Are macro-level relationships between demography, economy, and environmental impact significant at smaller scales of analysis? Identifying county-level age-specific drivers of CO_2 emissions in the US using age-structure and relative cohort size.

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INTRODUCTION

The demographic concept of age-structure has received a great deal of attention lately. In general terms, age-structure describes the distribution of the total population across the age spectrum. Demographers argue that the distribution of the population across cohorts has significant consequences for social, political, and economic dynamics (Pampel and Peters 1995; Pampel 1993). In particular, economic performance has been scrutinized as a potential outcome of a changing demographic composition (McNiccoll 2006; Macunovich 1999; Bloom and Freeman 1988; Brunello 2010). Aging societies, with many people out of the labor force (termed "dependents") are thought to have lower levels of economic growth, while populations that are disproportionately young are theorized to have higher growth potential. Evidence in favor of this hypothesis is mixed (Pampel and Peters 1995; Schapiro 1988).

More recently, this concept has been appropriated by the ecological modeling community as a lens to understand differential effects of population on global environmental change. In particular, the relationship between age structure and CO_2 emissions has garnered significant attention (Liddle 2000; Zagheni 2011; O'Neill et al. 2010). These papers posit that a high ratio of working-age people relative to the total population is positively correlated with CO_2 emissions (York, Rosa, and Dietz 2003b; Cole and Neumayer 2004). In particular, a high density of younger workers is strongly correlated with increased energy use (Liddle 2004), carbon dioxide emissions (Liddle and Lung 2010), and environmental change-driven out-migration (Massey, Axinn, and Ghimire 2010). Others have found more inconclusive results (Martínez-Zarzoso and Maruotti 2011).

In this research, I investigate the effects of age composition on county-level CO_2 emissions in the US. This analysis uses the STIRPAT econometric framework as the analytical platform for estimating the strength of these demographic variables on carbon emissions. STIRPAT is an estimation technique intended for adapting the well-known IPAT identity model of human drivers of environmental change (Commoner 1972; Ehrlich and Holdren 1971; York, Rosa, and Dietz 2003c). Recent investigations by environmental sociologists and ecological economists illustrate the empirical stability of population and affluence as correlates of CO_2 emissions with this stochastic framework (Cole and Neumayer 2004; Liddle 2004; Shi 2003). I aim to improve upon this research evaluating five metrics of age-structure as components of this model. Using an amended STIRPAT model, these estimates illustrate that prior county age compositions metrics are not significant in estimating CO_2 emissions. The total dependency ratio, previously hypothesized to be a negative correlate of CO_2 emissions, is not statistically significant in US counties. At the same time, the youth dependency ratio and relative cohort size are both positive predictors of county carbon dioxide emissions in the US, indicating that older working-age populations and a large youth population are positively correlated with carbon. These estimates contravene prior theories regarding age-structure and environmental degradation, suggesting instead that smaller units of analysis demand examination of age-specific consumption rates rather than age-specific production. These estimates are robust across a variety of specifications that control for spatial effects, fixed effects, and heteroskedasticity.

This work is of interest to geographers for several reasons. Prior STIRPAT analyses have largely neglected spatial effects in their modeling efforts. This is true in both an econometric and substantive sense. Though the preponderance of STIRPAT estimations utilize cross-sectional and spatial data, few address the specification issue of dependency in the dependent variable (Paudel and Schaefer 2009). The consequences of failing to account for this are well noted by geographers (Anselin 1988; Anselin and Griffith 1988). Second, the spatial disconnect between production and consumption—known in the STIRPAT literature by the political economy term “metabolic rift” (York, Rosa, and Dietz 2003b)—fosters a potentially misleading picture of affluence as a driver of carbon emissions. In short, utilizing affluence in a local-level estimate of IPAT opens up potential specification issues from the disparate geographies of production and consumption. Attributing all emissions to local sources of capital is problematic, since capital travels so widely. In this research, I argue that age-structure, serving as a proxy for the availability of economically active labor and consumption patterns, offers a more appropriate model specification.

BACKGROUND LITERATURE

STIRPAT modeling is a research endeavor that attempts to stochastically estimate the well-known IPAT model (Dietz and Rosa 1997; Commoner 1972; Ehrlich and Holdren 1971). Recognizing that the original identity framework of environmental impact *I* = population *P* x affluence *A* x technology *T* is problematic for empirical analysis, Dietz and Rosa (1997) reformulated it into a stochastic model, given in logarithmic form by:

$$\ln I = a + b_1(\ln P) + b_2(\ln A) + b_3(\ln T) + e \qquad (1)$$

where *I* is the metric of environmental impact, *P* is population, *A* is affluence, most commonly GDP per capita, and *T* is a measure of technology. The intercept is given by *a*, and *e* is the error term. Using natural logarithms allows the terms to be estimated as elasticities, where coefficients are given by percent changes. In this way, the model can be interpreted as a production function where changes in output are relational to changes in inputs.

A great deal of STIRPAT research uses this econometric framework as a starting point, adding or dropping variables in order to test various model specifications at different scales or using various countries or regions. Total population and GDP per capita are the most common metrics for *P* and *A*, while total CO_2 emissions and derivative metrics such as global warming potential (GWP) and CO_2 equivalent, are the most common units of *I*. Many studies simply drop *T* altogether, preferring to estimate *P*, *A*, and A^2 without the difficulty of pinning *T* down to a single metric (Dietz and Rosa 1997; Soulé and DeHart 1998; DeHart and Soulé 2000). Regardless of the specific approach, *T* remains difficult to translate into a singular variable and the (more common) method of approaching this problem is to estimate 'technology' using a wide theoretical lens. More recent research amends this I=PA framework with other social, economic, and demographic variables thought to contribute to carbon dioxide emissions (Scholz 2006; Lankao, Tribbia, and Nychka 2009; Jorgenson and Rice 2005; Jorgenson and Clark 2010).

The central demographic focus of STIRPAT modeling is age structure. The most basic assumption governing the demography-environment relationship is that the economically active population exerts disproportionate force on CO_2 emissions. The preponderance of research examining this relationship does so at the national level. Fan et al. (Fan et al. 2006) disaggregate a panel dataset of nation-states from 1975-2000, and find that the percentage of the working-age population (15-64) varies considerably from a negative determinant of CO_2 emissions in high-, upper-middle, and low-income countries, to a positive driver in China and other lower-middle-income countries. Cole and Neumayer (Cole and Neumayer 2004) illustrate that the population aged 15-64 is significant and positive (b = .995) for 86 countries over 24 years (1975-1998) using CO_2 as the dependent variable. The variable becomes non-significant when percent urbanized population is included, or the dependent variable is SO_2. York, Rosa, and Dietz (York, Rosa, and Dietz 2003a) specify several cross-sectional specifications for 142 nations in 1996 and find the non-dependent population to be positive and greater than unity (ranging from 1.302 to 1.594) for a variety of specifications and control factors in predicting national ecological footprint. These estimates also illustrate urbanization and an arctic or temperate latitude to be a positive determinant.

Several assessments using this metric have failed to confirm any significant role in producing CO_2 emissions. The common thread in these papers is the inclusion of an urbanization variable, suggesting that for national-level STIRPAT assessments urbanization and the non-dependent population are collinear effects. York, Rosa, and Dietz (York, Rosa, and Dietz 2003b, 2005) find non-dependent population to be non-significant in a Kuznets-modified STIRPAT for CO_2 and SO_2 of 137 countries in 1991. It is significant and positive (b = 1.536-1.780) for the combined global warming potential of CO_2 and CH_4. Martínez-Zarzoso and Maruotti (Martínez-Zarzoso and Maruotti 2011) estimate a panel model for developing countries , for CO_2 emissions from 1975-2003, and using GDP, population, and urbanization find an inverted U-shaped curve for urbanization but no significant contribution from age-structure.

Liddle (Liddle 2004) and Liddle and Lung (Liddle and Lung 2010) assess age-structure using more parsimonious terms. Controlling for GDP, density, and percent urban population, Little (2004) finds that the percent of the population aged 20-39 is positive and a near unit-elastic predictor of per capita road energy use in OECD countries and US households. Similarly, Liddle and Lung find aggregate CO_2 emissions to be higher among countries with younger populations in a panel estimate of seventeen developed countries in 5-year intervals, 1960-2005. These studies support hypotheses that posit greater production and consumption among younger (under age 35) adults.

Structural modelers make significant use of age-structure variables in creating emissions scenarios of future carbon dioxide emissions. Zagheni (Zagheni 2011), for example, finds that changes in US age-structure are likely to contribute to CO_2 emissions. Zagheni's input-output model estimates per capita CO_2 rises until age 60 among US households. Liddle (Liddle 2000) simulates population, GDP, and age-structure in a variety of emission scenarios for consumption. O'Neill et al. (O'Neill et al. 2010) find that aging is likely to reduce CO_2 emissions in industrialized countries in the coming decades.

A commonality of nearly all age structure STIRPAT studies is the use of national-level data. This is largely an issue of data availability; spatially disaggregated data of impacts (CO_2, SO_2, and other GHG) are difficult to obtain at sub-national units of analysis. Liddle (Liddle 2004) notes that reliable demographic data are also similarly temporally infrequent. Though many of these models are estimated at the national level for data or specification reasons (such as the inclusion of world-systems or political economy variables), the tremendous within-unit variation of demographic processes in large countries is potentially consequential in elucidating the relationships between components of society and environmental change. The spatial disjuncture between production and consumption, in particular, maybe of consequence in estimating STIRPAT models using age structure, since age-specific rates of production are different than age-specific rates of consumption. Assuming that similar arguments hold at smaller scales of analysis is a potential model mis-specification.

ESTIMATION METHODS AND DATA

This research utilizes the STIRPAT framework to estimate the role of county age composition on CO_2 emissions in the US. The primary aim is to assess three measures of age structure and two metrics of relative cohort size in addition to the traditional STIRPAT factors of population and affluence. Theoretically, these models engage the assumptions of the previous literature with respect to age-specific economic dynamics and the different geographies of production and consumption. Prior use in demography or ecological research, and a hypothesized relationship with various factors of production were two (primary) criteria in deciding to estimate using these metrics. While other STIRPAT analyses have examined, and broadly confirmed the relationship between the dependency ratio, age structure, and carbon dioxide emissions, this research is to the best of the author's knowledge the first attempt to model relative cohort size as a determinant of GHG.

In order to estimate the effects of age structure on CO_2 emissions in US counties, I use an econometric model of the following form:

$$\ln C_i = a + b_1(\ln P_i) + b_2(\ln A_i) + b_3(\ln A_i)^2 + b_4(\ln S_i) + e_i \tag{2}$$

Where C_i is the total CO_2 emissions in county i; P_i is the total county population, A_t is the median county household income, and S_t is the metric of age structure. Finally, a and e_i are an intercept and an error term, respectively. The sample used in this research is the 3107 counties of all US states and Washington, D.C. excluding Alaska and Hawaii; the latter are removed due to uncertainty in estimating spatial models with non-continuous data. Data are for 2002 and represent all counties for which data are consistent and available during the study year. Descriptions for each variable and the hypothesized sign are in Table 1.

Equation (2) is recognizable as a Kuznets-modified STIRPAT model, with population, affluence, and a squared affluence term estimated as drivers of CO_2 emissions. The model I specify here is a cross-sectional model. Shi (Shi 2003) and Cole and Neumayer (Cole and Neumayer 2004) favor using panel data over cross-sectional data, as both temporal and spatial effects can be modeled. This is particularly important in light of specific structural and development effects between countries that cannot be modeled consistently with static, single-year data. Trade, for example, is a well-known factor in biasing national-level carbon emissions profiles, since many countries import a significant quantity of goods manufactured in other places; several scholars have attempted to model these effects in STIRPAT models (Jorgenson and Rice 2005; Ehrlich and Holdren 1971; Stretesky and Lynch 2009; Bin and Harriss 2006). While I prefer to model the problems using panel econometric procedures in order to avoid problems from unobserved heterogeneity, data for county-level CO_2 emissions are only available for the year 2002. County CO_2 data are from the Vulcan Project (Gurney et al. 2009) and are given by the natural log of total county CO_2 emissions, in tonnes.

Econometric estimates of the environmental Kuznets model and STIRPAT modeling efforts have many commonalities in their functional form. One prior criticism of Kuznets models is the tendency to model population on the left-hand side of the equation, rather than as a variable to be tested (Cole and Neumayer 2004). Though prior research broadly confirms a unit-elastic relationship between population and carbon emissions (York, Rosa, and Dietz 2003c; Rosa, York, and Dietz 2004; Scholz 2006), the strength of this relationship at small analytical units is largely unconfirmed. In this research, I use the natural log of the total county population, the natural log of median household income, and a quadratic income term to test the basic, first-order demographic and economic drivers of CO_2 emissions. Using logged data allows the population term to be interpreted as an elasticity, where coefficients represent percent change. A coefficient near unity indicates a proportional (unit-to-unit) change between population and carbon emissions. The expected sign of population is positive and near unity.

I estimate median household income using a linear and quadratic term. Including a quadratic term tests for the statistical presence of an inverted **U**-shaped relationship between affluence and environmental impact. This curvilinear relationship is the basis for the environmental Kuznets hypothesis. In this model, the affluence terms are centered before squaring in order to mitigate problems arising from collinearity between the two terms. Per the STIRPAT framework, the expected sign of household income is positive for the linear term; a significant and negative quadratic term (in concert with a positive linear term) indicates the presence of an EKC.

Environmental Kuznets modeling has sustained a substantial amount of criticism, both from a methodological (Perman and Stern 2003; Auci and Becchetti 2006; Müller-Füstenberger and Wagner 2007; Romero-Ávila 2006), and a theoretical standpoint (Stern 2004). Furthermore, this empirical technique is generally used to understand economic-environment relationships borne out of long-run development trajectories and structural change. Finding statistical evidence in a local-level, cross-sectional dataset does not necessarily constitute substantive evidence in favor of a curve; a number of other unobserved effects may be at work in driving this model estimate. I include these terms in this model, however, because it has become standard practice to do so in STIRPAT. Income data estimates are obtained from the Census' Small Areas Income and Poverty Estimates program (Census 2002).

The major contribution of this research is the estimation of age structure effects on carbon emissions in US counties. In this research, I test five measures of age structure and composition on CO_2 emissions. Previous work focuses on the 'economically active' or non-dependent population—those aged 15 to 64. In these estimates, I model the prevalence of the economically active population as a ratio of population under age 15 (the 'youth' cohort) and the population aged 65 and over (the 'elderly' population) to the population aged 15 to 64 (defined as the ‘working age’ or non-dependent population). This is the total dependency ratio (TDR). Demographic explanations of the population-degradation relationship argue that the greater the proportion of the non-dependent population, the greater the productivity per capita and therefore GHG emissions. There are several reasons why we should expect this, but the principal factor driving this relationship is that dependent populations require capital that would otherwise be invested elsewhere. A negative coefficient for the total dependency ratio (TDR) confirms a hypothesis of declining carbon dioxide emission with increasing numbers of dependents.

In this investigation I disaggregate the relationship further by estimating the elderly and youth cohort ratios separately. These are termed the elderly dependency ratio (EDR) and youth dependency ratio (YDR), respectively. Parsing these two dependent cohorts into different variables allows for differing consumption patterns between the two age groups to be estimated. Although theories of age-structure argue that the size of the economically active labor force is the primary driving factor behind emissions, the relationship they bear to their dependents differs considerably depending on the age of the dependent. Places with a high elderly dependency ratio, for example, have many costs associated with caring for the aged and ensuring security during retirement. These costs are theorized to negatively impact the investment rate, and therefore put downward pressure on economic production. As in the TDR the expected sign of the EDR is negative.

The expected sign of the youth dependency ratio is potentially more complex. In theory, the same arguments regarding investment and production apply; greater numbers of dependents for each worker diverts greater resources from reinvestment and production. Additionally, higher fertility can have potentially negative consequences on productivity, as labor required to rear children displaces labor time in the workplace. Although prior work has treated this as another form of the dependency ratio, where the expected sign in places with high fertility is negative, I argue that the relationship is more complex; in many places additional children necessitate more labor and more work in order to financially support larger households. While this reasoning is not the inverse of the traditional DR hypothesis discussed above, it does complicate the argument and expected between the YDR and CO_2. The expected sign of the YDR is either positive or negative.

In contrast to the dependency ratio measures, I use relative cohort size (RCS) as an alternative metric of age structure and as a way to estimate the effects that different demographic "mixes" bring to the economy and environment. The intention of this metric in demographic research is to understand how non-constant variance in the size of age cohorts impacts various societal phenomena. Since different age groups produce and consume things at different rates during the lifecycle, the distribution of the population throughout these age cohorts is potentially of consequence. For the RCS measures oriented towards "economic" relationships, the working-age population is balanced between an older and younger cohort (thought to have qualitatively different relationships with production). Pampel and Peters (Pampel and Peters 1995) takes this ratio as ($_{30}Age_{64}$ / $_{15}Age_{29}$), while Brunello (Brunello 2010) uses a more balanced metric, given by: ($_{35}Age_{50}$ / $_{20}Age_{34}$).

In this research, I employ both the Pampel and Brunello RCS. A positive coefficient indicates a county labor force weighted towards older populations is producing higher levels of CO_2 emissions, while a negative coefficient indicates that labor forces weighted towards younger populations are associated with higher carbon emissions. The former represents a hypothesis of a mature workforce, where older, more experienced workers are more capitalized, and presumed to have greater levels of productivity. In the case of the latter, younger populations are assumed to have greater productivity borne out of a disadvantageous position in the labor market and the subsequent need to minimize this risk factor. Thus greater productivity is a byproduct of flexibility in location, time devoted to labor outside the home, and (marginally) fewer family constraints.

Out of concern for potential bias resulting from heteroskedasticity and spatial dependency in the error term, I use a three-fold modeling procedure to estimate Equation 2. First, I use a robust ordinary least squares procedure with White's heteroskedasticity-consistent standard errors (White 1978). Heteroskedasticity in the error term violates assumptions of the OLS regression model, and failing to correct for this may result in biased standard error estimates. White's covariance adjustment procedure has been shown to produce standard error estimates consistent under heteroskedasticity. Second, I estimate each model using spatial-econometric procedures. Failing to account for dependency in the dependent variable or error term can lead to biased estimates of coefficients or standard errors, respectively (Anselin 1988, 1995). Finally, I employ a state-level fixed-effects model in order to control for unobserved state-to-state differences. Although well-known state-to-state differences in the independent variables creates the risk for over-determination in a cross-sectional model, this procedure is a common method of controlling for unobserved differences at a common regulatory scale. I estimate the fixed-effects models using both a spatial-error procedure and a generalized least squares procedure in order to test whether the model is robust controlling for both spatial dependency and heteroskedasticity.

RESULTS AND DISCUSSION

Estimates for the dependency ratio models are presented in Tables 2 through 4. Broadly, each of these regressions performed similarly, explaining between sixty-nine and seventy-two percent of the variance. F-tests for ordinary least squares estimates are significant, and variance inflation factors (VIFs) and the multicollinearity index for each OLS and spatial error model show that collinearity is within generally accepted limits. Collinearity in the fixed-effects specifications is high; this is a common consequence of including spatial fixed effects terms, as the vector of terms for states serves as a surrogate metric for geographic differences in population and income. Spatial dependency in the error terms is significant in each of the models, and each of the fixed-effects models illustrate a high degree of heteroskedasticity.

Total county population and median household income are positive and significant determinants of CO_2 emissions. Population exhibits a near unit-elastic relationship with the dependent variable, with coefficients ranging from 0.847 to 0.897. These values are consistent with other STIRPAT estimates, which have confirmed a hypothesized unitary relationship with CO_2 emissions. At the same time, income and the quadratic of income are significant and consistent with the curvilinear relationship of Kuznets. For all dependency ratio specifications and procedures, the linear term is positive and significant and the quadratic term is negative and significant. Middle income counties in the US, then, are associated with the highest total CO_2 emissions.

The three dependency ratio measures illustrate a more complex relationship with CO_2 emissions (Table 2). Prior work has illustrated that the size of the working age population—assessed in numerically different ways—has a positive impact on carbon dioxide emissions (York, Rosa, and Dietz 2005; Liddle and Lung 2010; Cole and Neumayer 2004). These estimates paint a different picture. The total dependency ratio in 2002—estimated here as the ratio of those aged 0-15 and 65+ to the ratio of those aged 15-64—is a positive determinant of CO_2. Counties with higher proportions of non-working age people are correlated with higher carbon dioxide emissions, and a 10% change in the TDR is correlated with ~2-3% change in carbon emissions.

The estimates for the elderly dependency ratio (EDR) and youth dependency ratio (YDR) explore this relationship further (Table 3 and 4). Theories regarding age structure and environmental impact specify declining consumption with age, with working-age populations driving consumption and, therefore, CO_2 emissions. Using only the TDR to estimate this relationship is problematic, as populations under the age of 15 drive consumption indirectly. Disaggregating the TDR into two measures of EDR and YDR is an alternative for estimating whether different cohorts outside of the working-age population have differential effects on carbon dioxide emissions. According to demographic theories regarding age structure and environmental impact, the size of the elderly population should be negatively correlated with CO_2 emissions, while the size of the youth population is either positive or negative.

Regression procedures that substitute EDR and YDR are shown in Tables 3 and 4. None of the four specifications for the elderly dependency ratio are significant, while the YDR is significant and positive for each procedure. Coefficients range from *b* = 0.346-0.362 in the fixed-effects models to *b* = 0.504 in the robust OLS procedure. A ten percent change increase in the ratio of youth to economically active adults results in a ~3-5% increase in CO_2 emissions. The population and income terms are significant across all procedures and are not substantially different than those in Table 2.

There are several possible interpretations for these theoretically inconsistent estimates, but none suggest or support an aging hypothesis of decreased environmental impact. Put colloquially, these models find no correlation between the balance of the dependent population and the non-dependent population with carbon dioxide emissions. At the same time, the positive values for the youth dependency ratios can be viewed from a consumption perspective, where counties with greater fertility have greater total carbon emissions. Households with greater numbers of children require more resources than those with few or no children, resulting in higher levels of impact. While these results do not accord to prior age-structure work using CO_2 as an outcome variable (O'Neill et al. 2010; O'Neill, MacKellar, and Lutz 2001), local-level demographic processes and the consequent emissions levels do not necessarily share the same relationship as posited by macro-level studies of emissions and environmental impact. Macro-level relationships between age-structure, productivity, investment, and environmental impact do not account for the spatial circulation of capital that is particularly consequential at smaller scales of analysis. These regression estimates illustrate that a lacuna exists between the age-specific productivity and age-specific consumption, the latter of which would be 'spread' more thinly (or evenly) throughout the population. This difference in production and consumption patterns is thus apparent at smaller spatial units when carbon dioxide is the metric of environmental impact.

As a way of further understanding the role of demographic change and total CO_2 emissions, I substitute dependency ratio metrics with two ratio measures of relative cohort size. These measures are coded RCSP for Pampel's metric (given by: ${}_{30}Age_{64}/{}_{15}Age_{29}$) and RCSB for the ratio used by Brunello (given by: ${}_{35}Age_{50}/{}_{20}Age_{34}$). Pampel and Brunello specify these ratios differently, but both are intended to capture the balance of two qualitatively different components in the labor force. I have included both metrics as a measure of redundancy and test of consistency.

Tables 5 and 6 show the results for the RCS regressions. RCS-Pampel is significant and positive in all procedures excepting the robust least squares. The coefficients range from 0.150 to 0.213, which can be interpreted as a ~1.5-2.0% increase in CO_2 emissions for every 10% increase in the ratio of older workers to younger. Similarly, RCS-Brunello is significant and positive, ranging from 0.240 to 0.334. For both measures of RCS, counties with larger older cohorts have higher CO_2 emissions. Population retained unit-elasticity, and income terms remain significant according to the Kuznets hypothesis.

Though each of the relative cohort size estimates illustrated positive coefficients and a significant relationship between the size of the older labor force and CO_2 emissions, the coefficients for the Brunello estimates are much larger. The numerically sharper lens of the Brunello RCS—when compared with Pampel's numerator—suggests that the age cohorts with the greatest capacity for emissions are in the early-middle ages. These age cohorts also represent the portion of the population with the greatest capacity to consume, as well as those with the greatest number of dependents.

SUMMARY

A synthesis of these model estimates portends a complex demographic-environmental scenario that warrants further analysis. In general, places in 2002 that had greater numbers of people over the age of 30 to 35 had higher carbon emissions during that year. Additionally, counties that had proportionately large under 15 populations also had higher CO_2 emissions, even when controlling for population, income, and other spatial effects. That these are associated in the same way with respect to CO_2 may reflect that with increasing age the probability of having children increases, and that children and middle-age adults have greater levels of consumption than people in early adulthood and in the beginning stages of entering the workforce. Prior demographic work contravenes this interpretation, where younger, childless adults have higher levels of productivity, but the interpretation I am advancing here is more germane to a consumption-side argument, rather than the production-side arguments of prior dependency ratio models. These estimates, then, are not analogous to O'Neill et al.'s theories regarding investment and savings levels as correlates of age and productivity (O'Neill, MacKellar, and Lutz 2001). Rather, the age-structure correlations are stronger among the cohorts that have a greater propensity to consume, not produce. While this research does not take issue with the theoretical arguments used by scholars estimating macro-level models, it does suggest that estimating human-environment relationships at the local level requires a different conception of demographic-economic relationships and the way they relate to environmental change.

REFERENCES

Anselin, L. 1988. A Test for Spatial Autocorrelation in Seemingly Unrelated Regressions. *Economics Letters* 28:335-341.

———. 1995. Local Indicators of Spatial Association-LISA. *Geographical Analysis* 27 (2):93-115.

Anselin, L., and D. A. Griffith. 1988. Do Spatial Effects Really Matter in Regression Analysis? *Papers of the Regional Science Association* 65:11-34.

Auci, S., and L. Becchetti. 2006. The instability of the adjusted and the unadjusted environmental Kuznets curves. *Ecological Economics* 60:282-298.

Bin, S., and R. C. Harriss. 2006. The role of CO_2 embodiment in US-China trade. *Energy Policy* 34:4063-4068.

Bloom, D. E., and R. B. Freeman. 1988. Economic Development and Components of Population Growth. *Journal of Policy Modeling* 10 (1):57-81.

Brunello, G. 2010. The effects of cohort size on European earnings. *Journal of Population Economics* 23 (1):273-290.

Census, U. S. 2002. State and County Estimates for 2002, Small Area Income and Poverty Estimates, http://www.census.gov/did/www/saipe/data/statecounty/data/2002.html, last accessed: 8/30/2011.

Cole, M. A., and E. Neumayer. 2004. Examining the Impact of Demographic Factors on Air Pollution. *Population and Environment* 26 (1):5-21.

Commoner, B. 1972. The Environmental Cost of Economic Growth. In *Population, Resources and the Environment*, 339-363. Washington, DC: Government Printing Office.

DeHart, J. L., and P. T. Soulé. 2000. Does I=PAT Work in Local Places? *Professional Geographer* 52 (1):1-10.

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

Ehrlich, P. R., and J. P. Holdren. 1971. Impact of Population Growth. *Science* 171 (3977):1212-1217.

Fan, Y., L. Lan-Cui, G. Wu, and W. Yi-Ming. 2006. Analyzing impact factors of CO_2 emissions using the STIRPAT model. *Environmental Impact Assessment Review* 26:377-395.

Gurney, K. R., D. L. Mendoza, Y. Zhou, M. L. Fischer, C. Miller, C., S. Geethakumar, and S. de La Rue du Can. 2009. High Resolution Fossil Fuel Combustion CO_2 Emission Fluxes for the United States. *Environmental Science and Technology* 43 (14):5535–5541.

Jorgenson, A. K., and B. Clark. 2010. Assessing the temporal stability of the population/environment relationship in comparative perspective: a cross-national panel study of carbon dioxide emissions, 1960-2005. *Population and Environment* 32:27-41.

Jorgenson, A. K., and J. Rice. 2005. Structural Dynamics of International Trade and Material Consumption: A Cross-National Study of the Ecological Footprints of Less-Developed Countries. *Journal of World Systems Research* 11:56-77.

Lankao, P. R., J. L. Tribbia, and D. Nychka. 2009. Testing Theories to Explore the Drivers of Cities' Atmospheric Emissions. *AMBIO: A Journal of the Human Environment* 38 (4):236.

Liddle, B. 2000. Population Growth, Age Structure, and Environmental Impact. *Population and Environment* 21 (4):385-411.

———. 2004. Demographic Dynamics and Per Capita Environmental Impact: Using Panel Regressions and Household Decomposition to Examine Population and Transport. *Population and Environment* 24 (1):23-39.

Liddle, B., and S. Lung. 2010. Age-structure, urbanization, and climate change in developed countries: revisiting STIRPAT for disaggregated population and consumption-related environmental impacts. *Population and Environment* 31:317-343.

Macunovich, D. J. 1999. The fortunes of one's birth: Relative cohort size and the youth labor market in the United States. *Journal of Population Economics* 12 (2):215-272.

Martínez-Zarzoso, I., and A. Maruotti. 2011. The impact of urbanization on CO_2 emissions: Evidence from developing countries. *Ecological Economics* 70:1344-1353.

Massey, D. S., W. G. Axinn, and D. J. Ghimire. 2010. Environmental change in out-migration: evidence from Nepal. *Population and Environment* 32:109-136.

McNiccoll, G. 2006. Policy Lessons of the East Asian Demographic Transition. *Population and Development Review* 32 (1):1-25.

Müller-Füstenberger, G., and M. Wagner. 2007. Exploring the environmental Kuznets hypothesis: Theorertical and economic problems. *Ecological Economics* 62:648-660.

O'Neill, B. C., M. Dalton, R. Fuchs, L. Jiang, S. Pachauri, and K. Zigova. 2010. Global demographic trends and future carbon emissions. *Proceedings of the National Academy of Sciences* 107 (41):17521-17526.

O'Neill, B. C., F. L. MacKellar, and W. Lutz. 2001. *Population and Climate Change*. Cambridge: Cambridge University Press.

Pampel, F. C. 1993. Relative Cohort Size and Fertility: The Socio-Political Context of the Easterlin Effect. *American Sociological Review* 58 (4):496-514.

Pampel, F. C., and H. E. Peters. 1995. The Easterlin Effect. *Annual Review of Sociology* 21:163-194.

Paudel, K. P., and M. J. Schaefer. 2009. The Environmental Kuznets Curve Under a New Framework: The Role of Social Capital in Water Pollution. *Environmental and Resource Economics* 42:265-278.

Perman, R., and D. I. Stern. 2003. Evidence from panel unit root and cointegration tests that the Environmental Kuznets Curve does not exist. *Australian Journal of Agricultural and Resource Economics* 47 (3):325-347.

Romero-Ávila, D. 2006. Questioning the empirical basis of the environmental Kuznets curve for CO_2: New evidence from a panel stationarity test robust to multiple breaks and cross-dependence. *Ecological Economics* 64:559-574.

Rosa, E. A., R. York, and T. Dietz. 2004. Tracking the Anthropogenic Drivers of Ecological Impacts. *AMBIO: A Journal of the Human Environment* 33 (8):509.

Schapiro, M. O. 1988. Socio-economic effects of relative income and relative cohort size. *Social Science Research* 17 (4):362-383.

Scholz, S. 2006. The POETICS of industrial carbon dioxide emissions in Japan: an urban and institutional extension of the IPAT identity. *Carbon Balance and Management* 1 (11).

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

Soulé, P. T., and J. L. DeHart. 1998. Assessing IPAT Using Production- and Consumption-based Measures of I. *Social Science Quarterly* 79 (4):754-765.

Stern, D. I. 2004. The Rise and Fall of the Environmental Kuznets Curve. *World Development* 22 (8):1419-1439.

Stretesky, P. B., and M. J. Lynch. 2009. A cross-national study of the association between per capita carbon dioxide emissions and exports to the United States. *Social Science Research* 38:239-250.

White, H. 1978. A heteroscedasticity consistent covariance matrix and a direct test for heteroscedasticity. *Econometrica*:817-838.

York, R., E. A. Rosa, and T. Dietz. 2003a. Footprints on the Earth: The Environmental Consequences of Modernity. *American Sociological Review* 68 (2):279-300.

———. 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.

———. 2003c. STIRPAT, IPAT, and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. *Ecological Economics* 46:351-365.

———. 2005. The Ecological Footprint Intensity of National Economies. *Journal of Industrial Ecology* 8 (4):139-154.

Zagheni, E. 2011. The Leverage of Demographic Dynamics on Carbon Dioxide Emissions: Does Age Structure Matter? *Demography* 48:371-399.

Table 1) Definition of variables used and expected sign

Variable	Description	Expected sign
Population	Natural log of the total county population, 2002	+
Median Household Income	Natural log of the median household income, 2002, centered on the mean	+
Quadratic of Median Household Income	Squared natural log of the median household income, 2002, centered before squaring	-
Total Dependency Ratio	Natural log of the dependency ratio, given by: (Pop 0-15 + Pop 65+ / Pop 16-64)	-
Elderly Dependency Ratio	Natural log of the dependency ratio, given by: (Pop 65+ / Pop 16-64)	-
Youth Dependency Ratio	Natural log of the dependency ratio, given by: (Pop 0-15 / Pop 16-64)	+/-
Relative Cohort Size (Pampel)	Natural log given by: (Pop 30-64 / Pop15-29)	+
Relative Cohort Size (Brunello)	Natural log given by: (Pop 35-50 / Pop 20-34)	+

2) Total Dependency Ratio Regressions

	Pooled				Fixed effects			
	1		2		3		4	
	OLS		Spatial Error		Spatial Error		GLS	
Population	0.861	***	0.875	***	0.874	***	0.868	***
t-score	62.592		61.412		58.125		58.704	
Income	0.528	***	0.563	***	0.659	***	0.656	***
	6.580		6.430		7.096		7.354	
$Income^2$	-1.085	***	-1.020	***	-1.153	***	-1.214	***
	-7.150		-5.728		-6.617		-7.210	
TDR	0.171		0.246	*	0.167		0.114	
	1.660		2.174		1.430		0.979	
Intercept	3.209	***	3.101	***	4.097	***	4.147	***
	25.398		21.297		17.118		18.625	
Lambda			0.299	***	0.164	***		
			11.586		5.871			
R-squared	0.690		0.708		0.720			
F	1732.000							
	(0.000)							
Log likelihood			-3830.530		-3745.930		-3826.128	
AIC	7799.639		7671.060		7597.860		7760.257	
B-P	25.023		66.113		453.232			
	(0.000)		(0.000)		(0.000)			
Cond. Index			21.755		38.098			
VIF Avg.	1.313							
VIF Max.	1.477							

n=3107. All data are natural logs. Income terms are centered (before squaring, in the case of the quadratic term to avoid multicollinearity problems. White's robust standard errors are used in the OLS estimates.

3) Elderly Dependency Ratio Regressions

	Pooled				Fixed effects			
	1		2		3		4	
	OLS		Spatial Error		Spatial Error		GLS	
Population	0.848	***	0.866	***	0.869	***	0.862	***
t-score	60.514		59.363		55.881		56.348	
Income	0.493	***	0.532	***	0.632	***	0.622	***
	6.141		6.068		6.734		6.888	
$Income^2$	-1.183	***	-1.051	***	-1.160	***	-1.244	***
	-7.424		-5.742		-6.503		-7.197	
EDR	-0.093		-0.011		-0.001		-0.040	
	-1.598		-0.180		-0.014		-0.654	
Intercept	3.111	***	3.031	***	4.028	***	4.067	***
	24.791		20.570		16.853		18.275	
Lambda			0.296	***	0.161	***		
			11.435		5.747			
R-squared	0.690		0.707		0.720			
F	1732.000							
	(0.000)							
Log likelihood			-3832.871		-3746.946		-3827.030	
AIC	7799.405		7675.740		7599.890		7762.06	
B-P	41.767		124.784		490.004			
	(0.000)		(0.000)		(0.000)			
Cond. Index			21.812		38.078			
VIF Avg.	1.394							
VIF Max.	1.522							

n=3107. All data are natural logs. Income terms are centered (before squaring, in the case of the quadratic term to avoid multicollinearity problems. White's robust standard errors are used in the OLS estimates.

4) Youth Dependency Ratio Regressions

	Pooled				Fixed effects			
	1		2		3		4	
	OLS		Spatial Error		Spatial Error		GLS	
Population	0.855	***	0.865	***	0.865	***	0.861	***
t-score	69.332		63.404		58.704		59.264	
Income	0.528	***	0.549	***	0.639	***	0.644	***
	6.503		6.380		7.047		7.405	
$Income^2$	-1.225	***	-1.147	***	-1.248	***	-1.311	***
	-8.300		-6.424		-7.098		-7.699	
YDR	0.507	***	0.442	***	0.346	***	0.362	***
	5.067		4.169		3.143		0.109	
Intercept	3.768	***	3.579	***	4.498	***	4.591	***
	22.258		18.709		16.265		17.490	
Lambda			0.288	***	0.157			
			11.053		5.619			
R-squared	0.693		0.709		0.721			
F	1751.000							
	(0.000)							
Log likelihood			-3824.285		-3742.023		-3821.153	
AIC	7776.196		7658.570		7590.050		7750.306	
B-P	23.815		71.101		471.092			
	(0.000)		(0.000)		(0.000)			
Cond. Index			25.563		43.028			
VIF Avg.	1.242							
VIF Max.	1.415							

n=3107. All data are natural logs. Income terms are centered (before squaring, in the case of the quadratic term to avoid multicollinearity problems. White's robust standard errors are used in the OLS estimates.

5) Rel Cohort Size (Pampel) Regressions

	Pooled				Fixed effects			
	1		2		3		4	
	OLS		Spatial Error		Spatial Error		GLS	
Population	0.857	***	0.881	***	0.892	***	0.884	***
t-score	63.772		57.901		54.009		54.656	
Income	0.503	***	0.475	***	0.545	***	0.568	***
	5.855		5.195		5.706		6.228	
$Income^2$	-1.110	***	-1.056	***	-1.179	***	-1.237	***
	-7.367		-5.926		-6.766		-7.351	
RCSP	0.027		0.150	*	0.213	*	0.179	*
	0.434		2.158		3.023		2.531	
Intercept	3.124	***	2.758	***	3.626	***	3.771	***
	18.272		14.404		13.462		14.928	
Lambda			0.305	***	0.168	***		
			11.828		6.016			
R-squared	0.690		0.708		0.721			
F	1730.000							
	(0.000)							
Log likelihood			-3830.606		-3742.410		-3823.907	
AIC	7802.048		7671.210		7590.820		7755.813	
B-P	17.527		52.293		460.253			
	(0.002)		(0.000)		(0.000)			
Cond. Index			26.391		42.128			
VIF Avg.	1.360							
VIF Max.	1.593							

n=3107. All data are natural logs. Income terms are centered (before squaring, in the case of the quadratic term to avoid multicollinearity problems. White's robust standard errors are used in the OLS estimates.

6) Rel Cohort Size (Brunello) Regressions

	Pooled				Fixed effects			
	1		2		3		4	
	OLS		Spatial Error		Spatial Error		GLS	
Population	0.883	***	0.905	***	0.912	***	0.904	***
t-score	61.251		55.070		52.415		52.982	
Income	0.407	***	0.394	***	0.494	***	0.514	***
	4.681		4.239		5.153		5.612	
$Income^2$	-1.121	***	-1.068	***	-1.203	***	-1.260	***
	-7.474		-6.006		-6.913		-7.497	
RCSB	0.240	***	0.307	***	0.334	***	0.315	***
	3.743		4.208		4.504		4.241	
Intercept	2.822	***	2.572	***	3.529	***	3.638	***
	17.572		14.303		13.638		15.022	
Lambda			0.304	***	0.166	***		
			11.785		5.944			
R-squared	0.691		0.709		0.722			
F	1739.000							
	(0.000)							
Log likelihood			-3824.092		-3736.851		-3818.080	
AIC	7790.654		7658.180		7579.700		7744.178	
B-P	17.785		61.069		446.597			
	(0.001)		(0.000)		(0.000)			
Cond. Index			25.276		39.414			
VIF Avg.	1.537							
VIF Max.	1.951							

n=3107. All data are natural logs. Income terms are centered (before squaring, in the case of the quadratic term to avoid multicollinearity problems. White's robust standard errors are used in the OLS estimates.