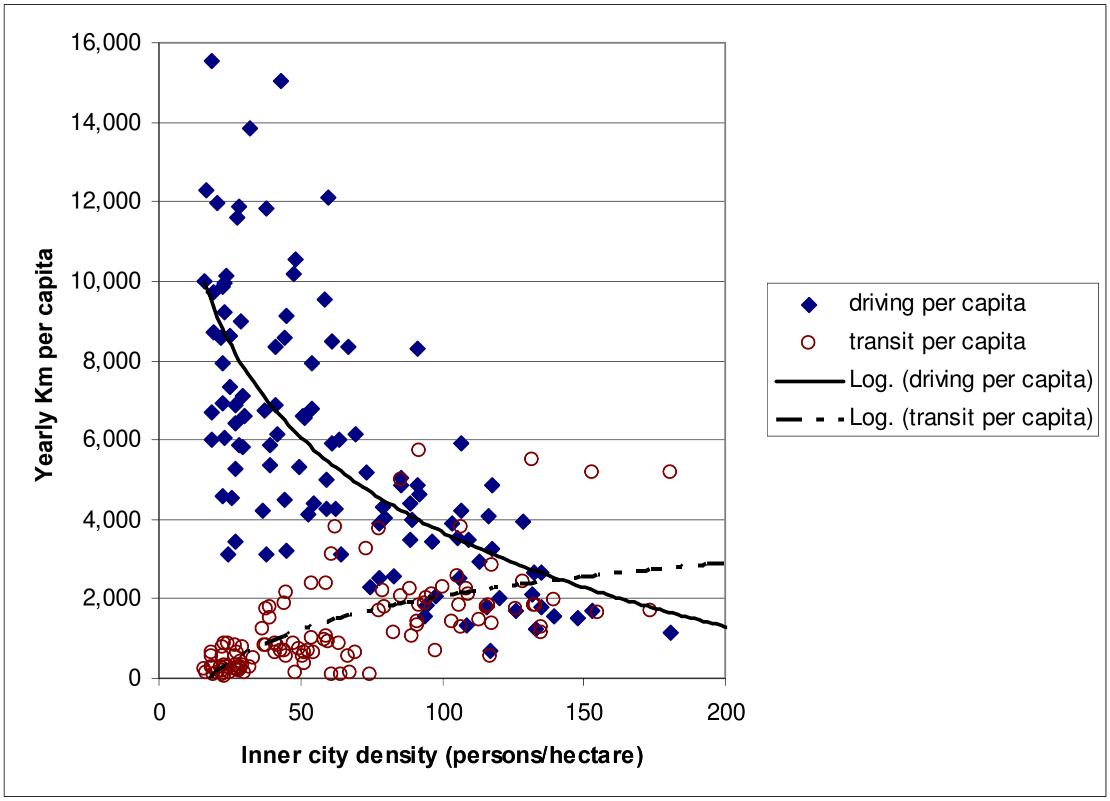

Figure 4. The relationship between inner city population density (persons/hectare) and yearly kilometers traveled per capita for driving (blue diamonds) and transit (red circles). Data are from 32 OECD cities taken from 1960, 1970, 1980, 1990, and were collected by Kenworthy el al. (1999). Logarithmic trend lines shown.

Supplemental Data

Country and period dummy coefficients for all regressions

Regression	I	II	III	IV	V	VI	VII	VIII
	Country coefficients							
AUS	0.097	0.121	0.029	0.027	-0.109	-0.073	-0.058	-0.043
AUT	0.301	0.272	-0.155	-0.136	0.691	0.344	0.007	0.026
BEL	0.201	0.196	-0.246	-0.236	0.447	0.221	0.005	0.077
CAN	-0.122	-0.084	0.255	0.244	-0.067	-0.011	-0.056	-0.058
DNK	0.414	0.389	-0.301	-0.275			0.027	
ESP	-0.151	-0.149	0.097	0.085	-0.673	-0.343	0.000	0.043
FIN	0.476	0.456	-0.002	0.027	1.346	0.819	0.012	0.080
FRA	-0.483	-0.470	-0.020	-0.043	-0.745	-0.411	-0.021	0.039
GBR	-0.374	-0.358	-0.050	-0.072	-0.802	-0.546	-0.043	-0.080
GRC	0.483	0.451	0.098	0.115	0.668	0.408	0.064	0.079
IRL	0.739	0.716	-0.074	-0.041	1.312	0.774	-0.003	-0.149
ITA	-0.364	-0.364	0.087	0.069	-0.579	-0.431	0.068	0.057
JPN	-0.580	-0.549	0.130	0.101	-1.146	-0.620	0.000	-0.006
NLD	-0.030	-0.031	-0.185	-0.180	0.274	0.086	0.020	-0.032
PRT	0.372	0.333	0.130	0.150	0.529	0.391	0.067	0.027
SWE	0.064	0.046	-0.154	-0.138	0.571	0.373	-0.016	0.023
USA	-1.045	-0.977	0.339	0.284	-1.717	-0.981	-0.073	-0.082
	Period coefficients							
1960	0.233	0.244						
1965	0.272	0.282	0.192	0.200	0.358	0.313		
1970	0.194	0.201	0.152	0.155	0.408	0.299		
1975	0.021	0.025	0.049	0.052	0.020	0.119		
1980	-0.009	-0.010	0.004	0.005	-0.100	0.005		
1985	-0.144	-0.144	-0.077	-0.078	-0.051	-0.073		
1990	-0.101	-0.106	-0.034	-0.036	-0.120	-0.136		
1995	-0.126	-0.133	-0.073	-0.078	-0.114	-0.152		
2000	-0.165	-0.174	-0.089	-0.093	-0.200	-0.194		
2005	-0.176	-0.185	-0.124	-0.127	-0.201	-0.181		