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Contents

Abstract

Demographic Impact (DI) models are multiplicative identities used to decompose environmental impacts into components due to population, economic and technological change. While such decompositions have played an important role in the population-environment literature, inconsistent and ambiguous methods have made their results difficult to interpret and nearly impossible to compare. This paper demonstrates and clarifies the differences between these methods using the example of anthropogenic greenhouse gas (GHG) emissions.

This paper locates two distinct approaches to DI model decomposition: The *annual growth rate decomposition* and the *multiplicative decomposition*. Stable indices are provided for each approach. Finally, the Divisia Index -- a common price index used by economists -- is suggested as an appropriate method to aggregate DI model results.

Decomposing Models of Demographic Impact on the Environment

Lee Wexler

Introduction

The logical first step to assessing the role of population in environmental impact is to consider the simple scale effect of population. In other words, we should assume the future level of *per capita* environmental impacts are unrelated to population growth, and consider the arithmetic impact of population change on the environment. Nathan Keyfitz has described this as the "direct" effect of population growth on the environment (Keyfitz 1992). This direct effect was the prime concern of Malthus, underlies the concern ecologists have about human population growth, and also dominates the view of the common man of the "population and environment" problem.

The direct effect of population on the environment is often illustrated with multiplicative models equating environmental impacts to the product of population, per capita consumption and technological factors. Theses models are typically described as "I=PAT" identities, referring to the memorable three variable identity coined by Ehrlich and Holdren (1972):

I= P*A*T

where

I = natural resources used ("impact")

P = population

A = per capita consumption ("affluence")

T = natural resources used or pollution produced per unit consumption ("technology").

In fact, Ehrlich and Holdren's I=PAT represents a whole family of multiplicative identities with two or more terms which yield an index of environmental impact. We call this broad family *Demographic Impact (DI)* models. For example, such identities have been used to consider the environmental impact of fertilizer use (Harrison 1992), i.e.

fertilizer use = population

* agricultural demand / person

* fertilizer use / agricultural production

or the pollution impact of automobiles (Commoner 1994), i.e.

pollutant (i) = population

* vehicle mile traveled / person

* pollutant (i) / vehicle miles traveled

or the impact of fossil fuel energy (MacKellar et al. 1995)

energy =	population
	* households / person
	* GNP / household
	* energy / GNP

Note the number of variables on the right hand side need not be three, but can be any number greater than or equal to two depending on the level of detail desired.

This paper presents general methods for decomposing change of impact in DI models to contributions of the factors on the right hand side. While such decompositions have formed the primary use of DI models, inconsistent and ambiguous methodology have made the results of such decompositions difficult to interpret and nearly impossible to compare. Three such problems are considered here in detail: consistent handling of growing and shrinking factors, the important difference between a contribution to a *rate* of growth, and a contribution to *absolute* growth, and appropriate aggregation methods.

Throughout the paper, example decompositions are given for historical and future anthropogenic greenhouse gas emissions.

A note on the simplicity of DI models

It must be noted that in the population and environment field DI models have been as heavily criticized as they have been relied upon. In particular, three important issues have emerged in the literature:

1) The fact that DI models are invariably linear; that is, their failure to model feedback relations between the decomposition variables (i.e. Preston 1994).

2) Sensitivity of DI models to the choice of decomposition variables (i.e. MacKellar et al. 1995).

3) Technical aspects of decomposition: Ambiguities over the choice of decomposition method and importance of accounting for heterogeneity (i.e. Lutz et al. 1993; Raskin 1995).

This paper focuses only on the third issue, which is crucial for the analysis of even the simplest of linear models. The first two issues are potentially very important, but concern with them cannot obscure the importance of good analysis of particular linear models. In the population-environment field, for example, for every optimist who cites an ameliorating effect of population growth on per capita resource use there is a pessimist who cites an exacerbating effect. In this contentious environment, simple linear models represent a vital default relation.[1] Furthermore, as we shall see, many of the decomposition methods presented here are directly extendible to more sophisticated non-linear DI models.

Decomposing a DI Model in a Single Region

Consider the general DI model

I(t,-)=P(t,-)*A(t,-)*T(t,-) [1]

where all variables are strictly positive for all time t. Now we want to somehow attribute changes in I during the period to changes in P, A, and T. Two methods are identified here: the *annual growth rate* (or logarithmic) decomposition and the *multiplicative* decomposition. As we shall see the methods yield very different results and can be interpreted very differently.

As an illustrative example, we now analyze the growth of carbon emissions from fossil fuels in the High Income countries between 1965 and 1990. This region as defined by the World Bank is essentially comprised of the OECD countries and accounted for about 55% of global emissions during the period. Applying equation [1], I represents emissions of carbon from fossil fuel combustion, P represents population, A represents GNP per person and T represents carbon emitted per GNP. The necessary data for the analysis, from World Bank (1992), is given in Table 1.

Table 1. Carbon emissions from fossil fuels: High income countries, 1965-1990. Source: World Bank (1992).

	emissions (GtC)	population (millions)	GNP/person (thousands $)	carbon/GNP (tC/thousand $)
1965	1901	671	9895	286
1990	2702	816	19,590	172
Avg. annual growth rate	1.5	0.8	2.7	-2.0
1990 value / 1960 value	1.44	1.22	1.98	0.60

[1] Keyfitz (1992), who labeled the discarding of linear models as his fifth "way of causing the less developed countries population problem to disappear--in theory" perhaps said it best:

> We need not multiply the examples of intermediate variables that writers have interposed and that they claim nullify the direct effect. Every one of the arguments can be supported by some anecdote; for none is their convincing empirical evidence. I submit that the direct effect of population ... is primary, and that the burden of proof is on the one who has introduced some intermediate effect that would upset it.

Annual growth rate decomposition

The annual growth rate decomposition has been the standard method used in the literature (i.e. Holdren 1991; Bongaarts 1992; Harrison 1992). It can be derived by simply dividing equation [1] at its final year values by equation [1] at its base year values and then taking logarithms of both sides of the resulting equation, i.e.

$$\ln(\frac{I(t)}{I(0)}) = \ln(\frac{P(t)}{P(0)}) + \ln(\frac{A(t)}{A(0)}) + \ln(\frac{T(t)}{T(0)}) \qquad [2]$$

which, dividing through by t is precisely equivalent to the sum of the continuous average growth rates during the period,

$$I' = P' + A' + T' \qquad [3]$$

Note that equation [3] is also approximately true for discrete annualized growth rates, when the growth rates are sufficiently small (i.e. less than 5% per year).[2] This condition is usually true for annual rates of change of environmental and economic variables. That the relationship holds for our example is easily verified by examining the growth rates in Table 1.

Assuming P, A and T are all independent of each other, P', A', and T' can be considered, respectively the contribution of the growth of the three factors to the growth rate of emissions.[3] That is, one could simply argue that halting population growth during the period would have reduced the emissions growth by 0.8% per year. By the same argument, halting per capita economic growth during the period would have reduced the emissions growth rate by over three times that amount yielding annual *decreases* of emissions of 1.2%.

Equation [3] is quite straightforward. Problems arise, however, when we attempt to normalize the equation in order to compare among regions, scenarios, time periods, or pollutants. The standard normalization is to divide all the growth rates through by the growth rate of I yielding "percentage contributions" of growth, i.e. Y_P=P'/I', Y_A=A'/I', and Y_T=T'/I', where $Y_A+Y_P+Y_T=1$. If one or more of the factors are shrinking, however, this normalization is confusing at best, and potentially highly misleading. Consider our example: Population growth (Y_P) accounts for 78% of the emissions growth, per capita income growth (Y_A) accounts for 273% of the emissions growth and technological change (Y_T) accounts for -205% of the emissions growth. Here considering the "population contribution" in isolation would erroneously lead one to conclude that population growth dominated the growth rate of emissions. Furthermore, one is unable to meaningfully compare the contributions of individual variables between regions: Under this scheme, for example, the population contribution to emissions growth of the High Income Region would be nearly twice the population contribution to emissions growth in Sub-Saharan Africa, where population was growing three times as fast, and per capita income growth was a tenth of that of the High Income countries![4] Finally, the metric is highly incomparable even between differing

[2] That is $e^{rt} \cong (1+r)^t$ for small enough r. This follow directly from Sterling's approximation (LN(1+x) = x for small x).

[3] The equivalent contribution of the variables to emissions growth for the non independent case is simply derived. In the example of population, it is P'(1- ε(P,A) -ε(P,T)), where ε(X,Y) represents the partial elasticity of X with respect to Y. In theory, this expressions could be substituted for the simple growth rates of this section without affecting the method.

[4] $Y_{P,afr} = P'_{afr}/I'_{afr} = 2.81/6.77 = 42\%$

scenarios within a region. For example, had income growth in our example been half as fast (1.35% instead of 2.7%), the metric would have shifted to Y_P=160%, Y_A=900%, Y_T=1300%.

Authors have sidestepped this problem in two ways. The first way is to cancel the decreasing T factor with the growing A factor by collapsing them (either implicitly or explicitly) into a single, more slowly growing "per capita" impact term. This is the approach taken by Holdren (1991), MacKellar et al. (1995), Raskin (1995), and Bongaarts (1992). This approach, however, artificially inflates our view of the importance of population and discards important information about the more rapid trends of consumption growth and declining resource use per unit output. In his widely cited article, for example, Bongaarts uses US EPA projections to calculate Y_P for global carbon emissions between 1985 and 2100 at 35%. What Bongaarts fails to report, however, is that Y_A and Y_T for the same projections, are 191% and -126%, respectively. A second, and more appropriate solution to the problem, used by Harrison (1992), is to normalize the increasing factors by the sum of the increasing factors and the decreasing factors by the sum of the decreasing factors. Unfortunately, Harrison's method loses information about the relative magnitudes of the increasing and decreasing factors.

Declining factors -- in particular the widespread trend of falling environmental impact per unit output -- are a fundamental and important characteristic of DI models. We now consider two normalizations which are appropriate when factors are declining and allow readers to consider the relative importance of factors across regions and scenarios without doing arithmetic. The first normalization, J, divides all factors growth rates through by one of the factor growth rates. For example, dividing through by population growth, yield J_P = 1, J_A = 3.5, and J_T = -2.4. This is a stable index of the magnitude of all factor growth rates relative to population and is appropriate for comparison across regions and across scenarios.

The second normalization, K, divides the absolute value of the growth rates by the sum of the absolute values of all the growth rates. This yields a percentage contribution to the magnitude of total factor change, which preserves the relative magnitudes of the growth rates, and yields a set of indices which always sum up to 100. For example the contribution of T would be given as:

$$K_T = \frac{|T'|}{|P'| + |A'| + |T'|} \qquad [4]$$

and for the example in Table 1, K_P = 14%, K_A = 49%, K_T = (36%). Here brackets are used to indicate that the contribution is a negative contribution. A single K_i is a useful and stable index which -- without reference to any other figure -- indicates the relative importance of variable i in determining the emissions growth rate. One drawback of this method is that one must be careful about the consistent maintenance of the signs.

Multiplicative decomposition

While the annual growth rate decomposition separates the factors elegantly its meaning must be interpreted carefully. After all, it is *total growth* of pollutant emissions and resource consumption which damage the environment, not annual growth rates of emissions and consumption. And decomposing total growth can be very different from decomposing annual growth. To give a simple analogy, consider two bank accounts, one yielding 1% interest per year and the second yielding 2% interest per year. Is the second account twice as profitable as the first account? In the first year, of course, yes. Over time, however, the second account is increasingly more profitable than the first ($e^{2t} / e^t = e^t$ times, to be exact). In the same way, over the 25 year period discussed above, consumption growth was not simply K_A / K_P times as important as population growth. The importance of the more rapid consumption growth relative to population growth should be even greater than the ratio of their annual growth rates.

The notion that annual growth rate decompositions underestimated the importance of more rapidly growing factors was most recently noted by Raskin (1995). Raskin proposed an ad-hoc method to decompose the growth in impact additively in proportion to the total percentage growth of each of two factors during the period. Unfortunately, his method is not directly generalizable to DI models with either decreasing factors or two or more factors.[5] It appears to be impossible to neatly decompose total impact growth in DI models into an additive sum of the form of equation [1].

Nevertheless, we can do a *multiplicative* decomposition, based on the following simple formula:

$$I(t) = P(0)A(0)T(0)M_P(0,t)M_A(0,t)M_T(0,t) \qquad [5]$$

where $M_i(0,t)$ represents the value of variable i in year t divided by the value of variable i in year 0. For the example given in Table 1, these indices are given in the final row. Population growth, consumption growth, and technology growth scaled total emissions by factors of 1.22, 1.98, and 0.6, respectively, during the 25 year period.

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[5] Assuming the model I=P*C, Raskin derives the standard formula

$$i = p + c + pc$$

where the small letters represent absolute growth rate during the period (i.e. $p = \Delta P / P_0$). The cross-term (pc), is too large to neglect when p and c are sufficiently large and has long prevented researchers from doing additive decompositions over long time periods. Raskin assigns this cross-term to population and per capita consumption in proportion to their total percentage growth during the period. For example, the contribution of population becomes:

$$y_p = p + \frac{|p|}{|p| + |c|}(pc)$$

and again, $i = y_p + y_c$. One problem with this formulation is that it underestimates the contribution of declining variables (to see this, merely note that absolute growth for a declining variable is limited at -100%). A second problem is that when extended to more than two variables the Raskin decomposition method violates basic additivity assumptions. For example, it can be shown that y_p in the model I = P*A*T is not equal to y_p in the model I = P*[AT], where A and T have been collapsed into a single variable.

How can we consistently compare these scale factors? One obvious use of these indices is to calculate for each factor the proportion of emissions in the final year which could have been averted by holding any one of the variables constant. This is simply $1-1/M_i$. This is the approach taken by Bartiaux and van Ypersele (1994) in their analysis of MDC and LDC contributions to historical carbon emissions. Although this calculation would appear to have direct relevance for policy analysis, over periods of significant change it can in fact give a very distorted view of the relative significance of the variables. Consider a period in which population quadrupled, and per capita income increased by a factor of ten ($M_P = 4$, and $M_A = 10$). This approach would calculate a percentage reduction of 75% from controlling population, and 95% from controlling economic growth. It fails to illuminate the fact that most of the impact reduced via holding population constant actually resulted from the massive income growth during the period.

A more appropriate comparison -- at least with regard to the relative importance of the factors -- is to compare the percentage growth of emissions that would have resulted from the change of each individual factor during the period had all the other variables been held constant. This is essentially the type of comparison suggested by Raskin, and has also been used, for example, by Howarth et al. (1995) in analyzing manufacturing energy. We do have to be slightly careful of our treatment of declining factors in order not to understate the importance of their scale effect (when M_i is less than one, recall that absolute growth is limited by -100%). Thus we can define a new index L_i, as

$$L_i = (M_i - 1) \quad \text{if } M_i > 1$$
$$L_i = (\frac{1}{M_i} - 1) \quad \text{if } M_i < 1 \qquad [6]$$

That L yields a consistent treatment of both increase and decrease is evident from noting that M values of 1/x and x yield L values of equal magnitude. Clearly L is more difficult to interpret in policy terms than the percentage reduction from the baseline calculated by Bartiaux and van Ypersele. Nevertheless, as a non-biased representation of the change implied by M it appears to yield a more consistent comparison of the importance of the variables in causing (or averting) emissions during the period. The best way to think of L might be as taking a minimum baseline resulting from the lowest observed values of each of the variables during the period and calculating for each variable the amount of emissions growth that would result from moving to a high value of that variable alone.

In the example of Table 1, we have $L_P = 22\%$, $L_A = 98\%$, and $L_T = (66\%)$. As with the construction of K, the brackets are used to indicate that the value results from a declining factor. (Note that because they are not derived from an additive decomposition, the L indices do not add up to one, and in no way "partition" emissions.) Using these figures, technology change is about three times as important as population during the period. Consumption growth is over four times as important as population growth. Comparing this with the K values calculated earlier in this section reveals that over a twenty-five year period a multiplicative decomposition places significantly greater weight on the faster changing factors of income and technology than does the annual growth decomposition.

Aggregating Regional Values

Demographic heterogeneity may bias DI model decompositions in two ways. The first source of bias arises because growth rates may be correlated to total levels of impacts. This has been recognized by Lutz et al. (1993) and Raskin (1995) in the case of carbon emissions and population growth: Because total per capita emissions are lowest where population growth is highest, calculations that are too global in nature will overstate the contribution of population growth to emissions growth. A second source of bias arises when the growth rates of a decomposition variable have different signs between regions. Considering such regions together as a single unit, the decline of the given variable in one sub-region cancels the growth of the variable in the other sub-region. In this way a variable which may have been important in determining emissions change in both sub-regions (albeit in opposite ways), becomes diminished in importance for the total region. The canceling problem in decomposition has been discussed in detail by Ang (1993) in his decomposition of industrial energy demand in Taiwan.

In order to avoid these biases, DI models need to be estimated at a level of aggregation for which populations are adequately homogenous in their resource use and economic consumption; only at such a level can DI decomposition results be credible for policy. In many instances we would like to be able to aggregate such regional results to a global level. This section describes and illustrates a common method for doing so, the *Divisia* decomposition.

In fact, constructing aggregate DI model decompositions is an instance of the general problem of *index numbers* in economics and statistics. The classic example of an index number is a price index which economists create to describe a set of good-specific price changes with a single figure. While many possible schemes exist for creating index numbers, it can be shown that none will accurately represent the entire process. The Divisia scheme, however, has favorable properties, which have made it popular in recent decomposition analyses of energy demand (i.e. Ang 1993; Boyd et al. 1987). In particular, it meets two great tests proposed by Fisher (1922) for evaluating the accuracy of index numbers: The factor reversal test ($M_P(0,t)*M_A(0,t)*M_T(0,t) = I(t)/I(0)$), that is the regional multiplicative identity holds in the aggregate and the time reversal test ($M(0,t)= 1/M(t,0)$).

The Divisia decomposition results from deriving a weighted aggregate rate of change for each factor from the regional rates of change. The first step is to derive a multi-region equivalent of equation [3]. We begin by relating the instantaneous aggregate growth rate, r(t), as a function of the constant growth rates of impact in the regions, I_j's.

$$r(t) = \sum_{\text{all j}} \frac{I_j(t)}{I(t)} I'_j \qquad [7]$$

Integrating both sides from 0 to T, and dividing by T yields

$$I' = \sum_{\text{all j}} I'_j \frac{\int_0^T \frac{I_j(t)}{I(t)} dt}{T} \qquad [8]$$

That is, the total growth rate of impact is simply the weighted sum of the regional growth rates. The weights, often denoted as *Divisia weights*, are simply the regional average shares of impact during the time period, and can be calculated through a discrete approximation of the integral in [8]. Denoting these weights as w_j and decomposing the regional rates of impact yields:

$$I' = \sum_{\text{all } j} w_j I_j' = \sum_{\text{all } j} w_j P_j' + \sum_{\text{all } j} w_j A_j' + \sum_{\text{all } j} w_j T_j' \qquad [9]$$

Equation [9] is the aggregate growth rate decomposition and can be used to produce indices of K and J as described in the previous section.[6] Note that for K two aggregate indices are possible; taking absolute values of each summation terms as a whole,

$$K_P^1 = \frac{\sum_{\text{all } j} w_j P_j'}{\left|\sum_{\text{all } j} w_j P_j'\right| + \left|\sum_{\text{all } j} w_j A_j'\right| + \left|\sum_{\text{all } j} w_j T_j'\right|} \qquad [10]$$

or taking absolute values of each of the terms *within* the summations,

$$K_P^2 = \frac{\sum_{\text{all}} \left|w_j P_j'\right|}{\sum_{\text{all}} \left|w_j P_j'\right| + \sum_{\text{all}} \left|w_j A_j'\right| + \sum_{\text{all}} \left|w_j T_j'\right|} \qquad [11]$$

K^1 allows canceling bias, but yields a common sign for the factor's global effect, K^2 avoids canceling bias, but loses the common sign of the factor's global influence.

The aggregate multiplicative decomposition is simply the set of factors implied by the weighted growth rates from equation [9]:

$$I(t) = P(0)A(0)T(0) * e^{\left(\sum_{\text{all } j} w_j P_j' + \sum_{\text{all } j} w_j A_j' + \sum_{\text{all } j} w_j T_j'\right) * t}$$

$$I(t) = P(0)A(0)T(0) * e^{t \sum_{\text{all } j} w_j P_j'} * e^{t \sum_{\text{all } j} w_j A_j'} * e^{t \sum_{\text{all } j} w_j T_j'} \qquad [12] \; \& \; [13]$$

Equation [13] is the aggregate multiplicative decomposition, where each of the final three terms represents the aggregate M_P, M_A, and M_T. There appears to be no direct way to avoid the cancellation problem in the multiplicative decomposition. Ang (1993), however, has proposed methods for measuring the magnitude of the cancellation effect in the context of industrial energy decompositions.

Note that the Divisia based aggregation is *not* equivalent to the aggregation method used in the recent population and environment literature (i.e. Bongaarts 1992; Harrison 1992), which is to weight the normalized contributions (Y_i) by their regional share in total emissions growth (i.e. $(I_j(T)-I_j(0))/(I(T)-I(0))$). Such a weighting is equivalent to weighting the right hand side terms in equation [9] by the share of *cumulative* emissions during the period, rather than the Divisia weight which is the *average* share of emissions during the period. In the standard method, the identities of equation [9] and equation [12] are not satisfied. However, if the regional shares are changing slowly enough the two weightings may be quite similar. Such is the case in the examples that we examine in the following sections.

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6 As with equation [3], a more complex model could substitute the elasticity derived expressions given in footnote 3 for the growth rates used here.

Example 1: Global Carbon Dioxide Emission from Fossil Fuels: 1965-1990

In this section we extend the decomposition of historical carbon dioxide emissions from fossil fuels to seven world regions. This source of emissions is a good focus area for studies of global warming both because of its important contribution to greenhouse warming, and because of the relatively high quality of the data available. It has been estimated that in 1990 carbon dioxide accounted for 57% of anthropogenic global warming, a figure that is likely to gradually increase as CFCs are phased out (MacKellar et al. 1996). Furthermore, over 80% of anthropogenic carbon dioxide emissions result from this source.

The seven regions are as defined according to World Bank categorizations. Data is from the World Bank (1992) and Marland et al. (1994).

Annual growth rate decomposition

Table 2 presents the results of the annual growth rate decomposition. Although the regional patterns of emissions change were quite varied, several broad patterns can be discerned. In South Asia, and the Middle East and North Africa, the relatively rapid growth in emissions can be assigned nearly equally to population growth, economic growth, and increasingly carbon intensive GNP. In East Asia, FSU and Eastern Europe, and Latin America, carbon intensity of GNP declined slowly during the period, slightly offsetting growth in the economy (which in East Asia, and FSU and Eastern Europe resulted mainly from consumption growth; in Latin America equally from population growth and consumption growth). At the extremes are the high income countries, where rapid economic growth was nearly fully offset by technological improvements, and Sub-Saharan Africa, where economic growth was stagnant and CO_2 intensity was increasing rapidly.

Looking at the weighted global average K values reveals income growth to have been the most important factor in determining the global emissions growth rate, accounting for 55% of the summed magnitudes of the factor growth rates. Population growth and technology growth were each nearly half as important as income growth, and with opposite signs. Based on this, one could make the useful (if somewhat simplistic) conclusion that population growth was enough to nearly nullify the effect of energy efficiency and cleaner technologies adopted during the period, leaving the emissions effect of per capita consumption growth unhindered.

Examining the MDC and LDC aggregations, we find that the global results mirror the MDC results fairly closely. This occurs simply because the two MDC regions (High Income and FSU and E. Europe) alone account for over 80% of the Divisia weighting. The LDC results are substantially different, however. In the LDCs, population growth accounts for a much greater share of the emissions growth rate (35%) and technology change has a positive, (albeit very small) impact on the growth rate.

Table 2. Fossil fuel CO_2 1965-1990. Annual growth rate decomposition.

	S-Saharan Africa	*East Asia*	*South Asia*	*M. East + N. Africa*	*Latin America*	*High Income*	*FSU + E.Europe*	*Whole World*	**Weighted Aggregates** *World*	*LDC*	*MDC*
Divisia Weights	0,7%	9,5%	2,5%	2,2%	4,0%	56,5%	24,8%				
Avg. annual growth rates											
Population	0,028	0,019	0,023	0,029	0,023	0,008	0,008	0,018	**0,011**	**0,004**	**0,006**
Income per capita	0,002	0,055	0,020	0,019	0,023	0,027	0,015	0,016	**0,026**	**0,007**	**0,019**
CO_2 intensity	0,037	-0,005	0,017	0,021	-0,006	-0,020	-0,001	-0,009	**-0,011**	**0,000**	**-0,012**
CO_2	0,068	0,070	0,061	0,068	0,041	0,015	0,022	0,026	**0,025**	**0,012**	**0,014**
Share in total factor change (K)										**K1 (with canceling)**	
Population	42%	25%	38%	42%	45%	14%	34%	42%	**22%**	**35%**	**17%**
Income per capita	4%	70%	34%	27%	45%	49%	64%	37%	**55%**	**60%**	**51%**
CO_2 intensity	55%	-6%	28%	30%	-11%	-37%	-3%	-21%	**-23%**	**4%**	**-31%**
										K2 (w/o canceling)	
									21%	**32%**	**17%**
									52%	**54%**	**51%**
									27%	**14%**	**31%**

The problem of bias from demographic heterogeneity can be seen by comparing the naive global calculation with the Divisia aggregated global calculation. The naive global calculation grossly overstates the role of population growth and understates the role of economic growth in determining the growth rate. This is the effect which was mentioned earlier; the global calculation places too much weight on developing regions' population growth, and not enough weight on developed regions' economic growth. Note that the standard MDC-LDC disaggregation avoids most of the heterogeneity bias observed in the global calculation. A two-region global calculation (not shown) yields K values within a percentage point of the seven-region values given here.

A good example of cancellation bias occurs in aggregating the CO_2 intensity factor during this period: Falling CO_2 intensities in East Asia and Latin America and the developed regions offset rises in CO_2 intensity in the remaining regions. The magnitude of this effect can be seen by examining the K values calculated according to equations [10] and [11]. In the LDCs, the net calculation underestimates the importance of CO_2 intensity change by over a factor of three. No canceling bias occurs in the MDCs during the period and globally the bias is minor.

Multiplicative Decomposition

Table 3 gives the multiplicative decomposition for the same period. The regional pattern of results are similar, with the important exception that the more rapidly growing variables appear to be relatively more important in driving emissions. For example, consider East Asia. Technology change forestalled a 12% rise in total emissions while income growth raised total emissions by over 295%. Thus one could say that economic growth was nearly 25 times as important as technology change during the period. Examining the annual growth rate decomposition in Table 2 would have shown economic growth to be only about ten times as important. Similar (although less dramatic) differences between the two approaches can be found for all regions.

Examining the weighted aggregates, we see that globally economic growth alone raised emissions by more than 92% during the period. This scaling was over three times as great as the 30% scale increase due to population and the 32% scale decrease due to declining CO_2 intensity during the period. Again, the multiplicative decomposition assigns greater importance to the more rapidly changing factors than the annual growth rate decomposition.

Table 3. Fossil fuel CO_2 1965-1990. Multiplicative decomposition.

	S-Saharan Africa	*East Asia*	*South Asia*	*M. East + N. Africa*	*Latin America*	*High Income*	*FSU + E.Europe*	*Whole World*	**Weighted Aggregates**		
									World	***LDC***	***MDC***
Divisia Weights	0,7%	9,5%	2,5%	2,2%	4,0%	56,5%	24,8%				
Scale Factor (M)											
Population	2,02	1,62	1,78	2,05	1,78	1,22	1,22	1,59	**1,30**	**1,74**	**1,22**
Income per capita	1,06	3,95	1,67	1,59	1,78	1,98	1,45	1,51	**1,92**	**2,55**	**1,80**
CO_2 intensity	2,54	0,89	1,53	1,68	0,87	0,60	0,98	0,79	**0,76**	**1,07**	**0,70**
Total	5,44	5,72	4,54	5,47	2,77	1,44	1,74	1,90	**1,89**	**4,73**	**1,53**
Percentage scaling (L)											
Population	102%	62%	78%	105%	78%	22%	22%	59%	**30%**	**74%**	**22%**
Income per capita	6%	295%	67%	59%	78%	98%	45%	51%	**92%**	**155%**	**80%**
CO_2 intensity	154%	-12%	53%	68%	-15%	-67%	-2%	-26%	**-32%**	**-7%**	**-43%**

Example 2: Projected Greenhouse Gas Emissions: 1990-2100

In this section we consider projected emissions of the three most important anthropogenic greenhouse gases: carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4). The gases have been weighted in term of their estimated 100-year *Global Warming Potential* (a measure of their ability to trap longwave radiation over 100 years) and are given in terms of their carbon equivalents. The per capita income and per capita emissions assumptions come from the IPCC's IS92a scenario (Pepper et al. 1992). The population projections are from IIASA's medium fertility, mortality and migration scenario (Lutz 1996). Global warming potentials are from Houghton et al. (1994).

Annual growth rate decomposition

The growth rate decomposition for the projected emissions is given in Table 4. Continued growth in income (1.6% globally) and improvements in carbon intensity (-1.4% globally) dominate the change in the emissions growth rate, globally and regionally. The only significant difference between the regions is that population growth remains an important factor in the LDCs (14% of the summed factor growth rates) because of continued population growth from population momentum. In the MDCs population growth is less than a tenth of a percent per year and only accounts for 2% of the summed factor growth rates.

Table 4. CO_2, CH_4, N_2O, 1990-2100. Annual growth decomposition.

		LDCs	*MDCs*	*Whole World*	***Divisia Aggregated World***
Divisia Weights		56%	45%		
Avg. annual growth rates					
	Population	0,007	0,001	0,006	**0,004**
	Income	0,025	0,015	0,016	**0,021**
	Carbon intensity	-0,020	-0,012	-0,014	**-0,017**
	Carbon	0,012	0,004	0,008	**0,008**
Share in total factor change (K)					
	Population	14%	2%	17%	**10%**
	Income	48%	55%	45%	**50%**
	Carbon intensity	-39%	-43%	-38%	**-40%**

Globally, economic growth and technological change are projected to be 4-5 times more important than population growth during this period. Heterogeneity bias remains significant during the period, with the single world calculation overestimating population's share of the emissions growth rate by nearly a factor of two. No cancellation bias occurs at this level of aggregation.

Multiplicative decomposition

Turning to the multiplicative decomposition (Table 5) we see how the 110 year time period attenuates the relative scale effects of the different annual growth rates. Globally, income growth is projected to scale emissions by over 900% during the period. This is nearly fifteen times the size of the scale effect due to population, and nearly twice the scale effect due to changes in carbon intensity. The long time period also attenuates the error due to heterogeneity. The naive global calculation underestimates L_A by over a factor of two.

Table 5. CO_2, CH_4, N_2O, 1990-2100. Multiplicative decomposition.

		LDCs	*MDCs*	*Whole World*	***Divisia Aggregated World***
Divisia Weights		56%	45%		
Scale Factors (M)					
	Population	2,20	1,06	1,96	**1,60**
	Income	16,02	5,29	5,93	**10,00**
	Carbon intensity	0,11	0,27	0,22	**0,16**
	Carbon	3,78	1,52	2,52	**2,54**
Percentage Scaling (L)					
	Population	120%	6%	96%	**60%**
	Income	1502%	429%	493%	**900%**
	Carbon intensity	-833%	271%	-360%	**-530%**

Conclusion

Even if a simple linear DI model is agreed upon -- that is one agrees to the choice of variables and to neglect potential interrelationships between them -- consistently decomposing the impacts into "contributions" of each of the variables to impact remains a surprisingly tricky business. Choice and interpretation of decomposition method, consistently comparing growing and declining factors, and avoiding aggregation biases are all important methodological concerns. If results from DI models are to be usefully compared in the literature, consistent methodology in these areas needs to be adopted. This paper has aimed to address this important problem.

This paper has also demonstrated that in a simple linear framework changes in historical and projected emissions of greenhouse gases are dominated by economic growth, and to a lesser degree technical change. Population change appears to play a significantly less important role. This conclusion, and the importance of time in compounding the relative importance of rapid income growth, is particularly emphasized in the multiplicative decomposition. It appears that future emissions, especially in the MDCs, will be determined largely by trends in future economic growth and technological change and *not* population growth.

While this is an important point it should not be misinterpreted or overstated. Decompositions are designed to compare the relative emissions effects of *total* change in these variables, and not necessarily the emissions effect of *feasible* change in the variables due to policies and the economic efficiency of such policies. While a comparison of the import of total change can be useful for policy purposes -- at worst, it indicates the limits to emissions control to be gained by policies affecting one variable, and at the best, it can accurately indicate where the significant gains in emissions control are to be found -- such analysis is no substitute for more policy specific analysis. Cost-benefit analyses, for example, have found population policy to be a very efficient strategy to control global warming. Birdsall (1992) compared the marginal costs of carbon abatement through reducing fertility in the developing world to technical abatement options, and found increased spending on population programs in the LDCs "likely to be part of any optimal carbon reduction strategy." Wexler (1995) extended this conclusion to MDC population policy as well, estimating the marginal greenhouse benefit per birth averted implied by the DICE macroeconomic model of global warming (Nordhaus 1994) in both the MDCs and the LDCs at on the order of thousands of dollars per birth.

Confusion on this point is one reason (among many) why ecologists such as Ehrlich and Ehrlich (1990) can describe the United States as "the world's most overpopulated nation", at the same time that the majority of economists and demographers primarily locate the "population-environment problem" solely in the developing world. The former view comes from thinking in efficiency terms: The marginal environmental benefit of reducing fertility in the United States, with its very high per capita resource use may be an order of magnitude higher than in many developing countries, and a very efficient lever with which to control environmental impact. The latter view comes from thinking in total terms: Halting US population growth, by itself, will do far less for the environment than the mix of policies that affect consumption growth, technology, and the more rapid population growth in the developing world. In fact, both views are correct and recognizing this would alleviate a good portion of needless debate in an already highly polarized field.

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