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Growing Up and Cleaning Up: The Environmental Kuznets Curve Redux

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Abstract

Borrowing from the Kuznets curve literature, researchers have coined the term “environmental Kuznets curve” or EKC to characterize the relationship between pollution levels and income: pollution levels will increase with income but some threshold of income will eventually be reached, beyond which pollution levels will decrease. The link between the original Kuznets curve, which posited a similar relationship between income and inequality, and its pollution-concerned offspring lies primarily with the shape of both curves (an upside-down U) and the central role played by income change. Although the EKC literature has burgeoned over the past several years, few concrete conclusions have been drawn, the main themes of the literature have remained constant, and no consensus has been reached regarding the existence of an environmental Kuznets curve. EKC research has used a variety of types of data and a range of geographical units to examine the effects of income levels on pollution. Changes in pollution levels might also be at least partly explained by countries’ position in the demographic transition and their general population structure, however little research has included this important aspect in the analysis. In addition, few analyses confine themselves to an evaluation for one country of the long-term relationship between income and pollution. Using United States CO₂ emissions as well as demographic, employment, trade and energy price data, this paper seeks to highlight the potential impact of population and economic structure in explaining the relationship between income and pollution levels.

Keywords

environmental Kuznets curve; demographic structure; CO₂ emissions

1. Introduction

The question whether environmental quality will improve or decline as countries develop continues to play a prominent role in environmental research and policy. In the 1970s and

80s the debate centered on the limits to growth (Meadows et al. 1972) and the roles that technology and population may play in overcoming those limits (Simon and Kahn 1984). First, emphasis was placed on the adequacy of natural resources to sustain economic growth and development. Then, as scientific evidence about eutrophication, acid rain, stratospheric ozone depletion and global warming increased, focus shifted towards the limits to environmental waste absorption. Much of the early debate was played out with the use of large-scale systems dynamics models (Barney 1991), carefully selected empirical evidence (e.g. Barnett 1979 and Smith 1979), or narrowly-conceived theoretical investigations (e.g. Solow 1974). The 1990s and 2000s have seen a revival of the debate – this time driven by empirical investigations into relationships first between pollution and development and later between environmental degradation, more broadly defined, and development.

Borrowing from the Kuznets curve literature (Kuznets 1955, 1998), which posits that the relationship between income and inequality follows an inverted U, researchers coined the term “environmental Kuznets curve” or EKC to characterize the relationship between pollution levels and income: pollution levels will increase with income but some threshold of income will eventually be reached, beyond which pollution levels will decrease (Grossman and Krueger 1994, Grossman 1995). The underlying logic behind the EKC presumed environmental quality to be a normal good, demand for which increases as income increases. Economies of scale, resource-saving technological change in the extractive and manufacturing sectors, trade liberalization leading to “out-migration” of dirty processes, and development of regulatory mechanisms and institutions to stimulate environmental protection, are all seen to contribute to a country’s improved environmental quality as economic development takes place (Panayotou 1993, Ausubel 1996, Komen et al. 1997, Suri and Chapman 1998, Andreoni and Levinson 2001).

The policy implications of the EKC have aptly been described as “grow first, then clean up” (Beckerman 1992, Dasgupta et al. 2002), a conclusion in stark contrast to the observation that economic growth itself is at the root of environmental harm (Hueting 1991). The ensuing debate attracted more detailed empirical analysis as well as theoretical research in the hopes of either substantiating or refuting the postulated relationships between environmental quality and development. Academic and policy discourse over the validity of the EKC logic and the methods used to uphold it has generated a rich literature on the topic, too extensive to thoroughly review here. Several key themes, though, have emerged that cast doubt on past analyses.

First, the simple cross-sectional empirical work, on which much of the early EKC literature rested, has been dismissed by some for doing injustice to the unique development paths of individual countries or regions of a country (Stern 1998, List and Gallet 1999, Unruh and Moomaw 1998). For example, while one group of countries or regions may undergo increases in pollution with increased development, others may exhibit the reverse behavior (Figure 1). Grouping them together in a cross-sectional analysis will consequently lead to an inverted-U pattern that does not adequately describe the behavior of *any* of the countries.

To ameliorate the shortcomings of simple cross-sectional analysis, panel data have been used to estimate EKC regression models of the forms such as

$$\ln\left(\frac{E}{P}\right)_{it} = \alpha_i + \beta_i + \gamma_1 \ln\left(\frac{G}{P}\right)_{it} + \gamma_2 \ln\left(\frac{G}{P}\right)_{it}^2 + \varepsilon_{it}$$

where E are annual emissions, P is population, G is income or GDP, and the first two terms on the right hand side of the equation are intercepts which vary across countries i and years t . The parameters γ capture influences of per capita GDP (G/P) and its squared values, α_i captures variation across all spatial units that does not change over time and β_i accounts for explanatory information that is time-varying but affects all spatial units. The error term of the equation is ε_{it} and, in a fixed effects model, the errors are assumed to be uncorrelated over time for each spatial unit. If α , β and the explanatory variables are correlated, then a model that treats α and β as components of the random disturbance ε (i.e. a random effects model) cannot be estimated consistently. Several studies have found this to be the case (see Stern 2004 for a review, and Dijkgraaf and Vollebergh 2005) and proceeded to estimate α and β as fixed effects regression parameters. Because the estimated parameters are conditional upon the country and time effects in the selected sample of data, however, they cannot be generalized to other samples of data (Hsiao 1986), limiting the insights that can be generated from industrialized countries' behaviors for future emissions paths of developing countries.

Second, per capita GDP and per capita emissions (as well as their logarithmic transformations) are typically considered to be unit root non-stationary processes (Bradford et al. 2005) and methods for (nonstationary) panel data are usually used. However, as Wagner (2008) points out, the strong independence assumption required for the application of first generation methods for cross-sectionally independent panels may not hold, and regressors involving nonlinear transformations of unit root process behave differently from the linear unit root cases usually considered because the stochastic behavior is fundamentally changed by such transformations. Thus, despite considering potential unit root behavior, several papers (e.g. Perman and Stern 2003) fail to acknowledge implications of nonlinear transformations. Developing and deploying adequate methods for nonlinear transformations of integrated regressors in non-stationary panels remains an area of active research (e.g. Breitung 2000, 2005), whose findings may further challenge past EKC analyses.

A third important point lies in the distinction between local and transnational air pollutants. Presumably, developing countries are concerned more with immediate environmental quality related to urban air or drinking water rather than with global environmental quality related to stratospheric ozone depletion or the greenhouse effect. Wealthy consumers in industrialized nations, in contrast, may be more able to distance themselves from the environmental repercussions of their material and energy consumption and may show heightened concern about global environmental impacts. As industrialized countries push off dirtier processes to the developing world, environmental performance, as measured by emissions or concentrations of local pollution, may improve in these countries. The EKC would then suggest that the developing world could do so too in due course. The extent of such advancements will depend, in part, on the diffusion of cleaner technology to

developing countries, which, in turn, may be driven by international environmental standards and on efforts by multi-national companies to raise standards in the countries in which they invest. Empirical evidence, however, seems to suggest the opposite – “transnationally controlled manufacturing within less-developed countries is relatively less ecoefficient and also contributes to the overall scale of environmental degradation” (Jorgenson 2009, p. 71).

The choice of a particular environmental quality indicator or type of pollution – emissions or local concentrations, regional or trans-boundary pollutants – that is used in empirical analysis will determine whether an inverted U can be found and how it is shaped, and thus limit the generalizability of empirical findings across countries and time (Barbier 1977, Kaufmann et al. 1998). Even if an inverted U exists for some kinds of pollution, such as the usual culprits SO₂, NO_x and CO₂, changes in technology and changes in demand for products may result in the rise of other pollutants (e.g. metals, dioxins), suggesting that, still, economic growth may not be compatible with long-term environmental improvement (e.g. Dasgupta et al. 2002, Perman and Stern 2003).

Additional critiques have centered on differences in the quality of data used in cross sectional studies (Dasgupta et al. 2002), the high degree of sensitivity of statistical results to variable choice and model specification (Harbaugh et al. 2002), the ability to reach zero or negative pollution when the inverted-U is extended despite the fact that zero or negative pollution are physically impossible, and a neglect of potential re-bound effects, leading in the long-run to an N-shaped pollution-development relationship (Borghesi 1999). Rather than dwell on these challenges of the EKC that have been well identified in the literature, we turn here to two interrelated issues that, to date, have received little attention, yet may affect a country's environmental performance through time: its demographic structure and its level of development – as contrasted by the size of its population (total population) and the size of its economy (GDP), as typically considered in the EKC literature. Moreover, we seek to provide a baseline understanding of the U.S. emissions/development relationship over the long term. Ideally, a wide range of data would be available for an extended time period; however, this is not the case. Only in the second half of the 20th century was information systematically collected on an annual basis and reported in ways that help us to explore some of the quantitative relationships between emissions and socioeconomic characteristics of the United States. In an effort to balance length of study period with data availability, we first examine the evidence for an EKC for the long term, 1800 to 2000, using the traditional or basic EKC model with only per capita GDP as an explanatory variable. We then incorporate demographic structure into the basic model, for the period 1900–2000, as age-specific annual demographic data are available for that entire period. Finally, we estimate EKC models with a full set of explanatory variables for the post-WWII era in the U.S., 1950 to 2000, a period for which the widest range of data is readily available.

The following section of this paper briefly reviews empirical evidence from the literature on the relationship between demographic changes and economic development on the one hand and emissions on the other. Section 3 provides a description of the data. Section 4 contains the analytical results for our EKC models and provides a discussion. We then close our paper in Section 5 with a summary and conclusions.

2. Demographic Change, Development, and Emissions

Recognizing that population growth causes environmental impact, Ehrlich and Holdren (1971) and Commoner (1972) began analysis of what has been coined the IPAT equation (for a review see Chertow 2001), in which environmental impact (I) is estimated as a function of population size (P), measures of affluence (A) and technology (T):

$$I=f(P, A, T)$$

In the broader context of the EKC discussion, Dietz and Rosa (1997) and York, et al. (2003a, b) draw on cross-sectional country-level data for a single year to estimate elasticities for CO₂ emissions and find values near 1, implying that a 1 percent change in population results in a 1 percent increase in emissions. In efforts to estimate how elasticities may change through time, Shi (2003) uses the IPAT model with panel data for CO₂ and finds values between 1.41 and 1.65, depending on the model used, but does not examine how these may vary with different population levels or other demographic features. Accounting for urbanization rates and household size, Cole and Neumayer (2004) find, for CO₂ emissions, unit elasticities for population size, but increasing emissions for higher urbanization rates and lower average household sizes. In contrast, using the Ecological Footprint of countries (Wackernagel et al. 1999) – in essence, their appropriation of materials and energy from around the globe – rather than air emissions as an indicator of environmental insult, Dietz et al. (2007) find that urbanization rates, age distribution and economic structure have significantly lower effects than population size and affluence. Drawing on some of their earlier work (Dietz and Rosa 1994, and on Bloom and Canning 2003), Dietz et al. (2007) argues that “the young (typically defined as those under 15) consume less and are less engaged in production activities than the rest of the population, so a higher proportion of adults in a population may increase impact even as it enhances economic growth” (p. 13).

However, an argument may be made that, *ceteris paribus*, a country with a predominantly young population may lay claim to a larger amount of resources and impact its environment more than one with an older population, owing to the resource-intensive needs of raising children, providing housing, clothing, education and more, and owing to the rapid expansion of preferences for energy and material-intensive goods and services. Conversely, a population that is largely older may experience stabilization or even decline in its material and energy needs.

Advertisement, which tends to expand with economic growth and the proliferation of mass communication, may further fuel expansion in personal consumption beyond the influences that come from higher personal income. Giving adequate access to personal credit, in turn, can magnify the ability of advertisement to shape demands for durable and luxury goods (Brulle and Young 2007), many of which tend to be material and energy intensive to produce and deliver. The rise in political freedom and civil liberties that also has come in many countries with economic development and mass communication, however, has not been seen as an influence on environmental impact (York et al. 2003b).

Income inequality, in turn, may add to the complexity of the environment-development relationship (Williamson 1998). More homogeneous societies may experience less inclination to use consumption as a means of internal differentiation and spend larger shares of their disposal income on basic goods (Deaton and Muellbauer, 1980), while in economically more stratified societies larger pressures may exist “to keep up with the Joneses”. However, the reverse argument could be made as well – the more homogenous the society, the more need there will be to find ways of internal differentiation through, for example, resource-intensive conspicuous consumption. By accounting for changes over time in the Gini coefficient, the analysis below will explore the extent to which income inequality is related to CO₂ emissions, holding other factors constant.

Insights generated from empirical analysis may have far-reaching implications for the conception and design of policy. If population characteristics indeed are key determinants of environmental quality, then effective environmental policies may require paying tribute to demographic attributes and the consumptive behaviors of individual sub-populations rather than concentrating institutional and regulatory efforts on resource extraction, manufacturing, and related polluting processes. Furthermore, if decreased birth rates and slower population growth contribute to an aging population, it is important to understand the impact a top-heavy population might have on overall emissions.

Closely intertwined with the issue of demographic change are issues of economic development. Virtually all of the empirical work on the EKC explores functional relationships between some measure of environmental insult (usually pollution per capita) and national income, or Gross Domestic Product (GDP), as one of the explanatory variables. However, problems abound with using GDP as a measure of a country’s development. First, GDP at best captures the size of the economy rather than its qualitative attributes (Daly and Cobb, 1994). Second, for industrialized countries, an ever larger share of economic activity is associated with the negative side effects of industrialization – from rising medical expenditures for pollution-induced morbidity to investment in infrastructures that reduce flooding caused by extensive land conversion, and more. Thus, in some sense the right hand side of the econometric equations used to estimate the EKC in itself contains a measure of pollution.

Augmenting the traditional conceptualization of development by using demographic variables and other descriptors of economic activity (such as the share of manufacturing in total employment) may avoid the issue that GDP is the primary variable with which development is captured. Furthermore, those demographic and economic variables may be less dependent on the level of environmental degradation than GDP – at least to the extent that a population’s fertility or overall demographic or employment structure is not a function of pollution.

Going one step further, corrections to GDP as a measure of development (or wealth) may be undertaken to reflect that economic activity inherently requires materials and energy, and that the conversion of materials and energy inevitably leads to waste generation (Ruth 1993). One such alternative measure to GDP is the Genuine Progress Indicator (FOE 2005, Talberth et al. 2009), which uses the same personal consumption data as GDP but makes

deductions to account for income inequality and costs of crime, environmental degradation, and loss of leisure and additions to account for the services from consumer durables and public infrastructure as well as the benefits of volunteering and housework. It thus separates more carefully the various elements of the EKC. Using GPI instead of GDP may further help address, at least in part, the methodological issues encountered when trying to separate the correlation between pollution and income from the correlation between pollution and the passage of time (Vollebergh et al 2009). Given the recent availability of GPI data for the U.S. for an extended time period, we incorporate this set of measures as an alternative to GDP for one set of models.

Taken as a whole, this paper augments the EKC to more adequately reflect development rather than simply economic growth and does so for one country over a relatively long time span. Towards this goal, we first assess whether the postulated inverted U can be found for the United States between 1800 and 2000, given data on per capita CO₂ emissions and GDP, using standard EKC specifications. An intermediate step in the analysis uses data for a shorter time period (1900–2000) and includes variables capturing the age structure of the population. In the third and final step of our analysis we explore relationships between per capita CO₂, per capita GDP and other variables intended to reflect potential impacts of the demographic and economic structure on emissions. Here, we also investigate implications of using the GPI, rather than GDP, to reflect economic wealth. Given data constraints, these refinements are carried out for a shorter time period, extending from 1950 to 2000. The outline of the following sections closely follows this three-step process. In all cases, we only concentrate on CO₂ emissions as a measure of pollution because of its ubiquitous nature in production, consumption, and transport and because its emissions are indicative of a wider class of pollutants, from particulates to metals to sulfur and nitrogen.

3. Data

Table 1 provides a succinct listing of the data used in this paper. All models make use of historical CO₂ data from Marland et al. (2003). The Marland dataset provides annual information on CO₂ emissions by type of fuel consumption as well as from all fossil fuels for a set of countries – from 1800 to 2000 for the United States. Estimates are given in thousand metric tons of carbon emitted annually. Our analysis uses the data on total emissions from fossil fuels. Estimates of real Gross Domestic Product are derived from Johnston and Williamson (2004). Per capita values for both CO₂ and GDP are calculated using the Johnston and Williamson population data (2004) for the 1800–2000 time period and U.S. Census Bureau population estimates for the shorter time periods (although the data match perfectly and the Johnston and Williamson data quite likely come from the Census Bureau). Using per capita values rather than absolute values corrects for changes in the size of the economy and the population, and therefore allows us to concentrate on changes in qualitative attributes.

Per capita CO₂ emissions from fossil fuels are used here instead of other measures of pollution because CO₂ emissions are the result of a wide range of production and consumption activities, with roughly one third each generated by the residential and commercial sectors, the industrial sector, and transportation (not counting emissions

associated with transformation losses in the energy sector). Furthermore, because CO₂ emissions are directly tied to energy consumption associated with a diverse set of economic activities – from the production of the food we eat and the fibers we wear, to the way in which we heat homes and move people and goods – they provide a convenient, though not necessarily ideal, surrogate for a large group of environmental impacts – ranging from effects on local air quality to longer-term, larger-scale global environmental change. While total CO₂ emissions have continued to increase in the US over the last 200 years (Figure 2) per capita CO₂ emissions have begun to somewhat level out (Figure 3).

Demographic variables include elderly and youth dependency ratios derived from the US Census Bureau's estimates program, as well as simple proportions of the population under 15 and over 65 years of age. Dependency ratios capture the relationship between the proportion of the population under 15 and/or 65 and older, relative to the share of the population between those ages – that is, the working-age population. During the post-World War II period in the United States, the share of the population assumed to be economically active ranged between 64 and 66 percent, sinking down to about 59 percent during the 1960s. In contrast, approximately 8 percent of the population was 65 and over in the 1950s, but this share had increased to about 12 percent of the population by the year 2000. From the mid-1950s to the early 1970s, around one third of the population was under the age of 15 (see Table 2 for dependency ratio values at select years).

Capturing changes in income distribution and economic structure with only one or two sets of numbers is difficult. To account for inequality-related aspects of resource use and pollution, we also include the Gini coefficient reported by the U.S. Census Bureau, as it is an accepted and commonly used measure of income inequality. To reflect changes in the sectoral mix of the economy, which is often associated with industrialization and development, we calculated service- and goods-producing employment shares of non-farm employment from data reported by the US Bureau of Labor Statistics (BLS 2004).

Following suggestions by Rotmans (1998) concerning the role of potential carbon leakage – i.e. transfer of emissions to other countries by importing their goods and services instead of producing them domestically – we calculated the ratio of exports (on an f.a.s. or free alongside ship basis) to imports (on an f.o.b. or free on board basis) from Historical Statistics of the United States (US Census Bureau 2004). Furthermore, since energy prices presumably affect CO₂ emissions, we included inflation-adjusted energy prices as an aggregate measure for the fossil fuel composite price, as reported by the US Energy Information Administration (EIA 2005).

4. Analysis and Discussion

Estimating statistical relationships over time presents econometric challenges that are not encountered in normal cross-sectional analyses. In the case of time series data, two bogies arise that must be assessed and, if necessary, dealt with before and during the estimation process. First, the potential lack of stationarity in the data may render any OLS results unreliable, even if a time trend variable has been included. Second, errors in a regression model are assumed to be uncorrelated; if this assumption does not hold – and it often fails to

in the case of time series data – standard errors will not be valid and resulting test statistics may be useless. All models below were first estimated using Ordinary Least Squares (OLS) as such:

$$CO2_t = \beta_0 + \beta_1 GDP_t + \beta_2 GDP_t^2 + \beta_3 GDP_t^3 + \beta_4 Time + \varepsilon_t$$

where $CO2$ and GDP are the per capita values at time t for each variable and $Time$ is a time trend variable. For shorter time periods, 1900–2000 and 1950–2000, additional parameters were estimated in the models to account for demographic and economic change. This follows the basic model laid out by Day and Grafton (2003), but without the logarithmic transformation of variables. Estimated models were then exposed to diagnostic tests for serial autocorrelation and heteroskedasticity of errors and stationarity of variables. Models were then re-estimated as appropriate. Across all models and time periods the goal of the model estimation process is to determine the existence of an EKC for CO_2 emissions in the United States. Positive coefficients on the $GDP/capita$ variable and negative coefficients on the $(GDP/capita)^2$ variable would indicate an upsidedown U shaped curve relationship for emissions and GDP. Often, a cubed GDP variable will also be included in the model, to test for the possibility of a rebound in emissions at higher levels of income per capita.

4.1 Long-Range EKC for the United States

Table 3 presents the results for the basic EKC regression model for the 1800 to 2000 time period (Model 1), estimated using Ordinary Least Squares. The coefficients suggest the existence of an EKC, or inverted-U curve, for the United States over the long term, with a positive and statistically significant coefficient on GDP per capita and a negative and statistically significant coefficient on the squared version of the variable. In addition, the cubed version of GDP per capita is positive and statistically significant, suggesting a rebound effect. However, the diagnostic test results shown in Table 2 unanimously suggest that the initial model (Model 1) suffers from heteroskedastic and autocorrelated errors. In addition, tests were conducted on both per capita GDP and CO_2 emissions to check for non-stationarity. The augmented Dickey-Fuller and Phillips-Perron tests for the existence of a unit root for CO_2 were unable to reject the null hypothesis of a unit root, suggesting the non-stationarity of the CO_2 variable. We were also unable to reject the null hypothesis of a unit root for per capita GDP. The results for both variables therefore indicate that estimating the typical EKC model using Ordinary Least Squares may result in a spurious regression and is an inappropriate estimation approach. Instead, using first differences of the variables is better, assuming that the differenced variables are stationary – which is the case here. The null hypothesis of a unit root, using the augmented Dickey-Fuller test, is handily rejected for both differenced variables.

Model 2 in Table 3 presents regression results from a Prais-Winsten AR(1) regression model, a first-order autoregressive model which mediates the issue with serial autocorrelation found in Model 1. Model 2 uses the first differences of the per capita CO_2 and GDP variables and specifies Huber-White heteroskedasticity-robust standard errors. The overall fit of the model is much lower, with an R^2 of 0.362, but this is a much more realistic estimation of model fit, given the small number of explanatory variables included in the

model. The disadvantage of the 1800 to 2000 time period is the relative scarcity of variables, in particular – given the focus of this paper – demographic variables. In this model, the rise of emissions for growing per capita GDP is never followed by a decline because of the strong and growing rebound effect for ever larger values of GDP per capita. Rather, emissions at first increase at a decreasing rate, then speed up again. The result is an inflection point that occurs at \$28,133 per capita, which corresponds to an annual 7.66 tons of CO₂ emissions per capita.

Estimating the model with first differences of the variables means the interpretation of the effects of income increases on emissions is different from Model 1, which simply included the levels of each variable. The general insights are maintained, though, with statistically significant parameter estimates for all versions of the GDP variables, as well as the expected signs. As seen in Model 1, the coefficient on the cubed version of GDP per capita is highly statistically significant, again suggesting the presence of a rebound effect.

4.2 Augmenting the EKC: Including Demographic Variables

A main intent of this paper, of course, is to examine the importance of changing demographic structure to trends in per capita CO₂ emissions, holding income constant. Unfortunately, detailed demographic data, even for a data-rich country such as the United States, are difficult to find for longer time periods, particularly in annual increments. The second stage of our analysis is therefore constrained to a shorter time period, but benefits from the inclusion of demographic variables. Specifically, we estimate EKC regression models that include measures of the size of the youth and elderly populations. These population groups are accounted for in two different ways in the models, first in terms of dependency ratios and, second, as the proportion of the total population in that age group. The new, more detailed time series extends for the years 1900 to 2000.

In the regression analysis of CO₂ emissions per capita shown in Table 4, the existence of the inverted U shape is confirmed for the 1900–2000 time series regardless of model specification, although neither the squared nor the cubed GDP term is statistically significant in Model 4. The OLS estimates (Models 1 and 2) indicate that serial autocorrelation of the errors is an issue but that heteroskedasticity of the errors is less of a concern than for the previous set of models. For these variables, tests for unit roots resulted in rejection of the null hypothesis or borderline statistical significance. In response, models for this time period were subsequently re-estimated to adjust for problems with the errors – a Prais-Winsten autoregressive framework with heteroskedasticity-robust standard errors – but variables were not differenced.

Model 3 is the preferred model shown in Table 4, with high explanatory value and issues of autocorrelated and heteroskedastic errors resolved. The negative value for the coefficient of the elderly dependency ratio suggests that, holding GDP per capita constant, as the share of elderly relative to the rest of the employed population increases, the lower the carbon emissions per capita will be. This suggests that the further along a country is in the demographic transition, the lower its CO₂ emissions will be, holding other factors constant. The “grow first, then clean up” perspective of earlier research (Beckerman 1992, Dasgupta et al. 2002) may thus more adequately be phrased as “grow up, then clean up”. Model 4,

which captures age structure in the population with the proportion of the population under 15 and over 64, also shows a negative and statistically significant coefficient on the elderly variable. So, measured either way, relative aging of the population is expected to have a dampening effect on emissions. In Model 3, increases in the youth dependency ratio are associated with increases in per capita CO₂ emissions and this coefficient is highly statistically significant. That result confirms our suggestion above that a society with a larger share of young individuals tends to demand more resources – from food and clothing to transportation and other services, many of which are energy and emission intensive to produce and deliver.

The regression analysis of this shorter, more detailed data set suggests the persistence of an inverted U and increased explanatory power of the regression model when parameters to describe demographic structure are taken into account (relative to model results shown for Model 2 in Table 3). Model 3 in Table 4 implies a turning point for the inverted U at a per capita GDP of \$30,010. For comparison, per capita GDP in the year 2000 in the US was \$34,760. The turning points found here are significantly higher than the \$5,000 – \$8,000 found in cross-sectional analyses of a wide range of water and air pollutants (Dasgupta et al. 2002), but closer to the range of \$37,000 – \$57,000 reported in earlier CO₂ emissions studies for the US (Cole et al. 1997, Yandle et al. 2004).

4.3 Estimation of the EKC, 1950–2000

Table 5 presents regression results for the 1950–2000 time period, but with a fuller suite of explanatory variables. As with the previous sets of models, serial autocorrelation and nonstationarity of variables render the OLS results (Models 1 through 4 in Table 5) unreliable. They are presented here to provide a backdrop to alternative specifications of the models on the far right of Table 5 (Models 5 and 6). Both alternate models account for serial autocorrelation with a Prais-Winsten autoregressive framework, with Model 6 estimated using differenced variables. In both cases, the coefficient on GDP per capita is statistically significant and positive and the coefficient on the squared variable is negative and statistically significant – suggesting the existence of an EKC for the U.S. Since both models are based on the OLS version of Model 3, in which the cubed term was not statistically significant, it does not appear in Models 5 or 6. Turning points for the EKC are at \$29,854 and \$31,446 respectively – values that are below, though close to the EKC peak of Model 3 in Table 4.

In both Models 5 and 6, the coefficient on the elderly dependency ratio is negative, as was seen for the 1900–2000 time period. However, only in Model 5 is the coefficient statistically significant. In neither model is the youth dependency ratio statistically significant. The coefficient on average household size, although not statistically significant, suggests that increases in household size are associated with increases in CO₂ emissions during this time period. Although it makes logical sense that larger households might consume more resources and be responsible for higher CO₂ emissions than smaller households, this result is likely confounded by the fact that the models are unable to control for the absolute number of households during the time period. That is, for a given population size, increases in average household size should represent an improvement (decrease) on the emissions front,

when compared to, for example, a majority of the population living in one-person households.

In point of fact, none of the additional explanatory variables included in the models for the shorter time period (Table 5) are statistically significant, although most of the coefficients have the expected sign. As inequality increases, as measured by the Gini coefficient, emissions will increase. Increases in composite fuel prices are associated with decreases in CO₂ emissions and increases in the proportion of total employment working in goods producing sectors (as opposed to service producing sectors) are related to increases in emissions. Across all models in which it was included, the export to import ratio is positively correlated with emissions, holding other factors constant. Although not statistically significant, the sign on this coefficient suggests that were the ratio to increase, CO₂ emissions would follow. In fact, the ratio has been more or less declining since the 1970s, as the U.S. has imported more than it has exported.

As discussed above, GDP is an inadequate indicator of wealth and economic development and may thus insufficiently capture the relationship between per capita emissions and changes in key qualitative socioeconomic attributes that describe a country's level of development, or "wealth". In a first attempt to mitigate this problem, we re-estimate the final models in Table 5, but substitute the GPI (Genuine Progress Indicator) for the GDP variables. Here, we did not use the Gini coefficient as an additional explanatory variable as it has already been incorporated into the calculation of the GPI.

The results are presented in Table 6. Aside from the confirmation of expected signs on many of the explanatory variables – few of which are statistically significant in either Model 2 or 3 – the model results are confounding. Estimating the model using the variables in levels (original values), as is done in Models 1 and 2, results in models that suggest increases in well-being, as measure by the per capita GPI are associated with decreases in CO₂ emissions. The squared GPI variable is then negative, resulting in a U shaped curve for emissions. It is worth noting, though, that, in Model 2, only the squared GPI coefficient is statistically significant. The model results using differenced variables (done to make nonstationary variables in levels stationary), in contrast, provide the expected EKC, but the coefficients are not statistically significant. All that is left here to explain changes in per capita CO₂ emissions, in essence, are a strong, positive influence of the share of employment in the goods producing sector, a negative impact of higher energy prices, and a negative impact of a higher youth dependency ratio, though the latter two parameters are barely significant at the 10 percent significance level. This result could suggest that, indeed, there is no discernible impact of "wealth", *per se*, on emissions but instead the energy intensity of the national economy, a declining youth dependency ratio and historically low energy prices have tended to drive up per capita CO₂ emissions. Combined with an overall increase in population size, environmental impact rose.

5. Summary and Conclusions

In this paper we first explored general relationships between per capita CO₂ emissions and per capita GDP over a 200-year time frame. The statistical results are consistent with the

hypothesis of an EKC but show a “rebound effect” suggesting that, continued upward trends in per capita CO₂ emissions with economic growth. Inverted U shaped EKCs are found in analyses of a shorter, more detailed data series extending over the 1900–2000 time span. In the latter, we augmented the traditional EKC to explicitly include variables that capture changes in population structures. We found the elderly dependency ratio to be negatively and the youth dependency positively correlated with per capita CO₂ emissions. That increases in the youth dependency ratio should be positively associated with increases in CO₂ emissions makes sense: raising children requires resources of all types. Correspondingly, as a population ages, it moves away from the resource-intensive dual demographic of child and parent – for example, housing and automobile may be downsized to reflect changing household needs. The material and energy intensive lifestyles of a younger population may give way to an increased demand for services which tend to have lower emissions associated with them.

Although beyond the analytical scope of this paper, it is interesting to speculate about the extent to which model results are driven by the characteristics of the generations involved. While children of the Great Depression (accounted for in this paper as part of the elderly dependency ratio) might be expected to restrict their consumption as they age and, by extension, reduce their CO₂ emissions, is it reasonable to expect the same of aging Baby Boomers? Might it not be more realistic to expect members of that generation to use their wealth and post-family-raising freedom to consume *more*?

In a third set of refinements we augmented our analysis with additional socioeconomic and demographic data, whose use limited the available time series to the period 1950–2000. Here we found that as income inequality increases, as measured by the Gini coefficient, emissions increase, lending support to the notion that higher emissions tend to be characteristic of a more unequal society. Consistent with economic theory, increases in composite fuel prices are associated with decreases in the use of traditional (carbon-based) fuels, and thus CO₂ emissions. Increases in the proportion of total employment working in the goods producing sectors, as opposed to less energy-intensive service producing sectors, are related to increases in emissions. However, replacing GPI for GDP in the regression equation, to reflect actual “wealth” generated rather than simply the size of the economy as a whole, we no longer find a correlation between wealth and emissions. Instead, it is the share of employment in the goods producing sector, energy prices and demography that drive much of the country’s CO₂ emissions.

In short, our results suggest that there are relevant relationships between demography and the productive structure of the economy on the one hand and CO₂ emissions on the other hand. While it is well established that movements in the economic base from manufacturing to services is typically associated with reduced (direct) environmental impact, the effects of changes in dependency ratios has not yet been investigated in detail. Our paper makes a first contribution to highlighting the role of demography in understanding a country’s environmental performance. Ideally, changes in population distribution (urbanization and counter urbanization, for example), as well as more fine-tuned measures of population structure would be considered. More research clearly needs to be carried out to illuminate the causal relationships between dependency ratios, domestic consumption of goods and

services, and associated CO₂ emissions. In addition to increased awareness of the importance of variable choice in understanding any EKC relationship, this analysis very clearly highlights the estimation, or econometric, difficulties in accurately measuring the relationship of economic growth or demographic structure to CO₂ emissions. Great potential remains for research on EKC model development and research. Nevertheless, the results presented here point towards a set of opportunities and constraints for policy.

First, and most obviously, even if long-run CO₂ emissions per capita tend to decline, total CO₂ emissions may continue to increase. A focus on per capita emissions alone may consequently present a misleading picture of the environmental impact of the developing society and unduly reduce pressures to change production and consumption processes. Second, even if total CO₂ emissions decline in the long run, the environmental impact of accumulated past emissions may persist, given the long mean residence time of carbon in the atmosphere. Combined with the fact that the climate system itself may respond in non-linear fashion to changes in atmospheric carbon concentrations, waiting for the economy to grow and change its structure may be insufficient to reduce environmental harm. Third, the relevance of the dependency ratios in explaining historical variation in per capita CO₂ emissions in the US points towards the need to explore in more detail the effects that an aging society has on consumption choices, and therefore on demand for materials, energy and environmental goods and services. For example, as elderly dependency ratios increase (or youth dependency ratios decline), personal savings may rise and economy-wide demand for consumer products may be deferred to periods in which material and energy intensive personal consumption is lower. The intertemporal, monetary effects of changes in consumption behavior are likely accompanied by real effects associated with changes in total and relative factor demand of manufacturing and service industries. Removing effects of demography on the shape of the EKC may even suggest long-run increases in emissions with little more than an inflection point along the way, making a dip along an N-shaped pattern look like an optimistic outcome of the analysis. For environmental policy to be more effective may require strategies that foster consumption choices consistent with those seen in a society with high elderly dependency ratios, rather than simply and predominantly being oriented towards changes in the efficiency of economic activities that meet the immediate needs of a highly productive young to middle-aged population.

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Pollution

Fig. 1.
The Kuznets curve in cross-sectional analysis.

Fig. 2.
Historical total CO₂ emissions from fossil fuels in the USA.

Fig. 3.
Historical per capita CO₂ emissions in the United States.

Table 1

Variables Used in Analysis

Variable	Description	Source
Population		
Total Population, 1800–2000		Louis Johnston and Samuel H. Williamson, “The Annual Real and Nominal GDP for the United States, 1789 - Present.” Economic History Services, March 2004, http://www.eh.net/hmit/gdp/
Age-Specific Population Data and Totals, 1900–2000	Resident population by age, including armed forces overseas for some decades	U.S. Census Bureau, Estimates Program
Average Household Size, 1950–2000		U.S. Census Bureau, Current Population Survey (available as annual Table, HH-6)
CO ₂ Emissions, 1800–2000	Total CO ₂ emissions from fossil-fuels (thousand metric tons of C)	Marland et al., Carbon Dioxide Information Analysis Center, http://cdiac.ornl.gov/trends/emis/em_cont.html
Real Gross Domestic Product, 1800–2000		Louis Johnston and Samuel H. Williamson, “The Annual Real and Nominal GDP for the United States, 1789 - Present.” Economic History Services, March 2004, URL : http://www.eh.net/hmit/gdp/
Service and Manufacturing Employment, 1950–2000	Proportion of employment in goods-producing and service-producing sectors	U.S. Bureau of Labor Statistics, Table HS-31. Nonfarm Establishments--Employees, Hours, and Earnings by Industry: 1919 to 2002
Gini Coefficient, 1950–2000	Measure of inequality in family income	U.S. Census Bureau, Table F-4, Gini Ratios for Families, by Race and Hispanic Origin of Householder, http://www.census.gov/hhes/www/income/data/historical/inequality/index.html
Trade, 1950–2000	Ratio of exports to imports	U.S. Census Bureau, No. HS-40. Economic Indicators for Construction and Real Estate, Manufacturing, Retail and Foreign Trade Sector: 1900 to 2002, www.census.gov/statab/hist/02HS0040.xls
Real Fuel Prices, 1950–2000,	Dollars per million BTU, in chained 2005 dollars	U.S. Energy Information Administration, Table 3.1 Fossil Fuel Production Prices, 1949–2009, http://www.eia.doe.gov/emeu/aer/txt/ptb0301.html
Genuine Progress Indicator, per capita, 1950–2000	Alternative measure to GDP that accounts for costs and benefits of environmental and social development	Talberth et al., Redefining Progress, “The Genuine Progress Indicator 2006: A Tool for Sustainable Development”

Table 2

Variable Characteristics, Selected Years, 1800–2000

Year	1800	1850	1900	1950	2000
Total U.S. Population	5,310,000	23,260,000	76,094,000	152,271,417	282,171,936
Per capita CO ₂ Emissions (thousand metric tons)	0.01	0.23	2.377	4.543	5.418
Per capita GDP (real \$2000)	\$1,425.61	\$2,034.82	\$4,309.14	\$11,669.95	\$34,790.84
Per capita GPI (in \$2000)				\$8,611.81	\$15,145.93
Proportion of the Population ages 0–14			0.344	0.269	0.214
Proportion of the Population Ages 65 and Up			0.041	0.081	0.124
Youth Dependency Ratio			55.812	41.463	32.267
Elderly Dependency Ratio			6.615	12.538	18.776
Average Household Size				3.37	2.62
Gini Coefficient				0.379	0.433
Proportion Non-Farm Employment in Goods-Producing Sectors				0.409	0.195
Proportion Non-Farm Employment in Services-Producing Sectors				0.591	0.805
Export to Import Ratio				1.161	0.642
Composite Price of Fossil Fuels (chained \$2005, dollars per million BTU)				\$1.74	\$2.930

Table 3Long-Run Relationship of per capita CO₂ Emissions and Gross Domestic Product, United States, 1800–2000

	Model 1 OLS	Model 2 Prais-Winsten AR(1) Differenced Variables
GDP per capita	0.000744 *** (8.01e-05)	0.000715 *** (0.000126)
(GDP per capita) ²	−3.63e-08 *** (4.54e-09)	−2.38e-08 *** (6.29e-09)
(GDP per capita) ³	5.50e-13 *** (8.19e-14)	2.82e-13 *** (1.01e-13)
Time	0.0111 *** (0.00252)	
Constant	−1.433 *** (0.0941)	−0.00782 (0.0120)
Observations	201	200
R-squared	0.954	0.362
Diagnostic tests:		
Breusch-Godfrey	0.0000 (p value)	
Durbin-Watson	0.175	2.146
Breusch-Pagan	0.003 (p value)	

The dependent variable in Model 1 is per capita CO₂ emissions and all variables are given as levels. In Model 2, all variables are included as first differences and Huber-White heteroskedasticity-robust errors are used. Standard errors are reported in parentheses.

*** indicates statistical significance at $p < 0.01$,

** at $p < 0.05$, and

* at $p < 0.1$.

Breusch-Godfrey is a Lagrange Multiplier (LM) test for serial autocorrelation. Breusch-Pagan tests for heteroskedastic errors. The Durbin-Watson test statistic for autocorrelation is also provided.

Table 4

Estimation of an Environmental Kuznets Curve with Demographic Variables, United States, 1900–2000

	OLS Regression		Prais-Winsten AR(1) Regression	
	Model 1	Model 2	Model 3	Model 4
GDP per capita	0.000529*** (6.39e-05)	0.000507*** (6.43e-05)	0.000578*** (0.000111)	0.000556*** (0.000121)
(GDP per capita) ²	−7.51e-09** (3.12e-09)	−5.41e-09* (3.17e-09)	−9.63e-09* (5.28e-09)	−7.72e-09 (5.64e-09)
(GDP per capita) ³	−3.78e-14 (5.42e-14)	−7.01e-14 (5.55e-14)	−7.19e-15 (8.58e-14)	−3.51e-14 (9.11e-14)
Youth Dependency Ratio	0.0623*** (0.00767)		0.0615*** (0.0153)	
Elderly Dependency Ratio	−0.667*** (0.0572)		−0.680*** (0.115)	
Time	0.0673*** (0.00854)	0.0548*** (0.00777)	0.0668*** (0.0182)	0.0535*** (0.0158)
Population 0–14 (proportion)		0.0348 (1.212)		−0.352 (2.208)
Population 65 and Up (proportion)		−105.3*** (9.219)		−106.4*** (18.02)
Constant	1.530*** (0.307)	4.927*** (0.495)	1.442*** (0.350)	4.893*** (0.748)
Observations	101	101	101	101
R-squared	0.926	0.924	0.805	0.790
Diagnostic tests:				
Breusch-Godfrey (p value)	0.000	0.000		
Durbin-Watson	0.9987	0.9406	1.9806	1.9523
Breusch-Pagan (p value)	0.0166	0.0492		

The dependent variable in all four models is per capita CO₂ emissions and all variables are given as levels. Standard errors are reported in parentheses. Models 3 and 4 are estimated using Huber-White robust standard errors.

*** indicates statistical significance at $p < 0.01$,

** at $p < 0.05$, and

* at $p < 0.1$.

Breusch-Godfrey is a Lagrange Multiplier (LM) test for serial autocorrelation. Breusch-Pagan tests for heteroskedastic errors. The Durbin-Watson test statistic for autocorrelation is also provided.

Table 5
Evaluating the Existence of an EKC with Additional Control Variables, United States, 1950–2000

	Ordinary Least Squares				Alternative Specifications	
	Model 1	Model 2	Model 3	Model 4	Model 5 Prais-Winsten AR(1)	Model 6 Prais-Winsten AR(1) Differenced Variables
GDP per capita	0.00175*** (0.000207)	-0.000118 (0.000369)	8.46e-05 (0.000515)	0.000401** (0.000169)	0.000615*** (0.000161)	0.000422** (0.000191)
(GDP per capita) ²	-5.74e-08*** (8.51e-09)	2.50e-08 (1.66e-08)	8.12e-09 (2.48e-08)	-8.00e-09*** (2.02e-09)	-1.03e-08*** (2.23e-09)	-6.71e-09* (3.43e-09)
(GDP per capita) ³	6.90e-13*** (1.23e-13)	-5.29e-13** (2.47e-13)	-2.42e-13 (3.71e-13)			
Time	-0.108*** (0.0209)	0.0879** (0.0367)	0.113* (0.0645)	0.106 (0.0630)	0.0407 (0.0589)	
Youth Dependency Ratio		0.0856*** (0.0175)	0.0487 (0.0621)	0.0190 (0.0420)	0.0163 (0.0367)	-0.0225 (0.0458)
Elderly Dependency Ratio		-0.867*** (0.148)	-0.734*** (0.250)	-0.594*** (0.128)	-0.500*** (0.162)	-0.286 (0.266)
Average Household Size			-0.785 (1.311)	-0.473 (1.212)	0.439 (1.083)	0.738 (0.973)
Gini Coefficient			-4.464 (3.699)	-4.084 (3.627)	1.578 (2.726)	3.994 (2.414)
Proportion of employment in goods-producing sectors			3.012 (7.790)	4.276 (7.490)	2.921 (6.168)	8.562 (5.469)
Export to Import Ratio			0.178 (0.247)	0.175 (0.246)	0.180 (0.202)	0.233 (0.176)
Composite Fossil Fuel Prices			-0.152** (0.0708)	-0.182*** (0.0537)	-0.0691 (0.0484)	-0.0542 (0.0476)

Ordinary Least Squares					Alternative Specifications	
	Model 1	Model 2	Model 3	Model 4	Model 5 Prais-Winsten AR(1)	Model 6 Prais-Winsten n AR(1) Differenced Variables
Constant	-9.525*** (1.549)	10.53*** (3.603)	12.86* (7.474)	8.792** (4.075)	0.909 (4.402)	0.0448 (0.0631)
Observations	51	51	51	51	51	50
R-squared	0.836	0.909	0.936	0.935	0.888	0.570
Diagnostic tests:						
Breusch-Godfrey (p value)	0.0000	0.0000	0.0006	0.0009		
Durbin-Watson	0.421	0.5853	1.0731	1.0731	1.5355	1.8833
Breusch-Pagan (p value)	0.5306	0.2388	0.9645	0.9429		

The dependent variable in the first five models is per capita CO₂ emissions and all variables are given as levels. In the final model, all variable are estimated using their first differences. Standard errors in parentheses.

*** p<0.01,
** p<0.05,
* p<0.1.

Breusch-Godfrey is a Lagrange Multiplier (LM) test for serial autocorrelation, estimated here with one lag. Breusch-Pagan tests for heteroskedastic errors. The Durbin-Watson test statistic for autocorrelation is also provided.

Table 6EKC Estimation Using the Genuine Progress Indicator and CO₂ Emissions, 1950–2000

	Model 1 Ordinary Least Squares	Model 2 Prais-Winsten AR(1)	Model 3 Prais-Winsten AR(1) Differenced Variables
GPI per capita	−0.0116*** (0.00364)	−0.00557 (0.00381)	0.00214 (0.00342)
(GPI per capita) ²	9.99e-07*** (2.87e-07)	5.21e-07* (3.02e-07)	−1.48e-07 (2.73e-07)
(GPI per capita) ³	−2.75e-11*** (7.40e-12)	−1.52e-11* (7.84e-12)	3.24e-12 (7.13e-12)
Time	0.0490*** (0.0164)	0.0630*** (0.0201)	
Youth Dependency Ratio	0.0336 (0.0325)	−0.0315 (0.0410)	−0.0898* (0.0511)
Elderly Dependency Ratio	−0.180* (0.101)	−0.139 (0.126)	−0.0756 (0.227)
Average Household Size	−1.179 (1.061)	0.558 (1.241)	1.508 (1.204)
Proportion of employment in goods-producing sectors	9.858** (4.235)	11.62*** (3.925)	17.21*** (3.384)
Export to Import Ratio	0.142 (0.229)	0.0931 (0.218)	0.0926 (0.181)
Composite Fossil Fuel Prices	−0.129*** (0.0317)	−0.118*** (0.0421)	−0.0902* (0.0471)
Constant	48.53*** (14.33)	19.94 (16.14)	0.105** (0.0426)
Observations	51	51	50
R-squared	0.944	0.889	0.535
Diagnostic tests:			
Breusch-Godfrey (p value)	0.0069		
Durbin-Watson	1.2954	1.7345	1.9103
Breusch-Pagan (p value)	0.3018		

Dependent variable in all models is CO₂. In first two models all variables are entered as levels; in third model as first differences. Standard errors in parentheses.

p<0.01,

**
p<0.05,

*
p<0.1.

Breusch-Godfrey is a Lagrange Multiplier (LM) test for serial autocorrelation, estimated here with one lag. Breusch-Pagan tests for heteroskedastic errors. The Durbin-Watson test statistic for autocorrelation is also provided.