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Impact of population, age structure, and urbanization on carbon emissions/energy consumption: Evidence from macro-level, cross-country analyses

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Abstract

This review summarizes the evidence from cross-country, macro-level studies on the way demographic factors and processesみspecifically, population, age structure, household size, urbanization, and population densityみinfluence carbon emissions and energy consumption. Analyses employing time-variant data have produced great variance in population elasticity estimationsみsometimes significantly greater than one, sometimes significantly less than one; whereas, cross-sectional analyses typically have estimated population elasticities near one. Studies that have considered age structure typically have used standard World Bank definitions, and mostly have found those variables to be insignificant. However, when researchers have considered levels of disaggregation that approximate life-cycle behavior like family size, they have uncovered relationships that are complex and nonlinear. Average household size has a negative relationship with road energy use and aggregate carbon emissions. Urbanization appears positively associated with energy consumption and carbon emissions. Higher population density is associated with lower levels of energy consumption and emissions.

Keywords: STIRPAT; IPAT; urbanization and energy/carbon emissions; age structure and environment; cross-country analyses.

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1. Introduction: review parameters and outline

As the interest has increased in how energy consumption and its resulting carbon emissions impact climate, and thus people, so too has the interest in how population and population processes impact energy consumption and carbon emissions. The availability of yearly, national-level data (from sources like the World Bank, International Energy Agency, and the Carbon Dioxide Information Analysis Center) covering energy consumption, carbon emissions, population, and socio-economic variables (like GDP per capita) has helped spur a substantial number of empirical analyses that estimate the socio-economic drivers of that consumption and emissions. Indeed, over half of the 28 papers listed in Table 1 were published since 2010—Table 1 presents some basic, summary information[1] from all studies that considered at least population size or age structure (studies considering only urbanization or population density are mentioned in the text), employed cross-country, macro-level data sets, and focused on some aggregation of either energy consumption or carbon emissions. Table 1 gives some indication of the sizeable diversity this literature has produced—in results, variables and countries considered, and data structure (among other dimensions of difference). This review presents/summarizes the evidence from cross-country, macro-level studies on the way demographic factors and processes—specifically, (i) population size and growth, (ii) urbanization and population density, and (iii) age structure and household size—influence carbon emissions and energy consumption. Hence, by considering all papers that examine those six factors (and that adhere to the described dependent variable and data parameters), the review

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[1] Several papers presented more than one regression; when authors articulated a favored regression, data was drawn from it. Also, when stationarity was not explicitly addressed, regressions performed in first differences were deemed to be more robust to stationarity, and thus, preferred. Lastly, an attempt was made to choose results that were most compatible with the results from the other studies listed in Table 1 (e.g., regressions that controlled for population and GDP per capita).

seeks to answer two questions: (1) what do we know about the impact of those six demographic factors; and (2) do we need to know anything more about their impact?

The following section (i) briefly reviews the typical models used and (ii) outlines some of the important empirical issues/challenges encountered. The next three sections summarize the evidence to date, considering in turn: population size and growth (Section 3), urbanization and population density (Section 4), and age structure and household size (Section 5). The paper concludes with some suggestions for modeling and methodological improvements to the common macro-level population-environment framework.

Table 1

2. Background: models and empirical issues/methods

Analyses interested in examining population's impacts on the environment often employ Dietz and Rosa's (1997) STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) framework. STIRPAT builds on IPAT/impact equation of Ehrlich and Holdren (1971):

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

where I is aggregate environmental impact, P is total population, A is affluence or consumption per capita, and T is technology or impact per unit of consumption. Dietz and Rosa (1997) proposed a flexible, log-linear, regression framework that allows for hypothesis testing:

$$\ln I_{it} = \alpha_i + \gamma_t + \beta_1 \ln P_{it} + \beta_2 \ln A_{it} + \beta_3 \ln T_{it} + \varepsilon_{it} \tag{2}$$

where subscripts it denote the ith cross-section and tth time period. The constants α and γ are the country or cross-sectional and time fixed effects, respectively, and ε is the error term. Affluence (A) is typically proxied by GDP per capita, and the T term is often treated like an intensity of use variable and sometimes modeled as a combination of log-linear factors (like urbanization or density).

A related literature, Environmental Kuznets Curve (EKC), tests whether pollution per capita first rises with income or GDP per capita and then falls after some threshold level of income/development is reached, thus forming an inverted U-shaped relationship. Empirical studies of the EKC typically take the following form:

$$\ln(C/P)_{it} = \alpha_i + \gamma_t + \beta_1 \ln(A)_{it} + \beta_2 (\ln A)^2_{it} + \beta_3 \ln(Z)_{it} + e_{it} \qquad (3)$$

where *Z* is a vector of other drivers (that is sometimes considered)—similar to *T* in Equation 2. Hence, the primary difference between the STIRPAT and EKC frameworks (i.e., between Equations 2 and 3) is that the EKC effectively assumes that population elasticity is unity and correspondingly converts the dependent variable into per capita terms.[2] An EKC between emissions/energy consumption per capita and income is said to exist if the coefficient β_1 is statistically significant and positive, while the coefficient β_2 is statistically significant and negative.

Still another framework, taken from economics, posits a demand-type relationship:

$$\ln(E/P)_{it} = \alpha_i + \gamma_t + \beta_1 \ln(A)_{it} + \beta_2 \ln(Pr)_{it} + \beta_3 \ln(Z)_{it} + e_{it} \qquad (4)$$

where *E* is (some aggregation of) energy consumption, *Pr* is energy price—for which data is available often only for OECD countries, and the *Z* vector sometimes includes terms like urbanization and population density. Naturally, many analyses, including some of those listed in Table 1, take a hybrid approach by combining elements of the three above described models—for example, some STIRPAT studies have included an affluence squared term.

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[2] Menz and Kuhling (2011) suggest that the STIRPAT framework is more popular among sociologists; whereas, the EKC framework is more popular among economists—naturally, such discipline distinctions would affect the choice of additional (*T* and *Z*) variables.

2.1. Empirical issues/methods

The earliest papers listed in Table 1 relied on cross-sectional data taken from a single year. Yet, the empirical consideration of many cross sectional units combined with observations taken at many time intervals (i.e., time seriesみcross sectional or panel data) offers substantial advantages over simple cross-sectional analysis, e.g., (i) using country and/or time fixed effects to control for some omitted variables (i.e., factors that may affect emissions that are not captured by variables specified in the regression model, such as economic shocks, changes in population policies, or other country specific development pathways); (ii) increasing substantially the degrees of freedom; and (iii) allowing for dynamic modeling (e.g., estimating short-run and long-run effects). However, employing such time seriesみcross-sectional data also both introduces statistical challenges and provides opportunities to address those challenges and other modeling issues: namely, serial correlation, nonstationarity, cross-sectional dependence, heterogeneity, nonlinearities, and endogeneity.

If regression errors are serially correlated, then ordinary least squares regressions (OLS) produce unbiased but inefficient estimations (i.e., t-tests and confidence intervals are inaccurate). Several time series-based estimation methods are robust to serial correlation (e.g., those used in Liddle 2011; Liddle 2012; and Liddle 2013a). Other papers employed the Prais-Winsten serial correlation correction (e.g., York 2007a; 2007b; and 2008). Beck and Katz (1996) argue that the Prais-Winsten correction is more difficult to interpret than the lagged dependent variable (LDV) model, which can address serial correlation, too. Hence, still other analyses listed in Table 1 (e.g., Liddle and Lung 2010; Menz and Welsch 2012) have included a LDV to address serial correlation. Elasticities estimated from a LDV model are considered short-run; however, those elasticities can be むscaledめ or divided by one minus the estimated LDV coefficient to arrive at long-run elasticities.

Most variables used in macro-population-environment 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 typically highly trending and quite possibly nonstationaryみi.e., their mean, variance, and/or covariance with other variables changes over time. When OLS is performed on 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. The studies listed in Table 1 that have addressed stationarity in their data, typically have done so via first differences (e.g., Cole and Neumayer 2004; and Martinez-Zarzoso et al. 2007). (A few papers mitigated stationarity by analyzing data observed at five year intervals.) Although first-differencing often transforms nonstationary variables into stationary ones, first-differencing means that the model is a short-run (rather than a long-run) model, and that the estimated coefficients, rather than being elasticities, are constants of proportionality between percentage changes in the independent variables and percentage changes in the measure of impact. Among the studies in Table 1, only Liddle (2011), Liddle (2012), and Liddle (2013a) employed time series-based techniques that address stationarity in the estimation of long-run elasticities.

Additionally, for variables like GDP per capita, carbon emissions, and energy consumption, cross-sectional dependence is likely because of, for example, regional and macroeconomic linkages that manifest themselves through (i) common global shocks, like the oil crises in the 1970s or the global financial crisis from 2007 onwards; (ii) shared institutions like the World Trade Organization; or (iii) local spillover effects between countries or regions. Yet, most estimation methods (e.g., OLS) assume that the cross-sections are independent. Disregarding this cross-sectional correlation in panel data models can lead to inconsistent parameter estimates and incorrect inference (Kapetanios et al. 2011). Converting variables to first differences or considering observations taken at limited intervals (e.g., every five or 10 years) can address/mitigate cross-sectional dependence (as can including time dummies to a more limited extent); however, only Liddle (2012) tested for and employed long-run estimation methods robust to cross-sectional dependence.

It may not be reasonable to assume the population-environment relationship is the same for each country analyzed; yet, nearly all studies have employed pooled estimators (that make that assumption).[3] If one mistakenly assumes that the parameters are homogeneous (when the true coefficients of a dynamic panel in fact are heterogeneous), then all of the parameter estimates of the panel will be inconsistent (Pesaran and Smith 1995). Heterogeneity, when considered, is typically addressed by splitting the panel along income lines—a distinction that appears justified by the results. (Alternatively, Martinez-Zarzoso and Maroutti 2011 used a semi-parametric mixture model to endogenously classify countries into homogenous groups/panels.) By contrast, the panel estimators used in Liddle (2011, 2012, and 2013a) first estimate each group/cross-section specific regression and then average the estimated coefficients across the groups/cross-sections (standard errors are constructed nonparametrically); and thus those estimators, allow for a high degree of heterogeneity. Indeed, Liddle (2011) demonstrated a substantial variation in individual STIRPAT elasticity estimations among OECD countries.

Analyses often focus on/consider whether a variable’s impact varies nonlinearly (again, the EKC literature asks this question in regard to income’s impact), and typically answer that

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[3] They do so, albeit, often after subtracting out country effects.

question of nonlinear relationships by including a squared term in the regressions. However, if the variables of interest (e.g., GDP per capita, population) are nonstationaryみas noted earlier, they likely areみthen regressions (using time-variant data and) involving nonlinear transformations of such nonstationary variables could be spurious, and their significance tests invalid (Wagner 2008). Furthermore, that polynomial model (e.g., Equation 3) does not allow for the possibility that elasticities are significantly different across development levels but still *positive* (Liddle 2013a). See Wagner (2008), Stern (2010), and Liddle (2012; 2013a) for different ways to address either or both of those two issues.

Lastly, according to a number of social science theories, the variables typically considered in population-environment studies have a degree of endogeneity among them. For example, affluence (or GDP per capita) is believed to affect populationみthrough both human capitalゃinfluence on birth rates (e.g., Becker et al. 1990) and higher incomeゃability to lower death rates. Likewise, population has been shown to impact affluenceみ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). The methods used by Liddle (2011 and 2013a) account for endogeneity among variables *implicitly* via error correction/cointegration modeling. Meanwhile, the system generalized method of moments (GMM) estimator employed by Martinez-Zarzoso and Maroutti (2011) and Fang et al. (2012) corrects for/mitigates endogeneity by using as instruments lags of the explanatory variables. However, I know of no population-environment studies that have *explicitly* addressed the endogeneity issue via multiple equation modeling.

3. Population and population growth

Table 1 shows that analyses employing time-variant data have produced a great variance in population elasticity estimationsみsometimes significantly greater than one, sometimes significantly less than one; whereas, cross-sectional analyses typically have estimated population elasticities very near one (e.g., Rosa et al. 2004; York et al. 2003a; York et al. 2003b; Dietz and Rosa 1997).[4] Again, some of the studies in Table 1 employed a lagged dependent variable (LDV) model. If those elasticities reported in the table were converted to long-run elasticities as described previously, the long-run population elasticities for Menz and Welsch (2012), Martinez-Zarzoso and Maroutti (2011), and Liddle and Lung (2010) would be 2.2, 1.0, and 2.1, respectively. However, none of those LDV analyses calculated new standard errors for that nonlinear combination of coefficients, and so we do not know whether those long-run elasticities are significantly different from one (or any other value). Also, some other studies analyzed models with all variables in first differences, and so, those values should be considered short-run estimates.[5]

Beyond the issues of short run vs. long run estimates and the effectiveness in addressing the statistical issues discussed above (e.g., stationarity, cross-sectional dependence), the various papers listed in Table 1 analyzed different dependent variables, considered different additional explanatory variables (including non-population variables not listed in the table), and examined different panels of countries. Thus, in order to accurately assess the true measure of the population elasticity, one might proceed to a meta-analysis. Yet, perhaps we should not expect population’ elasticity to be different from one anyway, since as O’Neill et al. (2012) argued, “if all other influences on emissions are controlled for, and indirect effects of population on

[4] Interestingly, this phenomenon of a population elasticity of unity for cross-sectional analyses is true even for studies considering different dependent variables (e.g., fuelwood consumption by Knight and Rosa 2012) or different units/scales of analysis (e.g., US county-level data in Roberts 2011; international city-level data in Liddle 2013b).

[5] Fang et al. (2012) first differenced their data and included a LDV; thus, it is difficult to compare their results with those of other studies. Perhaps, if one applies the one minus the LDV coefficient transformation (i.e., divides by 1-0.92 for their all countries panel), their results would be comparable to other first differenced, short run models.

emissions through other variables are excluded, then population can only act as a scale factor[,] and its elasticity should therefore be 1.め

Indeed, Liddle (2012) performed a substantial robustness exercise on the STIRPAT framework employing estimation methods that were designed to address the six econometric/modeling issues outlined in the previous section; that analysis determined that, even after correcting for the modeling and methodological short-comings of previous STIRPAT analyses, the population elasticity of carbon emissions was not conclusively significantly different from one. While the estimated (mean) population elasticity was greater than one and was unstable/inconsistentみi.e., it varied considerably depending on the panel (OECD vs. non-OECD), method (long-run vs. short-run/first difference estimation), and time-span consideredみits accompanying standard errors were large; as a result, the elasticity was typically not statistically different from one, nor statistically different between developed and developing countries. By contrast, the affluence (or GDP per capita) elasticity of carbon emissions was highly stable/consistentみit was statistically less than one for OECD countries, and statistically smaller for OECD countries than for non-OECD countries (but not statistically different from one for non-OECD countries).

Furthermore, the lack of stability of the population elasticity over time was not evidence that the elasticity had changedみthe sensitivity analysis revealed no evidence that the size, significance, or sign of the population elasticity may have changed over-time (e.g., from 1970-1990 to 1990-2006). Rather, the more extreme estimated values (i.e., particularly large or insignificant estimations) typically occurred whenever the time span was shortest (e.g., 1971-1990, 1975-1995, 1980-2000, and 1985-2006).[6] Jorgenson and Clark (2010), using different methods, similarly concluded that their population elasticity estimations did not change over

[6] See Liddle (2012) for details of the models, estimators, and regression diagnostics.

time. Hence, Liddle (2012) recommended that modelers divide Equation 2 by population, and thus, convert the depended variable into per capita terms, unless modelers specifically want the population variable むヘto capture もther influencesやor missing variables by research designみto compare urban vs. rural populations, for example.め

3.2 Population growth

To my knowledge population growthやimpact on the level of national carbon emissions has not been explicitly explored (a conclusion also reached in another review by Rosa and Dietz 2012). Yet, since many of the analyses listed in Table 1 employ an elasticity model, i.e., all variables in natural logs, the estimated coefficient for population represents the percentage change impact on the dependent variable that a one percent change in population would cause. Hence, one could argue that these elasticity studies (e.g., those using the STIRPAT framework) indeed investigate the impact of population change or growth. Furthermore, several studies have employed models with all the variables in logged first differences; as such those models investigated the impact of population growth on emissions growth. In other words, the estimated population coefficient in those studies reflects the percentage change in the emissions growth rate that a one percent change in the population growth rate would cause.

Yet, it is not clear why population *growth rates* would affect contemporaneously the *level* of emissions/energy consumption. (Lagged population growth might have such an effect directly through its impact on population size.) Moreover, similar to the OやNeill et al. (2012) argument about population acting only as a scale factor, unless indirect effects are present, we would expect a change in the growth of population to have a proportional effect on the growth of emissions/energy consumption. Of course, we may be interested in population growth precisely because of its indirect effects on emissions/energy consumption through its impact on population processes like urbanization, population density, age structure, and household size. Because it is probably better to model those four processes directly, we now turn to assessing the literature's findings on their emissions/energy consumption impact.

4. Urbanization and population density

Urbanization may lead to higher emissions/energy consumption through urbanization's association with industrialization—i.e., the shift from agriculture to industry and services. The co-evolving movement of people from rural to urban areas and from agricultural to industrial employment causes energy consumption to increase in three ways: (1) agricultural operations must mechanize as they become less labor intensive; (2) urbanization spatially separates food consumers from food producers, thus necessitating a transport requirement that did not exist under traditional agriculture and settlement patterns; and (3) modern industry/manufacturing uses more energy per unit of output and per worker than does traditional agricultural and manufacturing (Jones 1991). Furthermore, urbanization is associated with economic growth, and so urbanization may lead to greater energy consumption since energy consumption is a normal good. Lastly, urbanization is a proxy for the amount of people with access to a country's energy/electricity grid, and thus, urbanization would be associated with more consumption of such energy.

On the other hand, urbanization could lead to lower levels of energy consumption since cities benefit from energy efficiencies by providing/encouraging living in high-rise buildings and using public transit networks or energy-free transport modes (walking and cycling). Yet, it is not at all clear whether national levels of urbanization are really measures of the density of the types of activity that might lead (via efficiencies) to less energy consumption or emissions (Liddle and Lung 2010). Indeed, Liddle (2013b) calculated that for a large sample of the world's largest cities from both developed and developing countries, the correlation (俦between urban density and the corresponding national population density was only 0.35, and national urbanization levels were actually negatively correlated with urban density (俦= -0.59).

Studies that examine the influence of urbanization (share of population living in urban areas) on carbon emissions/energy consumption tend to come in two flavors: (i) those that assume a one-way causal direction (urbanization causes emissions/energy consumption) and test for the significance and sign of that relationship; and (ii) those that test for the possibility of a mutual causal relationship between urbanization and emissions/energy consumption.[7] That second group of studies employs so-called Granger-causality and vector error correction modeling, typically considers multivariate models, and analyzes the variables in first differences to test for short-run relationships.[8]

The earliest of the first type of studies focused on developing countries and found a positive, significant relationship between urbanization and energy consumption (Jones 1989; Burney 1995; Parikh and Shukla 1995). More recent, similar studies have considered developed as well as developing countries, carbon emissions and disaggregated energy consumption, and additional explanatory variables. These studies typically have confirmed the positive relationship between urbanization and emissions/energy consumption (e.g., York et al. 2003a and 2003b; Cole and Neumayer 2004; Fan et al. 2006; York 2007a; Poumanyvong and Kaneko 2010; Martinez-Zarzoso and Maruotii 2011; Menz and Welsch 2012; Poumanyvong et al. 2012; Zhu et al. 2012; Knight et al. 2013).

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[7] That first group of studies includes papers employing GMM or instrumental variables (e.g., Martinez-Zarzoso and Maruotti 2011; and Fang et al. 2012). Such techniques include lags of the independent variables to indirectly mitigate endogeneity; however, they do not formally test for the presence of a mutually causal relationship as the second group of studies does.

[8] Most of the mutual causality studies to date have been focused on single countries, and thus, are beyond the scope of this review.

By contrast, Liddle and Lung (2010) found that urbanization had an insignificant influence on total carbon emissions in OECD countries; similarly, Jorgenson (2007), Jorgenson (2012), and Jorgenson and Clark (2010 and 2012) found a significant, but very small influence (elasticity of 0.02) for urbanization in both developed and developing countries. Whereas, Jorgenson et al. (2010) studied total energy consumption in less developed countries and found that urbanization had a significant positive influence, but that the share of the population living in urban slum conditions had a significant negative influence on energy consumption. Fang et al. (2012) found an insignificant impact for urbanization on energy consumption in low-income countries, but a significant (albeit small), negative impact for urbanization in high-income countries. Lastly, Liddle (2004) and Liddle and Lung (2010) considered more disaggregated forms of energy and carbon emissions. Liddle (2004) uncovered a significant, negative relationship between urbanization and per capita road energy use in OECD countries. However, Liddle and Lung (2010) ultimately determined that urbanization had no effect on aggregate carbon dioxide emissions from transport in their analysis of developed countries, but they did find that urbanization had a significant *positive* and, relative to GDP per capita, large impact on aggregate residential electricity consumption in those same countries.

A different impact for urbanization in less developed countries than in developed countries (also uncovered by Poumanyvong and Kaneko 2010 for energy consumption) is not surprising. The most developed/OECD countries are likely to be "fully urbanized" (Henderson 2003)—i.e., their urbanization levels no longer change. Furthermore, even for countries in similar development/income levels, the urbanization-energy consumption/emissions relationship should be heterogeneous since, taking OECD countries as an example, the level of urbanization for fully urbanized countries varies considerably. For example, the level of urbanization has changed very little since 1950 for both Austria and Belgium (having increased by only 6% since then or 0.1% per year); yet, their current urbanization levels are substantially different, 68% and 97%, respectively.

Among the multi-country, Granger causality studies, Mishra et al. (2009) found one-way short-run causality from urbanization to energy consumption for a panel of Pacific Island countries; Hossain (2011) found no causal relationship between urbanization and carbon emissions in the short-run for a panel of newly industrialized countries; and Al-mulali et al. (2013) found a positive bi-directional long run relationship between urbanization and both energy consumption and carbon emissions for a panel of Middle East and North African countries.

Yet, it is plausible that energy/electricity consumption could cause urbanization too. For example, rural to urban migration to fill manufacturing jobs would be associated with higher energy consumption (since manufacturing should consume more energy than traditional agriculture). Likewise, migration motivated by the improved quality of life that energy/electricity may bring means that energy causes urbanization. Indeed, Liddle and Lung (2014) uncovered a long-run, causal relationship from several aggregations of electricity consumption (i.e., total electricity consumption, industry electricity consumption, and residential electricity consumption) to urbanization for panels of high, middle, and low income countries, as well as for panels of non-OECD countries pooled geographically (i.e., Africa, Asia, and Latin America). In other words, the employment and quality of life opportunities that access to electricity afford likely encourage migration to cities, and thus, "cause" urbanization. However, Liddle and Lung (2014) could not reject pervasively causality from urbanization to electricity consumption, i.e., there was evidence of heterogeneity within the panels.

4.1 Population density

Despite the well-established relationship between *urban* density and (i) lower levels of transport energy consumption (e.g., Newman and Kenworthy 1989; Kenworthy and Laube 1999; Liddle 2013b), (ii) lower levels of electricity consumption in buildings (e.g., Lariviere and Lafrance 1999), and (iii) lower levels of greenhouse gas emissions (e.g., Marcotullio et al. 2012) by studies employing city-level data, few national-level studies have considered population density. Among those few studies, Hilton and Levinson (1998) found a significant, negative relationship between national population density and gasoline use in a study of 48 (developed and developing) countries. Similarly, Liddle (2004) found a significant, negative relationship between national population density and per capita road energy use in OECD countries. By contrast, early studies on electricity or energy consumption per capita found a small positive to insignificant effect for national population density (Jones 1989; Burney 1995; Parikh and Shukla 1995).

5. Age structure & household size

Macro-level studies that have considered age structure typically have used the World Bank definitions/data, i.e., the share of people aged less than 15, aged 15-64, and aged over 64, and those studies mostly have found those age structure variables to be insignificant (see Table 1). However, when researchers examining the link between age structure and emissions/energy consumption have considered levels of disaggregation that approximate life-cycle behavior like family or household size, they have uncovered relationships that are complex and nonlinear.

For example, among the first studies to disaggregate the working-age population, Liddle and Lung (2010) uncovered a positive elasticity for young adults (aged 20-34) and a negative elasticity for older adults (aged 35-64). Menz and Welsch (2012), also analyzing aggregate carbon emissions, estimated differential age-structure elasticities too, with the middle ages (30-59) having negative elasticities. Menz and Welsch considered cohort effects as well, and determined that people born after 1960 are associated with increased carbon emissions. Yet, age structure is less likely to directly impact national, aggregate carbon dioxide emissions; instead, those emissions should be heavily influenced by the size, 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).

By contrast, researchers employing micro- (i.e., household-) 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 et al. 2004). In general, age structure matters because: (i) people in different age groups or at different stages of life have different levels of economic activity and resulting energy consumption; and (ii) the age of household head is associated with size of household (younger and older/retired-age adults typically have smaller households), and larger households consume more energy in aggregate, but less per person than smaller households.

Recently, studies using cross-country, macro-level data have shown a similar age-structure relationship. For example, Liddle (2011) determined that for transport energy consumption, young adults (20-34) were intensive consumers, whereas the other age groups had negative coefficients; yet, for residential electricity consumption, age structure had a U-shaped impact: the youngest and oldest age groups had positive coefficients, while the age middle groups had negative coefficients. Liddle and Lung (2010), using different methods than Liddle (2011), similarly found that, compared to younger ones, older age groups had a lower elasticity for CO_2 emissions from transport (i.e., negative for ages 35-64 but positive for ages 20-34), yet a higher elasticity for residential electricity use (i.e., negative for ages 35-49, but positive for ages 50-64). Okada (2012), using different methods and models than Liddle (2011), confirmed the result that a larger share of population over 65 is associated with lower CO_2 emissions from road transport.

5.1 Household size

The only two studies to consider household size both estimated a significant, negative relationship.[9] Liddle (2004) found that larger households were associated with lower levels of per capita road energy use in OECD countries, while Cole and Neumayer (2004) found that larger households were associated with lower levels of aggregate carbon emissions in both developed and developing countries.

6. Conclusions and suggestions for future work

Heterogeneity, stationarity, cross-sectional dependence, endogeneity, and potential nonlinearities present serious statistical challenges for analyzing/estimating cross-country, macro-level population and environment models. Indeed, simultaneously addressing those issues currently is an area of active research for time-series, panel data econometric theory. Yet, despite the recent, increased interest in macro-level population and environment studies, other social science literatures that work with similar data sets (e.g., energy-GDP literature)[10] seem to be further ahead than the macro-level population and environment literature (e.g., STIRPAT) in employing more advanced time-series, panel data empirical methods. For example, the statistical package STATA has several estimators that address heterogeneity, stationarity, and cross-

[9] Cross-national data on average household size is difficult to collect; however, there are a few other studies that have analyzed this variable (e.g., Knight and Rosa 2012), but since those studies considered dependent variables other than energy consumption or carbon emissions, they are beyond the scope of this review.

[10] See reviews by Payne (2010a and 2010b).

sectional dependence,[11] and there is some evidence that standard OLS with all variables in first differences is robust to both stationarity and cross-sectional dependence (Eberhardt et al. 2012; Liddle 2012).

In addition to improvements in methods, the models used could be better motivated. It is not clear why total population should be anything more than a scaling factor (i.e., an elasticity of one)—particularly for aggregate environmental indicators like total carbon emissions or total energy consumption. Nor is it clear why more refined population variables like urbanization or working-age population share would directly affect those aggregate indicators. By contrast, empirical evidence exists supporting an argument that what drive consumption of environmentally important activities like transport and residential energy/electricity use are population factors/processes—like disaggregated age structure (i.e., beyond just 15-64 or over 65) and average household size, life-cycle effects, and concentration measures (e.g., population density).

Hence, one way to advance the macro-level population and environment literature would be to focus on, as dependent variables, environmental impacts like transport and residential demand, and to include as explanatory variables population processes like age and household structure (in order to proxy life-cycle effects). Also, likely to be illuminating would be more advanced, perhaps multiple equation, models that could more fully and explicitly express the potential mutual feedbacks among the variables. In other words, develop models that separately analyze (i) age and household structure's and population density's potentially mutual causal relationship with economic development, and (ii) population and development processes' impact on emissions/energy consumption.

[11] Some of these estimators were developed/coded by Markus Eberhardt, who also maintains a very helpful website: https://sites.google.com/site/medevecon/home.

Finally, the clear consensus of evidence is that urbanization is positively associated with energy consumption and carbon emissionsみbut, perhaps, that association is entirely a function of income ゃs/development ゃpositive association with both urbanization and energy/emissions. Additionally, most to every OECD country has been fully urbanized since the start of typical data sets (i.e., 1960-1980), and it is possible to likely that higher levels of energy consumption lead to/むcauseめgreater urbanization elsewhere. By contrast, higher population density is (unambiguously and uni-directionally) associated with lower levels of energy consumption in transport and buildings, as well as with lower emissions. Furthermore, national urbanization levels (i.e., the share of national population living in urban areas) are a poor proxy for population density; and thus, density, rather than urbanization, is associated with energy efficiency (savings). Some modelers may include urbanization as a proxy for development/modernization; yet, there is little reason to believe urbanization is any better, if even as good, a measure of that phenomenon than income (GDP per capita). Moreover, it is not at all clear whether urbanization has any relevance as a policy variable (in contrast to urban form measures). Hence, those interested in exploring the environmental impact of urban agglomeration are advised to focus on population density (rather than national urbanization), and perhaps employ data at a more appropriate level of spatial aggregation for such considerations, i.e., at a regional or city-level.

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Table 1: Cross-national population-environment studies estimating the effects of (several) demographic changes on CO_2 emissions/energy consumption. Values indicate elasticities of emissions with respect to changes in demographic variables.

Study	Dependent variable(s)	Population size	Urbanization	Age structure	Data structure
Knight et al., 2013 [b]	Total CO_2 emissions	2.25	1.09		29 OECD countries; 1970-2007, annual obs.
Liddle, 2013a [g]	CO_2 emissions from domestic transport Total residential electricity use	1.05 (overall); 0.68 (HI); 0.86 (MI); 0.70 (LI) 0.85 (overall); 0.23 (HI); 0.10 (MI); 1.02 (LI)			23 HI, 25 MI, & 37 LI countries; 1971-2007, annual obs.
Liddle, 2012	Total CO_2 emissions	1.16 (OECD); 1.28 (non-OECD)			26 OECD & 45 non-OECD countries; 1971-2006, annual obs.
Fang et al., 2012 [b]	Total primary energy use	0.08 (overall); 0.03 (HI); 0.12 (LI)	-0.01 (overall); -0.01 (HI); NS (LI)		94 countries; 1981-2007, annual obs.
Jorgenson & Clark, 2012	Total CO_2 emissions	1.55	0.02		86 countries; 1960-2005 at 5-yr intervals
Zhu et al., 2012 [b]	Total CO_2 emissions	0.79	3.55 (levels); -0.47 (quadratic)		20 non-OECD, "emerging" countries; 1992-2008, annual obs.
Poumanyvong et al., 2012	Total road energy use	1.15 (overall); 1.15 (HI); 1.37 (MI); 0.72 (LI)	0.49 (overall); 1.32 (HI); 0.84 (MI); 0.81 (LI)		31 HI, 40 MI, & 21 LI countries; 1975-2005, annual obs.
Okada, 2012 [b]	CO_2 emissions from road transport per capita			64.10 (65+, levels) -2.47 (65+, quadratic)	25 OECD countries; 1978-2008, annual obs.
Menz & Welsch, 2012 [b]	Total CO_2 emissions	0.78	0.31	-1.17 (30-44); -1.77 (45-59)	26 OECD countries; 1960-2005 at 5-yr intervals
Martinez-Zarzoso & Maruotti, 2011 [b]	Total CO_2 emissions	0.32	0.76 (levels); -0.12 (quadratic)	NS (15-64) ; NS (65+)	88 non-OECD countries; 1975-2003, annual obs.
Liddle, 2011	CO_2 emissions from domestic transport Total residential electricity use	2.35 2.69		0.82 (20-34); -0.22 (35-49); -0.77 (50-69); -0.36 (70+) 0.22 (20-34); -0.42 (35-49); -0.40 (50-69); -0.55 (70+)	22 OECD countries; 1960-2007, annual obs.
Poumanyvong & Kaneko, 2010 [b]	Total CO_2 emissions Total energy use	1.12 (overall); 1.12 (HI); 1.23 (MI); 1.75 (LI) 1.22 (overall); 1.20 (HI); 1.70 (MI); 0.60 (LI)	0.45 (overall); 0.36 [a] (HI); 0.51 (MI); 0.43 (LI) NS (overall); 0.91 (HI); 0.51 [a] (MI); -0.12 [a] (LI)		33 HI, 43 MI, & 23 LI countries; 1975-2005, annual obs.
Jorgenson & Clark, 2010 [b]	Total CO_2 emissions	1.43 (overall); 1.65 (DC); 1.27 (LDC)	0.02 (for all three panels)		22 DC and 64 LDC; 1960-2005 at 5-yr intervals
Jorgenson et al., 2010 [b c]	Total energy use	0.70	0.37	0.99 (15-64)	57 LDC; 1990-2005, annual obs.
Liddle & Lung, 2010 [b]	Total CO_2 emissions CO_2 emissions from	0.69	NS	0.20 [a] (20-34); -0.36 [a] (35-64)	17 OECD countries; 1960-2005 at 5-yr intervals

	domestic transport Total residential electricity use	1.34 2.24	NS 1.92	0.30 (20-34); -0.48 (35-64)[a] NS (20-34); -0.67 (35-49); -0.67 (50-64); NS (65-79)	
York, 2008	Total CO_2 emissions	1.87	2.80	-2.51 (dependency ratio)	14 FS countries; 1992-2000, annual obs.
Jorgenson, 2007	Total CO_2 emissions	0.80	0.02		37 LDC; 1975-2000, annual obs.
Martinez-Zarzoso et al., 2007 [b]	Total CO_2 emissions	NS (overall); 0.71[a] (15 old EU); 2.73 (8 new EU)			23 EU countries; 1975-1999, annual obs.
York, 2007a	Total energy use	2.75	0.53	0.96 (65+)	14 EU countries; 1960-2000, annual obs.
York, 2007b	Total energy use	0.84	-0.22 (levels); 0.37 (quadratic)	1.74 (15-64)	14 Asian countries; 1971-2002, annual obs.
Fan et al., 2006 [d]	Total CO_2 emissions	0.30 (overall); 0.54 (HI); 0.21 (UMI); 0.28 (LMI); 0.33 (LI)	0.24 (overall); 0.57 (HI); 0.23 (UMI); 0.23 (LMI); 0.33 (LI)	0.34 (overall); -0.70 (HI); 0.17 (UMI); 0.57 (LMI); 0.23 (LI) (15-64)	218 countries; 1975-2000, annual obs.
Cole & Neumayer, 2004 [b e]	Total CO_2 emissions	0.98	0.70	NS (aged < 15) NS (aged 15-64)	86 countries; 1975-1998, annual obs.
Liddle, 2004 [f]	Road energy use per capita		-0.47	1.16 (20-39)	23 OECD countries; 1960-2000 at 10-yr intervals
Rosa et al., 2004	Total CO_2 emissions	1.02			Cross section: 146 countries, late 1990s
York et al., 2003a	Total CO_2 emissions	0.99	0.72	NS (15-64)	Cross section: 137 countries, 1991
York et al., 2003b	Total CO_2 emissions	0.98	0.62	NS (15-64)	Cross section: 146 countries, 1996
Shi, 2003	Total CO_2 emissions	1.43 (overall); 0.83 (HI); 1.42 (UMI); 1.97 (LMI); 1.58 (LI)		0.63 (15-64)	88 countries; 1975-1996, annual obs.
Dietz & Rosa, 1997	Total CO_2 emissions	1.15			Cross section: 111 countries, 1989

Notes: [a] statistically significant at $p < 0.10$. [b] estimations were performed in first differences and/or with a lagged dependent variable; and thus, those elasticities could be interpreted as short-run (as opposed to long-run). [c] Also considered percentage of population living in urban slums and calculated an elasticity of -0.10. [d] estimations were performed via partial least squares. [e] Also considered average house-hold size and calculated an elasticity of -0.50. [f] Also considered average house-hold size and population density and calculated coefficients of -0.10 and -0.001, respectively. [g] Considered urban population (population x share living in urban areas).

NS= not statistically significant at the $p < 0.10$ level or higher; OECD=Organization for Economic Cooperation and Development; EU=European Union; FS=former Soviet countries; DC=developed countries; LDC=less developed countries; HI=high income; MI=middle income; LI=low income; UMI=upper-middle income; LMI=lower-middle income. Studies whose main focus was not population-environment interactions are not listed in the table but are mentioned in the text.