The Impact of Demographic Dynamics on Natural Resources

A Discussion within the Framework of Input-Output Models

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1 Introduction

In 1970 the *U.S. Commission on Population Growth and the American Future* asked the research organization *Resources for the Future* to undertake a project to identify the principal resource and environmental consequences of future population growth in the United States. Two years later, the results of the research were published in the volume *Population, Resources, and the Environment*, edited by Ronald G. Ridker [24]. The project represented an important attempt to assess the environmental consequences of population, economic and technological dynamics under several different assumptions.

More than 30 years later, the scientific community is still debating on the same issues. A vast literature has been formed and a good deal of knowledge has been accumulated since the 1970s; however, the mechanisms through which population dynamics affects the environment and the feedback response from the environment on populations are still unclear.

The model developed by *Resources for the Future* is based on a set of standard input-output equations and turns out to be a powerful tool to investigate the consequences of population growth on resource requirements. Personal consumption expenditures provide one of the key linkages between changes in demographic characteristics and the resource and environmental consequences of these changes.

This paper is inspired by the economic input-output modeling proposed by *Resources for the Future* and more recent developments in the field of integrated economic input-output modeling and life cycle analysis methods (Hendrickson et al., 2006).

The first part of the paper discusses the model and the role of demographic dynamics within the framework of the stable population model. The second part is dedicated to the estimation of consumption patterns by age and to the evaluation of the impact of demographic trends, in terms of comparative statics, on energy requirement and emission of greenhouse gases. The third part provides a discussion of model in the context of urn processes and path-dependence.

2 The model

2.1 The input-output approach

The input-output approach to model the economy and its environmental requirements dates back to the pioneering work of Leontief (1970, 1986). In what follows we briefly give a representation of an input-output model, as it appears in Hendrickson et al. (2006), and we introduce the role of demography within an input-output framework.

Consider an economy with m sectors, indexed by i. The total sector output in monetary terms, O_i, can be written as:

$$O_i = z_{i1} + z_{i2} + \cdots + z_{im} + d_i \tag{1}$$

where z_{ij} is the (monetary) flow of goods from sector i to sector j and d_i is the final demand for the good i. The model is typically rewritten in order to represent the flows between sectors as a percentage of sectoral output. Thus, if we write:

$$q_{ij} = \frac{z_{ij}}{O_j}$$

the model can be expressed as:

$$O_i = q_{i1}O_1 + q_{i2}O_2 + \cdots + q_{im}O_m + d_i \tag{2}$$

or, equivalently:

$$-q_{i1}O_1 - q_{i2}O_2 - \cdots + (1 - q_{ii})O_i - \cdots - q_{im}O_m = d_i \tag{3}$$

By letting Q be the matrix containing all the coefficients q_{ij}, o the vector containing all the output O_i terms, and d the vector of final demands d_i, the model can be written in matrix form as:

$$o - Qo = [I - Q]o = d \tag{4}$$

This way, given the vector of final demands, and the matrix of coefficients q_{ij}, the vector of outputs by sector can be obtained as:

$$o = [I - Q]^{-1}d \tag{5}$$

Hendrickson et al. (2006) make use of this model to evaluate human environmental impact. In particular, they provide estimates for a set of coefficients that transform economic output of each sector into 'direct environmental impact'. They then multiply the output at each stage by the environmental impact per dollar of output:

$$b = Ro = R[I - Q]^{-1}d \tag{6}$$

b is the $m \times 1$ vector of environmental burdens (such as toxic emissions or electricity use) for each production sector; R is a $m \times m$ matrix with diagonal elements representing the impact per dollar of output for each stage. Alternatively, if we would like b to be a scalar representing the overall environmental burden (in terms of carbon dioxide emissions or energy use, etc.), we can substitute the $m \times m$ matrix R with the $1 \times m$ vector that contains the elements on the main diagonal of R.

The role of demographic factors can be analyzed within this conceptual framework. For instance, we can write

$$d = CK \tag{7}$$

where

$$d = \begin{bmatrix} d_1 \\ d_2 \\ \cdot \\ \cdot \\ d_m \end{bmatrix}$$

$$C = \begin{bmatrix} {}_5C_0^1 & {}_5C_{10}^1 & \cdot & \cdot & {}_5C_{110}^1 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ {}_5C_0^m & \cdot & \cdot & \cdot & {}_5C_{110}^m \end{bmatrix}$$

$$K = \begin{bmatrix} {}_5K_0 \\ {}_5K_{10} \\ \cdot \\ \cdot \\ {}_5K_{110} \end{bmatrix}$$

C is a matrix whose row i represents the profile of average consumption by age for the output produced in sector i. ${}_nK_x$ is a vector whose elements represent the number of people whose age is between x and $x + n$.

The model thus becomes:

$$b = R[I - Q]^{-1}CK \tag{8}$$

Such a model is a generalization of the well-known IPAT equation (Ehrlich and Holdren, 1971; Commoner, 1972), that simply states that environmental impact (I) is the product of population (P), affluence (A), and technology (T):

$$I = P \times A \times T \tag{9}$$

In the input-output model, b is the environmental impact. K has the role of P, that is the demographic factor. C is the level of affluence: it depicts the level of consumption for the population. Such a term is 'weighted' by $[I-Q]^{-1}$ in order to differentiate consumption according to the sectors of the economy to which we can impute the production of the final goods. Finally, R is the term that is analogous to T and it expresses the 'impact' per unit of production in each sector. We may think of our input-output model as a generalization of the IPAT equation to a multi-sector economy. When we consider an economy with only one sector, the model basically reduces to the one depicted by the IPAT equation.

2.2 Demographic and Economic growth

In this section we try to get some insights on the effects of demographic and economic dynamics on the environment (for instance in terms of consumption of natural resources), within the framework of the input-output model described in the previous section. We use two stylized representations of the demographic and economic world, namely a stable population and the Solow model of economic growth.

Since we assume that the population has a stable age structure, a good linear approximation for the population growth rate is given by

$$\frac{\dot{P}}{P} = r \approx \frac{\ln(NRR)}{a_f} \tag{10}$$

where NRR is the net reproduction ratio and a_f is the mean age at childbearing.

The assumption that the Solow model well describes the economic growth process implies that the GDP is modeled according to an aggregate production function that takes the Cobb-Douglas form:

$$Y_t = \Gamma_t {M_t}^{\alpha} {L_t}^{1-\alpha}, 0 < \alpha < 1 \tag{11}$$

where M_t is capital input, L_t is labor input and Γ_t is a measure of the level of technology or productive efficiency. The subscript t stands for time.

Technological progress grows at a rate g:

$$\frac{\dot{\Gamma}_t}{\Gamma_t} = g \tag{12}$$

Labor input grows at a rate r, equal to the population growth rate, since we assume a stable age structure:

$$\frac{\dot{L}_t}{L_t} = r \approx \frac{\ln(NRR)}{a_f} \tag{13}$$

The Solow-model economy tends to converge over time to a steady-state growth path such that:

$$\frac{\dot{Y}_t}{Y_t} = \frac{g}{1-\alpha} + r \tag{14}$$

The growth rate of technology, g, together with the factor controlling for the extent of diminishing marginal returns to capital, α, are the determinants of the growth rate of output per worker.

If we assume that the consumption profile by age at time t, C_t, for the goods produced in the economy, is a fraction of the GDP of the country, cY_t, then we have:

$$C_t = C_0 e^{(\frac{g}{1-\alpha}+r)t} \tag{15}$$

The population, on the other hand, grows at a rate r:

$$K_t = K_0 e^{rt} \tag{16}$$

If we plug equations 15 and 16 into 8, we find that the vector of environmental burdens, b, grows at a rate $(\frac{g}{1-\alpha} + 2r)$:

$$\frac{\dot{b}_t}{b_t} = \frac{g}{1-\alpha} + 2r \tag{17}$$

This is true provided that the technological and economic progress do not influence the relative prices of production or, in other words, that the structure of the economy does not change. Another underlying assumption is that the environmental impact per unit of production in each sector stays constant.

These hypotheses are related to the linearity of the model and are realistic for short term analyses or for the interpretation of early stages of environmental disruption due to the introduction of a new ‘pollutant’. In the long term nonlinearities should be taken into account.

Consider, as an example, the use of methyl bromide as an agricultural soil fumigant for controlling a wide variety of pests, or the use of chlorofluorocarbons (CFCs) as air conditioners, refrigerator coolants or aerosol can propellants. In these two situations, on the one hand, the introduction of new technologies into the production process allowed for gains in efficiency and fueled economic growth. On the other hand, it had negative effects on the environment, since it contributed to the depletion of the ozone layer. As long as the effects of the dispersion of substances like CFCs or methyl bromide into the atmosphere did not have any perceivable impact on the ozone layer, technological progress based on those chemical elements kept on fueling economic growth, on the one hand, and depleting the ozone layer, on the other hand. It is only when the use of these technologies became widespread, the hole in the ozone layer increased to a considerable size (enough to have an impact on human health), and a causal relationship between emission of those chemical elements and disruption of the ozone layer was proven, that technological progress in the sectors became more environmentally oriented. Production systems started to be conceived with the aim of minimizing the dispersion of such gases into the atmosphere, and substitutes for those substances and processes were discovered. This means that, after a certain point, economic progress and sustainability in the sectors considered became positively related, implying that, after a certain threshold, nonlinearities play a considerable role.

2.3 The impact of a change in mortality levels

In this section we consider the effect of changes in mortality on environmental burdens: increases in life expectancy at birth bring about increases in the number of consumers and the labor force, thus expanding economic production and environmental burdens.

We set up the analysis within the framework of a stable population: in such a context, the growth rate of population and labor force are affected in the same manner by an increase of life expectancy at birth.

By plugging equation 13 into 17 we represent the growth rate of environmental burdens as:

$$\frac{\dot{b}_t}{b_t} \approx \frac{g}{1-\alpha} + 2\frac{\ln(p(a_f) \times F \times f_{fab})}{a_f} \tag{18}$$

where F is the total fertility rate, f_{fab} is the fraction of females at birth and $p(a_f)$ is the proportion of female births surviving to the mean age at childbearing.

Lee (1994) discussed an approach to the study of the formal demography of aging: among others, he quantified the effect of changes of fertility and mortality on the growth rate of a stable population. if we apply that approach to our case we see that the effect on the growth rate of carbon dioxide emissions of a change in mortality, indexed by i, is:

$$\frac{\partial \frac{\dot{b}_t}{b_t}}{\partial i} \approx 2\frac{\partial p(a_f)/\partial i}{p(a_f) \times a_f} \tag{19}$$

The impact of a change in mortality on population growth is independent of the level of fertility: mortality decline, for instance, is associated with increasing $p(x)$. The effect on the age distribution is ambiguous, though. At the individual level, people live longer and thus the population gets older. However, at the population level, lower mortality means also that more women survive to the childbearing age, thus making the population younger.

Consider a stable population with radix l_0 equal to 1: the proportion of people whose age is between x and $x+n$ may be written as

$$\frac{{}_nK_x}{{}_\infty K_0} = \eta({}_nL_x)e^{-rx} = \frac{\eta n}{2}(p(x)+p(x+n))e^{-rx} \tag{20}$$

where ${}_nK_x$ is the number of people whose age is between x and $x+n$ in a stable population, ${}_\infty K_0$ is the size of the population, η is the birth rate, ${}_nL_x$ is the number of person-years lived between age x and $x+n$, $p(x)$ is the probability to survive until age x, r is the intrinsic growth rate.

Let i be an index of the level of mortality: the effect on ${}_nK_x/{}_\infty K_0$ of a change in mortality is given by its partial derivative with respect to i

$$\frac{\partial(\frac{{}_nK_x}{{}_\infty K_0})}{\partial i} \approx \frac{\eta n}{2}[(\frac{\partial p(x)}{\partial i}+\frac{\partial p(x+n)}{\partial i})e^{-rx} - x(p(x)+p(x+n))\frac{\partial p(a_f)/\partial i}{p(a_f)*a_f}e^{-rx}] \tag{21}$$

The age structure of the population plays an important role in our model of environmental burdens: given an age profile of consumption, the age structure determines the level of environmental burdens.

2.4 The impact of a change in fertility levels

The analysis discussed in the previous section in the context of mortality changes can be done also with respect to fertility (Lee, 1994). Fertility changes affect the rate of growth of a population, r, but not the probability of survivorship, $p(x)$. In terms of age structure, higher fertility is associated with increasing size of more recently born cohorts, relative to older ones, and it thus makes the population younger. Formally:

$$\frac{\partial r}{\partial F} \approx \frac{1}{F \times a_f} \tag{22}$$

Thus:

$$\frac{\partial \frac{\dot{b}_t}{b_t}}{\partial F} \approx \frac{2}{F \times a_f} \tag{23}$$

When we look at the effect of fertility change on the age structure we find that:

$$\frac{\partial(\frac{{}_nK_x}{{}_\infty K_0})}{\partial i} \approx \frac{n}{2}(p(x)+p(x+n))(\frac{\partial \eta}{\partial F} - \frac{\eta x}{a_f F})e^{-rx} \tag{24}$$

It is important to mention that, for this formal exercise, we do not take into account the effect of changes in fertility on the average household size: the presence of economies of scale at the household level may partially counteract the effect of changes in fertility levels.

3 Empirical analysis

In this section we try to estimate the effect of changing population age structure on environmental burdens. We refer our analysis to the United States: we make estimates of consumption profiles by age and we use the model developed by Hendrickson et al. (2006) to assess the impact of demographic changes on environmental burdens.

3.1 Data

The empirical analysis focuses on the United States: we estimate a consumption profile by age by using data from the Consumer Expenditure Survey (2003), provided by the Bureau of Labor Statistics of the U.S. Department of Labor. The survey provides data on the amount of money spent on several consumption goods and services by household units. Demographic and economic variables for household units are also collected.

3.2 Methods

Given data on consumption of several items by household units, our goal is to assign to each member of the household his/her share of consumption (in monetary terms). We also would like to estimate the extent of economies of scale and to separate the income effects from purely demographic effects.

Our first approach consists of modeling household consumption of goods and services as an additive function of the consumption of its members. This method has been used, for instance, by Mankiw and Weil (1989) to model demand for housing.

Let c_{ij} be the consumption of good i by household j. Then,

$$c_{ij} = \sum_{k=1}^{M} c_{ijk} \tag{25}$$

where c_{ijk} is the demand of the kth member and M is the total number of people in the household.

The consumption of the good i for each individual is a function of age: each age has its own consumption parameter, so that an individual demand is given by:

$$c_{ijk} = \beta_0 Ind(0)_k + \beta_1 Ind(1)_k + \cdots + \beta_{80} Ind(80)_k \tag{26}$$

where:

$$Ind(h)_k = \begin{cases} 1 & \text{if age of individual k is equal to h} \\ 0 & \text{otherwise} \end{cases}$$

The parameter β_h is the amount of consumption demanded by a person of age h. Combining equation 25 with 26 we obtain the equation for household consumption:

$$c_{ij} = \beta_0 \sum_k Ind(0)_k + \beta_1 \sum_k Ind(1)_k + \cdots + \beta_{80} \sum_k Ind(80)_k \qquad (27)$$

The parameters of equation 27 can be estimated by using the least squares technique. After appropriately smoothing the sequence of estimated parameters over age, we get a consumption profile by age for the good i.

To the extent that there are not economies of scale in household consumption (or they are negligible) and to the extent that household formation is fairly constant, this approach should be accurate.

If we want to separate the effect of age from the one of income, we can use the same method applied to fraction of household expenditures, instead of overall consumption.

In order to assess the importance of economies of scale, we can estimate an equivalence scale that takes into account the fact that children consume less than adults and that living arrangements with more than one person may be more efficient.

Let n_{cj}, n_{aj}, n_{ej} be, respectively, the number of children, adults and elderly that live in household j, where we define children those people whose age is between 0 and 14 years, adults those between 15 and 64 and elderly those whose age is 65 and over; let S_{ia} and S_{ie} be respectively the average consumption of good i by adults and elderly who live alone. Then we can write an equivalence scale as:

$$c_{ij} = (n_{cj}\gamma_i S_{ia} + n_{aj} S_{ia} + n_{ej} S_{ie})^{\theta_i} + \epsilon_j \qquad (28)$$

where γ_i is a parameter that represents the relative consumption of children, with respect to adults, within households: $\gamma_i = 0$ means that only adults are considered responsible for the consumption of the good i; $\gamma_i = 1$ means that no distinction is made between adults and children in terms of consumption of the good i. θ_i is a parameter that represents the extent of economies of scale from cohabitation for the good i: $\theta_i < 1$ means that cohabitation generates economies of scale; $\theta_i > 1$ means that cohabitation generates diseconomies of scale. ϵ_j is an error term.

We can estimate the parameters γ_i and θ_i for the different consumption goods by using the least squares technique. Given the values for S_{ia} and S_{ie}, we chose the pair ($\hat{\gamma_i}$, $\hat{\theta_i}$) such that:

$$(\hat{\gamma_i}, \hat{\theta_i}) = argmin_{\hat{\gamma_i},\hat{\theta_i}} \sum_j \left(c_{ij} - (n_{cj}\gamma_i S_{ia} + n_{aj} S_{ia} + n_{ej} S_{ie})^{\theta_i}\right)^2 \qquad (29)$$

A consumption profile can be then estimated from the equivalence scale. We can assume that, within a family, the relative consumption of good i by the elderly, with respect to the adults, is the same as the one observed for singles, that is $\frac{S_{ie}}{S_{ia}} = \hat{\psi}_i$. Then the equivalence scale becomes:

$$c_{ij} = (n_{cj}\hat{\gamma}_i cons_{ija} + n_{aj} cons_{ija} + n_{ej}\hat{\psi}_i cons_{ija})^{\hat{\theta}_i} \quad (30)$$

where $cons_{ija}$ is the average consumption of good i by an adult in the household j. It can be retrieved as

$$cons_{ija} = \frac{c_{ij}^{(1/\hat{\theta}_i)}}{n_{cj}\hat{\gamma}_i + n_{aj} + n_{ej}\hat{\psi}_i} \quad (31)$$

Then, for the household j, the average consumption of a child will be $cons_{ija}\hat{\gamma}_i$ and the average consumption of an old person will be $cons_{ija}\hat{\psi}_i$. For each household, the consumption of the good i can be divided among its members this way. Then we can compute the average consumption by age and get a smooth profile of consumption by age.

3.3 Confidence intervals for the parameters of the equivalence scale

In this section we deal with the problem of evaluating the uncertainty for the parameters of the equivalence scale that we introduced in equation 28. The model is a nonlinear model with two parameters, γ and θ. Estimates of the parameters are obtained using the method of least squares. In practice, this involves a preliminary grid search on a set of admissible values. The results of the grid search are then used as a starting point for the implementation of a Gauss-Newton algorithm.

Once point estimates for the parameters are obtained, $\hat{\gamma}_i$ and $\hat{\theta}_i$, then the problem of the evaluation of their uncertainty arises. The assessment of uncertainty about parameter values can be made using confidence intervals. For linear models, a well developed and elegant theory has been developed (see, for instance, Seber, 1977). In the context of nonlinear models, linear approximations may be used to evaluate the uncertainty of the estimates: such local approximations may be more or less accurate depending on the relevance of nonlinearities (see, for instance, Seber and Wild, 1989). Alternatively, resampling methods, such as the bootstrap (Efron and Tibshirani, 1993) are very useful for estimating the accuracy of an estimator. In this section we follow closely the discussion of confidence intervals for nonlinear models given in Huet et al. (2003) and we draw some elements from Seber and Wild (1989) and the vast literature that has been formed on resampling techniques.

3.3.1 Asymptotic confidence intervals

In this section we descibe how to calculate confidence intervals for a parameter of a nonlinear model within the framework of classical asymptotic theory. Consider the parameter θ of the model we described in equation 28 (the same reasoning applies to the parameter γ). $\hat{\theta}_i$ is a function of c_{ij} and when the number of observations tends to infinity, according to results from classical asymptotic theory, $\hat{\theta}_i$ - θ tends to 0, and $\sigma_{\hat{\theta}_i}^{-1}(\hat{\theta}_i - \theta)$ is distributed according to a normal distribution with expectation 0 and variance 1, where $\sigma_{\hat{\theta}_i}$ is the estimated asymptotic variance of θ.

Now, consider:

$$\hat{T} = \frac{\hat{\theta} - \theta}{\hat{s}}$$

where $\hat{s}$ is an estimate of the standard error of θ. If the distribution of $\hat{T}$ were known, say $F(u) = Pr(\hat{T} \leq u)$, then we would calculate the $\alpha/2$ and $1 - \alpha/2$ percentiles of $\hat{T}$, say u_α, $u_{1-\alpha/2}$, and we would obtain the $(1 - \alpha)$ confidence interval for θ as $[\hat{\theta} - u_{1-\alpha/2}\hat{s}; \hat{\theta} - u_{\alpha/2}\hat{s}]$. We can approximate the distribution of $\hat{T}$ when the number of observations, N, is large. By analogy to the Gaussian linear regression case, a $(1 - \alpha)$ confidence interval for θ is given by:

$$\hat{C.I.}_{\tau} = [\hat{\theta} - \sqrt{\frac{N}{N-p}} t_{1-\alpha/2}\hat{s}; \hat{\theta} + \sqrt{\frac{N}{N-p}} t_{1-\alpha/2}\hat{s}] \qquad (32)$$

where t_α is the α percentile of a Student random variable with $(N-p)$ degrees of freedom.

Alternatively, we can build a confidence interval with the same asymptotic level of $\hat{C.I.}_{\tau}$, $(1 - \alpha)$, that is based on the quantiles of the Gaussian distribution. Let ν_α be the α percentile of a random variable that is distributed according to a Gaussian distribution with mean 0 and variance 1, then we can deduce a confidence interval for θ as:

$$\hat{C.I.}_{G} = [\hat{\theta} - \nu_{1-\alpha/2}\hat{s}; \hat{\theta} + \nu_{1-\alpha/2}\hat{s}] \qquad (33)$$

$\hat{C.I.}_{\tau}$ and $\hat{C.I.}_{G}$ are both symmetric around $\hat{\theta}$ and have the same asymptotic level, but $\hat{C.I.}_{\tau}$ is wider than $\hat{C.I.}_{G}$ and it thus has a larger coverage probability. It has been shown that $\hat{C.I.}_{\tau}$ has a coverage probability that is closer to $(1 - \alpha)$ than $\hat{C.I.}_{G}$ (Huet et al., 1989).

3.3.2 Bootstrap confidence intervals

Resampling methods, such as the bootstrap and the jackknife, are powerful and useful techniques for estimating the accuracy of an estimator. The bootstrap has had an enormous impact on statistical applications and it has refocused some of the theory in statistics (Casella, 2003). The journal *Statistical Science* dedicated a volume in 2003, "Silver anniversary of the bootstrap", to the discussion of the impact of the bootstrap since the seminal work of Efron (1979). The voulme discusses the impact of bootstrap on several branches of statistics, from sample surveys (Shao, 2003; Lahiri, 2003) to time series (Politis, 2003) and phylogenetic trees (Holmes, 2003; Soltis et al., 2003). In the context of regression analysis, there is a vast literature on the use of bootstrap, jackknife and other resampling methods (e.g. Freedman, 1981; Wu, 1986). Assesment of confidence intervals by using the bootstrap is also widely discussed in the literature (e.g. Hall, 1986, 1986b, 1988; Efron and Tibshirani, 1993; Seber and Wild, 1989; Huet et al., 1989; Huet et al., 2003).

Bootstrap methods represent a way to mimic the repetition of an experiment: estimations are based on estimates of the parameters obtained from artificial bootstrap samples. Recall our equivalence scale model for consumption of the good i by the household j:

$$c_{ij} = (n_{cj}\gamma_i S_{ia} + n_{aj} S_{ia} + n_{ej} S_{ie})^{\theta_i} + \epsilon_j$$

For every bootstrap simulation we have that:

$$c^\star_{ij} = (n_{cj}\hat{\gamma}_i S_{ia} + n_{aj} S_{ia} + n_{ej} S_{ie})^{\hat{\theta}_i} + \epsilon^\star_j \tag{34}$$

The errors $\epsilon^\star_j$ are simulated in the following way: let $\hat{\epsilon_j} = c_{ij} - (n_{cj}\gamma_i S_{ia} + n_{aj} S_{ia} + n_{ej} S_{ie})^{\theta_i}$ be the residuals, and let $\tilde{\epsilon_j} = \hat{\epsilon_j} - \hat{\epsilon}.$ be the centered residuals, where $\hat{\epsilon}.$ is the sample mean of the residuals. The set of $\epsilon^\star_j$, for the N observations, is a random sample from the empirical distribution function based on the $\tilde{\epsilon_j}$. In other words, we draw with replacement N times from $\tilde{\epsilon_j}$ in order to obtain a set of $\epsilon^\star_j$. The pair $(\hat{\gamma^\star_i}, \hat{\theta^\star_i})$ is obtained such that:

$$(\hat{\gamma^\star_i}, \hat{\theta^\star_i}) = argmin_{\hat{\gamma^\star_i}, \hat{\theta^\star_i}} \sum_j \left(c^\star_{ij} - (n_{cj}\hat{\gamma}_i S_{ia} + n_{aj} S_{ia} + n_{ej} S_{ie})^{\hat{\theta}_i}\right)^2 \tag{35}$$

Consider the parameter θ (the same reasoning applies to the parameter γ). Let B be the number of bootstrap simulations, then we will obtain B bootstrap estimates for the parameter we are interested in: say, $\hat{\theta^{\star,1}}, \hat{\theta^{\star,2}} \ldots, \hat{\theta^{\star,B}}$. The relevant result is that the distribution of $\hat{\theta^{\star,1}}$, estimated by the empirical distribution function of the bootstrap estimates of θ, approximates the distribution of $\hat{\theta}$. Let

$$\hat{T^\star} = \frac{\hat{\theta^\star} - \hat{\theta}}{s_{\hat{\theta^\star}}}$$

then the difference between $\hat{T}$ and $\hat{T^\star}$ tends to 0 when the number of observations is large. This means that confidence intervals can be computed using the quantiles of $\hat{T^\star}$ instead of those of $\hat{T}$. Let b_α be the α percentile of $\hat{T^\star}$, then $\Pr(\hat{T} \leq b_\alpha)$ tends to α when n tends to infinity. The bootstrap confidence interval for θ can thus be calculated as follows:

$$\hat{C.I.}_B = [\hat{\theta} - b_{1-\alpha/2}\hat{s}^\star; \hat{\theta} - b_{\alpha/2}\hat{s}^\star] \tag{36}$$

where $\hat{s}^\star$ is the sample standard deviation of the bootstrap estimates for θ.

3.4 Results

3.4.1 Consumption profiles by age

Figures 1 to 8 show estimates of consumption profiles by age for several consumption goods. For each good, the consumption profile has been estimated with both the method based on the construction of equivalence scales and the linear method that relies on the use of indicator functions. The linear approach has been applied to fraction of household expenditure as well, in order to get insights on the role of income effects. Table 1 gives average consumption of several consumption goods for adults living alone and for elderly living alone in the U.S.. Table 2 gives the least-squares estimates for the parameters of the equivalence scales for several consumption goods, together with their bootstrap 95% confidence intervals.

In this section we would like to focus on some interesting aspects that emerge from the estimates. First, it is interesting to note that the two different methods give estimates that in most cases are consistent. We observe that individual consumption tends to increase with age until the person reaches the adult state of life. For some goods such as electricity, natural gas or home nursing, consumption increases with age also for the elderly. For other goods such as gasoline, airfare and number of vehicles owned, consumption declines with age after the adult stage of life. It is interesting to note that some of the upward trend in consumption of goods is probably driven by levels of income by age. For instance, the profile of consumption of food at home by age is pretty flat after around age 50; however the proportion of income devoted to food at home keeps on increasing after age 50. The consumption of air flights declines with age for the elderly; however, their proportion of income devoted to air flights remains pretty much constant.

Home nursing (see figure 8) is a case for which the results obtained with the linear approach are different than the ones obtained with the equivalence scale approach: the method based on equivalence scales gives an estimate of old age consumption that is much bigger that the one obtained from the linear method. The reason for such a deviation is probably related to the fact that consumption profiles obtained from equivalence scales rely on the hypothesis that the relative proportion of adult consumption with respect to elderly, in a household, is the same as the one observed for people who live alone. This is a reasonable assumption for most goods, but may not be as appropriate for the case of nursing home. As a matter of fact, there could be big differences in the demand for nursing home depending on whether people live alone or with other household members.

For the method based on the equivalence scale, we constrained the parameters to be positive. The idea behind the equivalence scale approach is to allocate the observed consumption of a household to its members. On the other hand, we do not impose constraints on the linear approach: we can interpret the negative values that we obtain for $\hat{\gamma}$ in some circumstances as the negative impact on consumption of a specific good associated to the presence of children in a household. For instance, the presence of children in a household may have a negative impact on the number of cigarettes smoked by adults or the amount of money spent on air flights.

3.4.2 The environmental consequences of aging

In this section we would like to discuss the role of aging and age distribution on energy requirements and carbon dioxide emissions. Consumption profiles represent the mediating factor between population dynamics and environmental impact.

When we consider a population, it is difficult to separate out the effect of fertility and mortality on the age structure. In order to get insights on the effect of mortality alone, for instance, we can assume that the population is in a stable state, so that we can observe the effect of a change in mortality, given all other things equal.

Consider, for instance, the population of the United States and construct its Leslie matrix. By projecting the U.S. population over a long period, say 200 years, we can get the stable age structure associated with the current vital rates. We can then repeat the simulation by maintaining everything equal except for the ${}_nL_x$ schedule: we may want to know, for instance, how the stable age distribution would change if the current level of mortality were the one of the 1930s.

We consider the U.S. population in 2001 and in 1933: we use the female life tables provided by the Human Mortality Database and the fertility rates provided by the U.S. Census Bureau to construct a Leslie matrix based on the vital rates of 2001 and a Leslie matrix based on fertility rates of 2001 and mortality rates of 1933. The two Leslie matrices lead to the stable age structures shown in figure 9: the two profiles show the impact of an increase in life expectancy at birth of 16.7 years, from a starting value of 63.02 years to a value of 79.68, given the U.S. age-specific fertility rates of 2001.

Figure 9 shows the net effect of aging on the age structure, independently of its growth rate effect. Given our estimates of consumption profiles based on the equivalence scale, we can do some comparative statics: the change in the age structure is associated to a modest reduction of consumption of gasoline (-0.7%) and tobacco products (-2%). On the other hand, this reduction in consumption would be more than counteracted by the increase in consumption of other energy intensive goods. Consumption of electricity and gas would increase by about 4% and spending in air flights would increase by about 1%. In terms of vehicles owned, we could expect an increase of the order of 1%.

The changes that we present are related only to the age distribution of a population and not to its size. We also would like to remind the reader that the numbers that we obtain are the result of an exercise of comparative statics and are not a forecast of the effect of a change in life expectancy on consumption of certain goods. Finally, it is important to notice that we do not take into account the fact that aging may have an impact on economic growth and saving rates: according to classical life cycle models, aging would reduce the overall level of savings in a population (see, for instance, Borsch-Supan, 2005) and may thus imply a reduction of carbon emissions (Dalton et al., 2008).

If we consider the population of the United States in 2007 and its forecast for 2050 according to the U.S. Census Bureau, we can repeat the comparative statics exercise on these figures in order to get an idea of the effects of changing age structure and size over the next decades, all other factors held constant. In this case both the change in the age structure and the change in population size puts pressures on energy requirements, with the changing population size driving the trend. The overall consumption of electricity and natural gas would increase by about 44%; the consumption of gasoline would increase by about 35% and that of air flights by 39%. Consumption of tobacco products would increase by about 33%. Now, if we look at changes in consumption that are related only to different age distributions over the period, holding the population size constant, then from the comparative statics exercise we observe an increase in consumption of natural gas and electricity of about 4%. Air flight consumption would increase by 1%. Gasoline and tobacco products consumption would decrease by, respectively, about 2% and 4%.

Changes in consumption of one specific good leads to changes in levels of production in several sectors, according to our input-output economic model. We thus may want to explore the consequences of changing levels of consumption of certain goods on the overall energy requirements and greenhouse gases emissions for a country. In order to account for inter-sectoral flows, we use the model discussed in Hendrickson et al. (2006), and developed at Carnegie Mellon University [3], to estimate the impact of these changes in consumption on environmental burdens.

If we consider electricity, for instance, we observe that an increase in consumption would affect, by order of importance, the power generation and supply sector, oil and gas extraction, stone mining and quarrying, rail transportation, etc. An increase of about 4% in electricity consumption would result, for a country like the US, in additional consumption of 4523 millions of dollars, which means an increase of emissions of carbon dioxide of 45.3 million metric tons. The same percentage change of natural gas consumption would result in additional consumption of 2983 millions of dollars and that would imply additional emissions of carbon dioxide in the order of 4.2 million metric tons only from extraction and distribution of natural gas. The 1% increase in air flights expenditures (or 512 millions of dollars) would translate into an extra 0.86 million metric tons of carbon dioxide emissions. On the other hand, the changing age distribution would entail a reduction of gasoline consumption by 1% (or 919 millions of dollars): this would involve a reduction of carbon dioxide emissions of 0.53 million metric tons from oil extraction and distribution.

The comparative statics exercise gives us a general idea of the importance of a demographic factor such as the age distribution in the explanation of energy requirements and carbon dioxide emissions of an economy such as the one of the United States. The impact of a changing age distribution is not extremely large if we consider that the annual total level of carbon dioxide emissions for the US is in the order of 6000 million metric tons and that large gains in terms of life expectancy may occur through a rather long period of time. The combined effect of changing age distribution and population growth for a forecasted period of about 40 years is much larger, in the order of ten times more than the age distribution by itself.

4 A discussion of the model in the context of urn processes

In the previous parts of the paper we discussed a static model of environmental impact based on the economic input-output approach, and we tried to get some insights on the impact of demographic trends by means of comparative statics exercises. In this section we would like to give some interpretation of the equilibria that we were considering by discussing them within the context of urn processes. First, we will give a brief introduction to urn processes and path-dependence theory. Second, we will discuss two simple simulations of path-dependent processes in absence and presence of feedback mechanisms.

4.1 Path-dependency and urn processes

The concept of increasing returns has a long history in economic analysis. However, a formal analysis of positive feedbacks and early random influences on long term economic outcomes has been developed recently, starting in the early eighties, in a series of papers by Arthur, Kaniovski and Ermoliev (see for instance Arthur, 1994). They interpret path dependence in terms of non-ergodicity of a stochastic process and they build a generalization of the Polya urn process.

The concept of urn processes is quite intuitive. Consider an urn of infinite capacity with balls of two different colors, say color 1 and color 2 (the generalization to N colors is straightforward). Let X_n be the proportion of balls of color 1 at stage n, and let X_0 be equal to 0.5: we start the process with one ball of color 1 and one ball of color 2 in the urn. Let w be the total number of balls contained in the urn and let f be a mapping from the unit interval to itself. We assume that at every step a ball of color 1 is is added to the urn with probability $f(y)$ and a ball of color 2 is added with probability $1 - f(y)$. We obtain X_1 as the updated proportion of balls of color 1 and we iterate the procedure to generate an urn process. Let B_n be a binary random variable such that

$$B_n = \begin{cases} 1 & \text{if the } n^{th} \text{ ball added to the urn is of color 1} \\ \\ 0 & \text{otherwise} \end{cases}$$

Given X_n, B_n is chosen independently of all other choices according to the response function f. The number of balls of color 1 at step $n + 1$ may be written as $(w + n)X_{n+1}$, which is equal to $(w + n - 1)X_n + B_{n+1}$. Thus the proportion of balls of color 1 at step $n + 1$, X_{n+1} may be written recursively as:

$$X_{n+1} = (1 - \frac{1}{w+n})X_n + \frac{1}{w+n}B_{n+1} \tag{37}$$

or

$$X_{n+1} = X_n + \frac{f(X_n) - X_n}{w+n} + \frac{B_{n+1} - f(X_n)}{w+n} \tag{38}$$

Equation 38 decomposes the evolution of X_n into two components: a deterministic one ($X_n + \frac{f(X_n)-X_n}{w+n}$) and a random one ($B_{n+1} - f(X_n)$). The random perturbations have zero expectation, and thus $E(X_{n+1}|X_n) = X_n + \frac{f(X_n)-X_n}{w+n}$. The expected value of X_{n+1} is larger than X_n whenever $f(X_n)$ is bigger than X_n.

A very interesting results for applications is that the process X_n converges to one of the fixed points of f .

4.2 A path-dependency approach to input-output modeling

The path-dependecy approach based on urn processes offers an interesting framework for the discussion of the environmental impact within the context of input-output economic models. In particular, input-output economic models are static and do not give any information about the processes that lead to equilibria. Conversely, path dependence theory focuses on processes.

In this section we discuss a simple model in which there is not any feedback from the environment on the economy. We consider a three-sector economy and we initialize the flows between sectors (z_{ij}) in a 3×3 matrix and the demand for final goods (d_i) in a 3×1 vector. We also create a 3×3 matrix which contains coefficients that represents the degree of substitutability between sectors. The combination of sectoral flows and demand for final goods give the overall monetary output for each sector (O_i). These data allow us to write the flows between sectors in terms of percentages of sectoral output (q_{ij}) and to obtain what we may call a multiplier of the demand, $[I - Q]^{-1}$ (see equation 5).

At each step of the simulation we let the demand for the goods produced in each sector evolve as a random walk with positive drift. In addition, we assume that competition between sectors may lead to changes in market shares according to a path-dependent mechanism. More precisely, we assume that the chance that a sector wins the competition in the market at each step is generated according to a Polya urn process. We have an urn with 3 numbered balls (e.g. $1, 2, 3$), one for every sector, and at each step of the simulation we draw one ball and then we put it back in the urn, together with another ball marked with the same number (that is representing the same sector).

The idea is that sectors that have an initial advantage over others in the early phases of economic development may take advantage of increasing returns and get an even larger market share. At each step of the simulation we update the vector of demand, that is evolving according to a random walk, we then use the multiplier of the demand estimated at the previous step to update the level of output produced in each sector and we transfer a market share of 5% to the leading sector obtained from the Polya urn from a substitute sector that is chosen with probability proportional to the coefficients of substitutability that we set for the economy. We finally assume that a specific level of environmental burden per dollar of production is associated to each sector: in particular, we assign a positive burden coefficient to two sectors and one negative to the other sector. This would mean that in the economy there could be sectors that have a greater impact on environmental burden, expressed, for instance in terms of carbon dioxide emissions (e.g. air transportation, fuel combustion, etc.) and other ones that have a negative impact (e.g. solar power supply, use of hybrid cars, etc.) since the production of goods in those sectors actually tends to reduce the overall environmental impact of the economy.

Figures 10, 11, 12 and 13 show some realizations of the Polya urn process that determines the choice of sectors that are leading the market at each step of the simulation and the associated outcome in terms of environmental burden. The interesting element that emerges from the simulations is that very different outcomes in terms of environmental burden may be observed depending on the configuration of the economy that is associated to the evolution of the Polya urn process. In particular, the early competition between sectors may lead to larger or smaller market shares for those sectors that are less environmentally friendly and this has a large impact on long term consequences for the environmental burden.

4.3 Introduction of feedback mechanisms

In the previous section we discussed the long term environmental consequences of early competition dynamics in the economy when there is not any feedback mechanism that regulates the competition in the economy based on the levels of environmental burden for each sector.

In this section, we keep the same conceptual scheme that we developed in the previous section, but we introduce a modification to the process that regulates the probability for each sector of being the leader in the competition at a particular step of the simulation. When the overall environmental burden is less than 3000 we assume that at each step of the simulation the probability of each sector being chosen as the leader is given by the proportion of balls in the Polya urn whose number is associated to the sector. When the level of environmental burden is larger than 3000, we switch from the Polya urn scheme to a generalized urn scheme in which the sectors with lower environmental burden are more likely to be chosen as leaders in the competition at each step of the simulation. For instance the probability that the sector i is chosen as leader in the competition (and thus it is the sector which increases its market share) at the next step of simulation may be assumed to be equal to $\frac{e^{-b_i}}{\sum_I e^{-b_i}}$. Figures 14 and 15 show two realizations of the simulation of the evolution of both the probabilities of each sector to be the leader in the competition at each step, and the environmental burden. One interesting aspect that emerges from these simulations is that the probabilities for each sector to be the leader tend initially to converge to some values, according to what we expect for the Polya urn process. However, when we reach a level of environmental burden of 3000, we switch to a different urn process and the proportions of balls in the urn converges to different values. In certain instances, the change of process allows for a reduction of the overall environmental burden to levels below 3000. In other cases, the initial steps in the competition lead to a structure of the economy from which the introduction of feedback mechanisms may not be enough to counteract the initial path towards less environmentally friendly sectors and the environmental burden keeps on increasing.

The examples that we provided are somewhat artificial cases: we choose a three-sectors economy, the level of burden per sector, the level of substitutability between sectors, the trend for the demand of consumption goods, etc. Very different outcomes may be obtained depending on the choice of key parameters of the models. The model is certainly simple and somewhat naive; however, some important insights emerge. For instance, time plays an extremely relevant role in these models: early changes in the structure of the economy may lead towards more or less sustainable scenarios. In addition, the early development of the structure of an economy may lead to situations in which the possibility to reverse certain patterns or trends may be compromised. In real societies, several responses to environmental pressure, from technological progress to behaviors, may play relevant roles in shaping the trend for the environmental burden of a society. The cost of late interventions may be much bigger than the one of early interventions. In this regard, our modeling seems consistent with the suggestion that the impact of societies on their environments should be monitored in order to keep the economies along paths that, even though uncertain in their outcomes, may give future generations enough space of choice to curb trends in act.

5 Conclusion

The paper is an attempt to discuss the role of demographic dynamics on environmental disruption, within the framework of input-output models. It originates from the desire of analyzing the consequences of population dynamics with a model that takes into account, at least partially, the complex relationships between sectors of an economy.

We first discussed the role of some demographic dynamics from a theoretical viewpoint, and we then tried to apply our reasoning to real data. One important message that emerges from the study is that demographic dynamics have a relevant impact on resource requirements and greenhouse gases emissions. The demographic aspect of the impact can be decomposed into several sources. Fertility and mortality have a growth rate effect and an age structure effect: the impact of these effects on environmental burdens is not always clear. For instance, improvements in mortality can increase the consumption of gasoline through the growth rate effect; at the same time, the age structure effect tends to reduce gasoline consumption.

In the paper we based our discussion on a stylized model, the stable population, and we tried to look at 'limiting' age distributions. We also look at population projections for the U.S. from the U.S. Census Bureau and we discuss the impact that may be related to the future population size and distibution of the U.S.

We foresee further research within this framework to be pursued. Several important aspects of the relationship between population and environment have not been discussed in the paper. Household dynamics, for instance, is likely to have a relevant role in shaping consumption patterns and should be taken into account. Household projection or microsimulations could be important tools in this regard.

In our approach, a consumption pattern has been estimated and then held constant to evaluate the environmental impact associated only to changes in size and distribution of the population. However, by doing this, we do not take into account any cohort effect: the existence and extent of these effects may need some investigation. In addition, consumption profiles by age may change for reasons that are not related solely to demographic change. A combined time series analysis of consumption profiles and demographic rates may be relevant for the evaluation of the impact of demographic trends, together with the associated uncertainty.

Finally, another aspect to take into account is the fact that the input-output model is a static representation of the economy and therefore has some limitations. Demographic changes influence the economy in a dynamic way and not only through consumption patterns, but also through other factors such as saving rates. In particular, the level of savings is very relevant in closed economies, whereas its impact may be less important in economies more open to international flows of capital.

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Tables

Consumption good	S_a	S_e
Electricity	482 $	711 $
Natural Gas	355 $	527 $
Number of vehicles owned	0.96	0.77
Gasoline	503 $	342 $
Tobacco products	156 $	92 $
Airfare	122 $	153 $
Food at home	1376 $	1708 $
Nursing home	2 $	177 $

Table 1: Average consumption of several consumption goods for adults living alone, S_a, and for elderly living alone, S_e in the U.S.. Data source: Consumer Expenditure Survey 2003.

Consumption good	$\hat{\gamma}$	95% C.I.	$\hat{\theta}$	95% C.I.
Electricity	0.27	(0.208; 0.325)	0.952	(0.948; 0.955)
Natural Gas	0.249	(0.146; 0.341)	0.924	(0.917; 0.93)
Number of vehicles owned	0.022	(0; 0.045)	0.85	(0.83; 0.87)
Gasoline	0.054	(0.013; 0.092)	1.004	(1.001; 1.008)
Tobacco products	0	(0; 0)	0.941	(0.933; 0.953)
Airfare	0	(0; 0)	0.948	(0.935; 0.963)
Food at home	0.347	(0.307; 0.385)	0.99	(0.988; 0.992)
Nursing home	0.945	(0; 1.89)	0.79	(0.705; 0.847)

Table 2: Estimates of the parameters of the equivalence scale, $\hat{\gamma}$ and $\hat{\theta}$, together with their bootstrap 95% confidence intervals, for several consumption goods in the U.S. Data source: Consumer Expenditure Survey 2003.

Figures

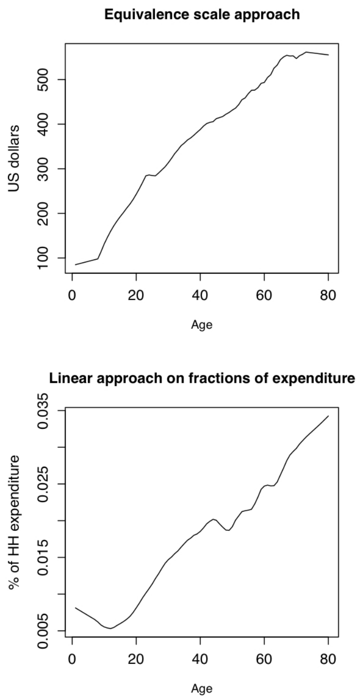

Figure 1: Yearly average consumption profiles of **electricity** by age estimated with different methods. Data source: Consumer Expenditure Survey 2003.

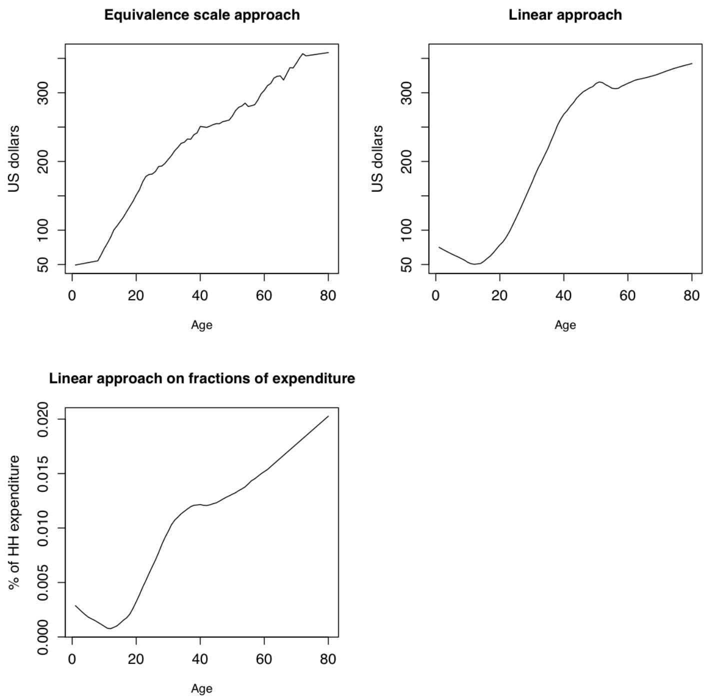

Figure 2: Yearly average consumption profiles of **gas** by age estimated with different methods. Data source: Consumer Expenditure Survey 2003.

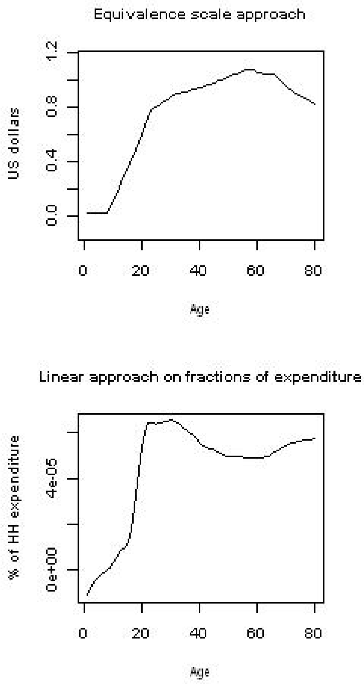

Figure 3: Average **number of vehicles owned** by age estimated with different methods. Data source: Consumer Expenditure Survey 2003.

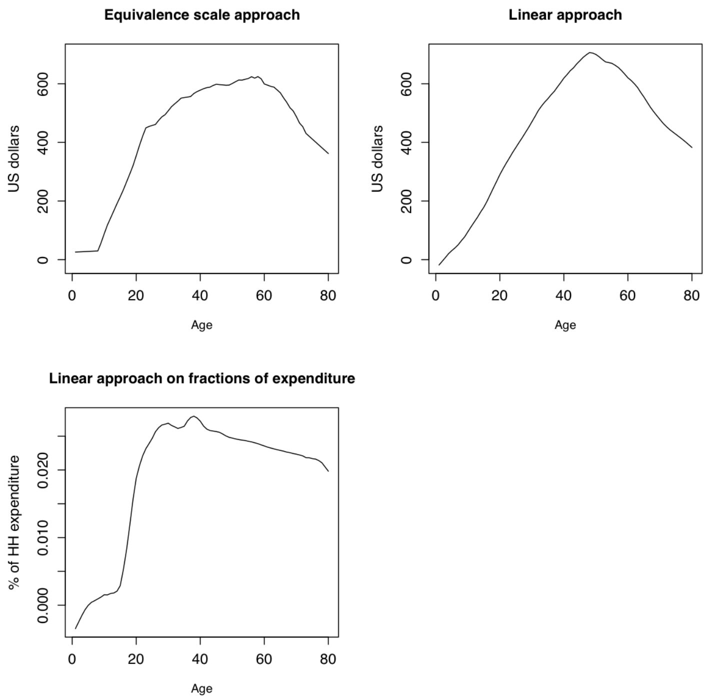

Figure 4: Yearly average consumption profiles of **gasoline** by age estimated with different methods. Data source: Consumer Expenditure Survey 2003.

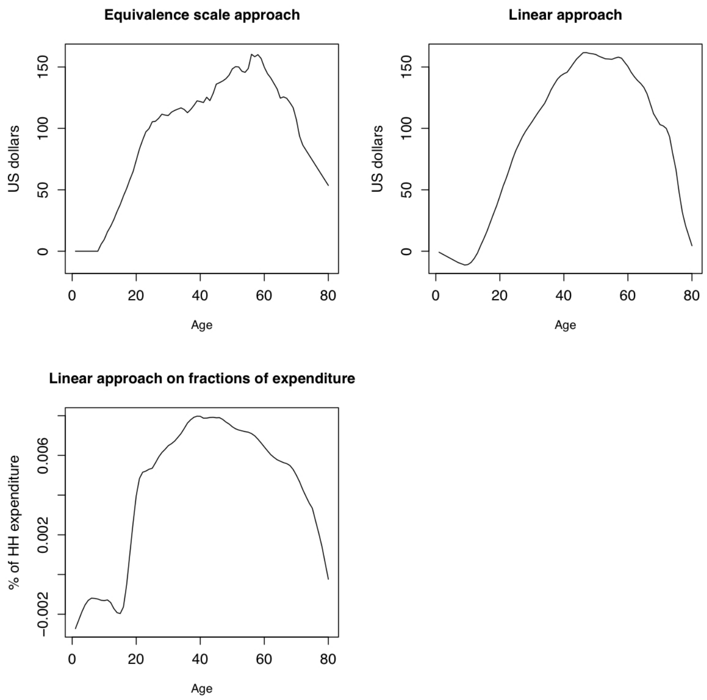

Figure 5: Yearly average consumption profiles of **tobacco products** by age estimated with different methods. Data source: Consumer Expenditure Survey 2003.

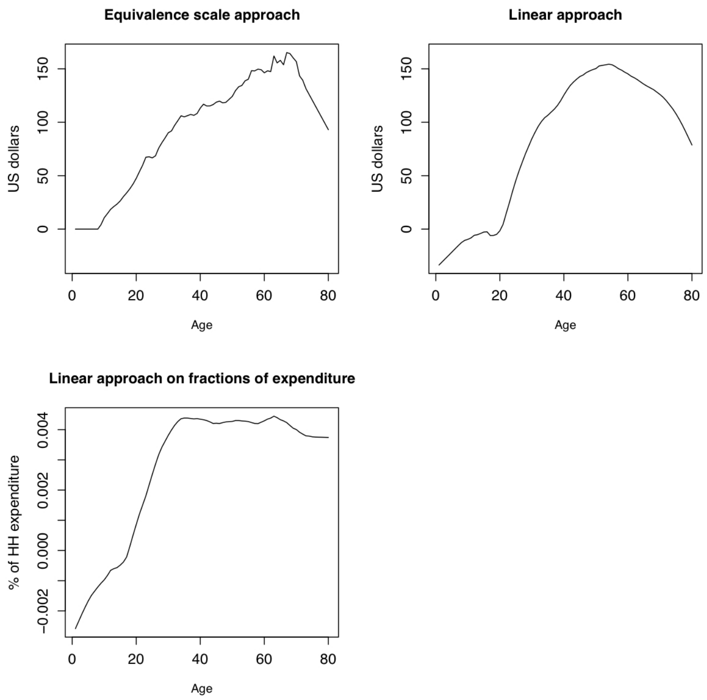

Figure 6: Yearly average consumption profiles of **air flights** by age estimated with different methods. Data source: Consumer Expenditure Survey 2003.

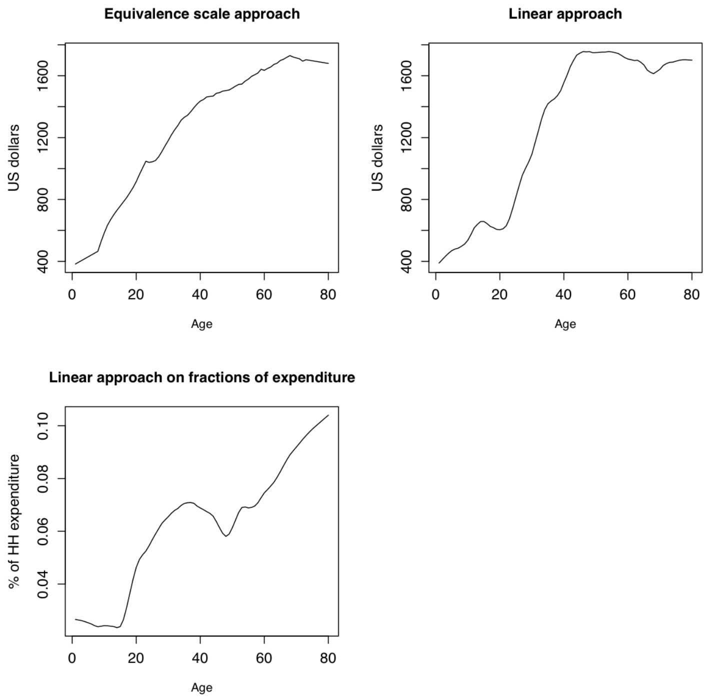

Figure 7: Yearly average consumption profiles of **food at home** by age estimated with different methods. Data source: Consumer Expenditure Survey 2003.

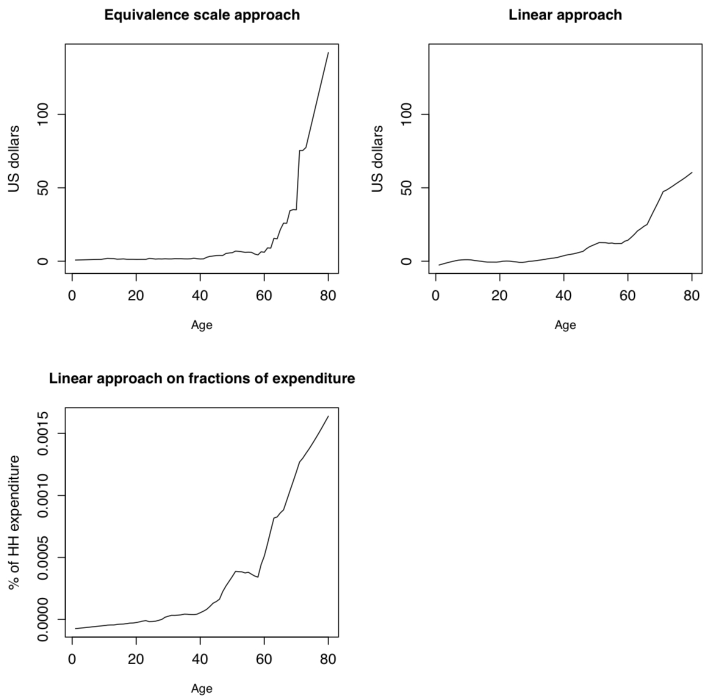

Figure 8: Yearly average consumption profiles of **nursing at home** by age estimated with different methods. Data source: Consumer Expenditure Survey 2003.

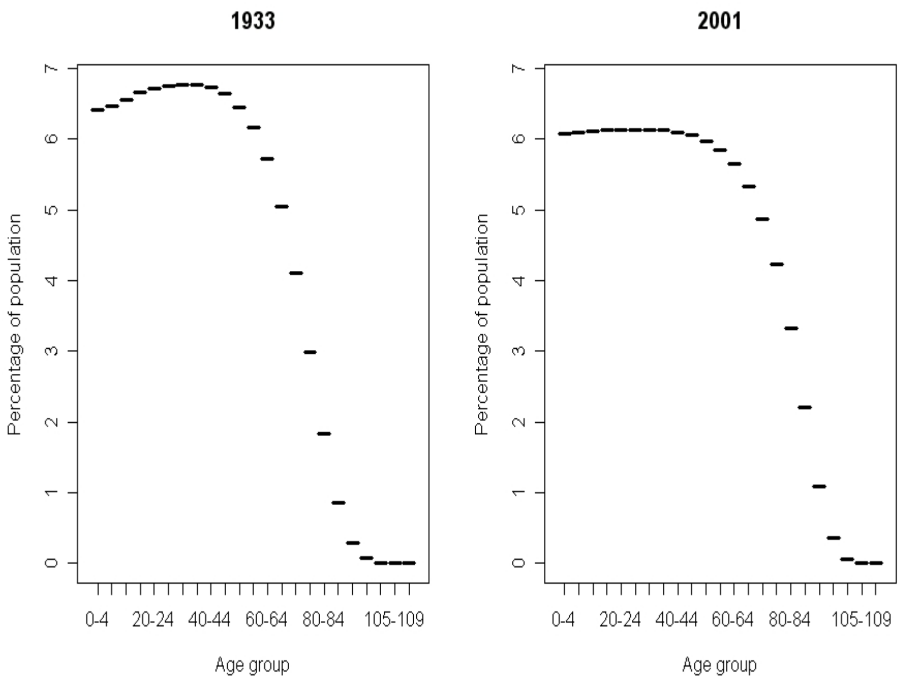

Figure 9: Stable age structures resulting from the projection over the long run of populations with the fertility rates of U.S. in 2001, and the mortality rates of the U.S. respectively in 1933 and 2001. Data source: HMD and U.S. Census Bureau.

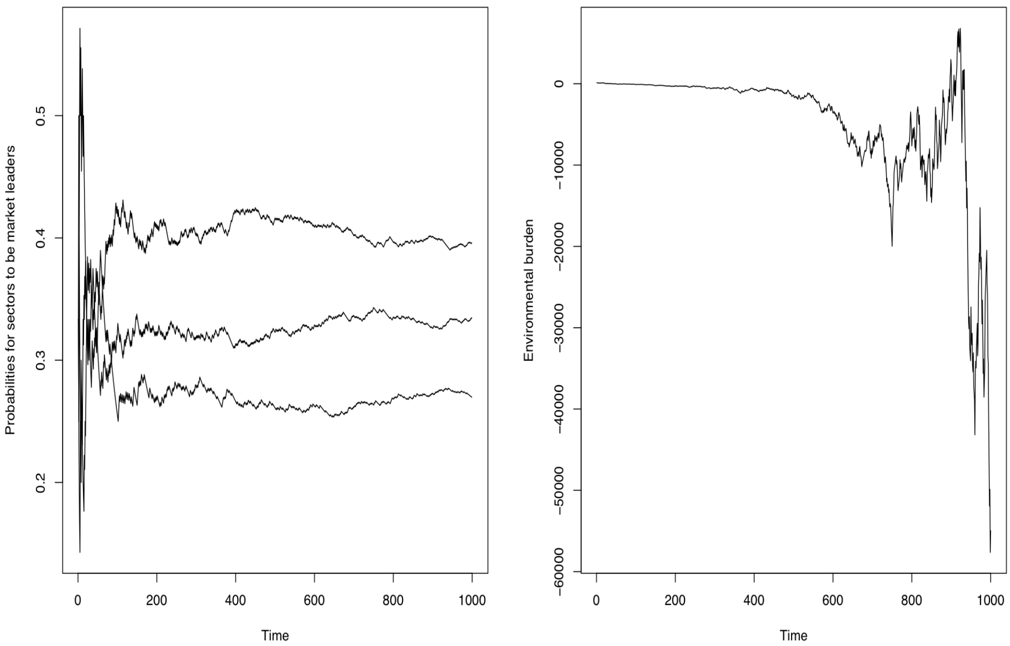

Figure 10: A realization of the simulation of the evolution of environmental burden for the path-dependency model without feedback.

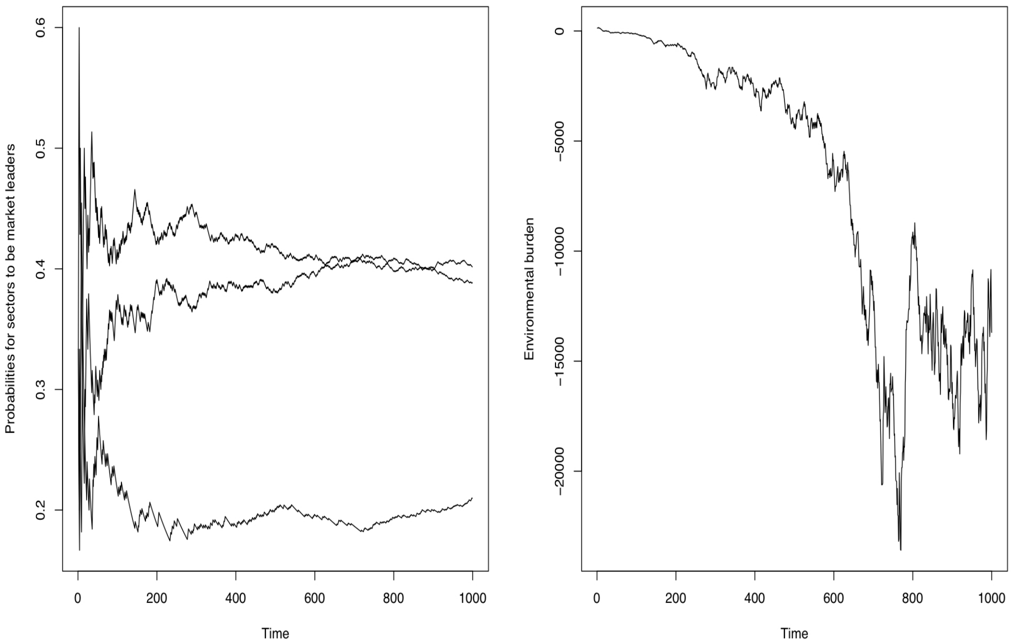

Figure 11: A realization of the simulation of the evolution of environmental burden for the path-dependency model without feedback.

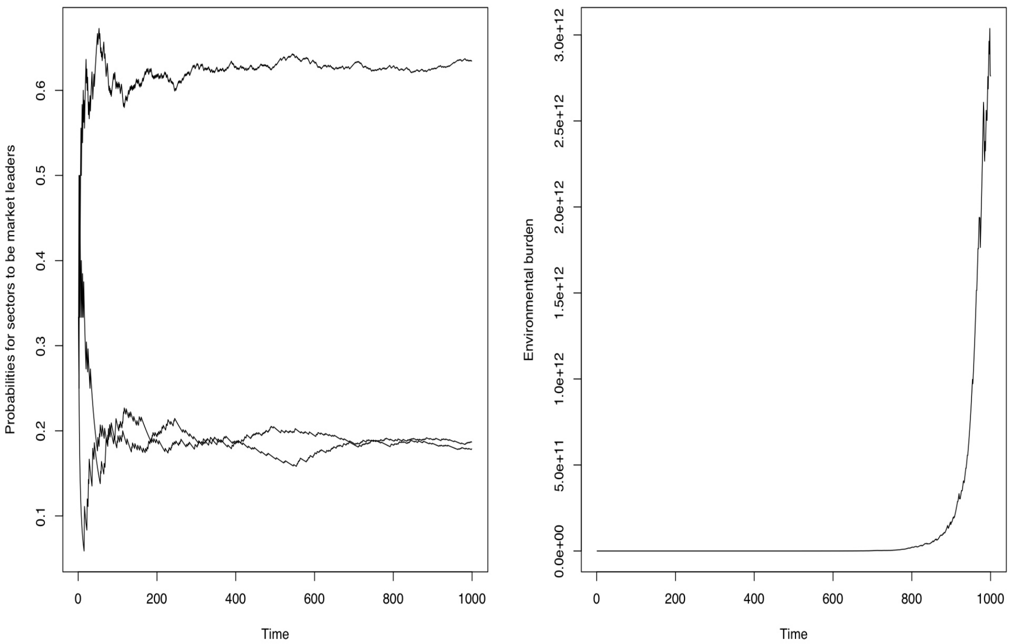

Figure 12: A realization of the simulation of the evolution of environmental burden for the path-dependency model without feedback.

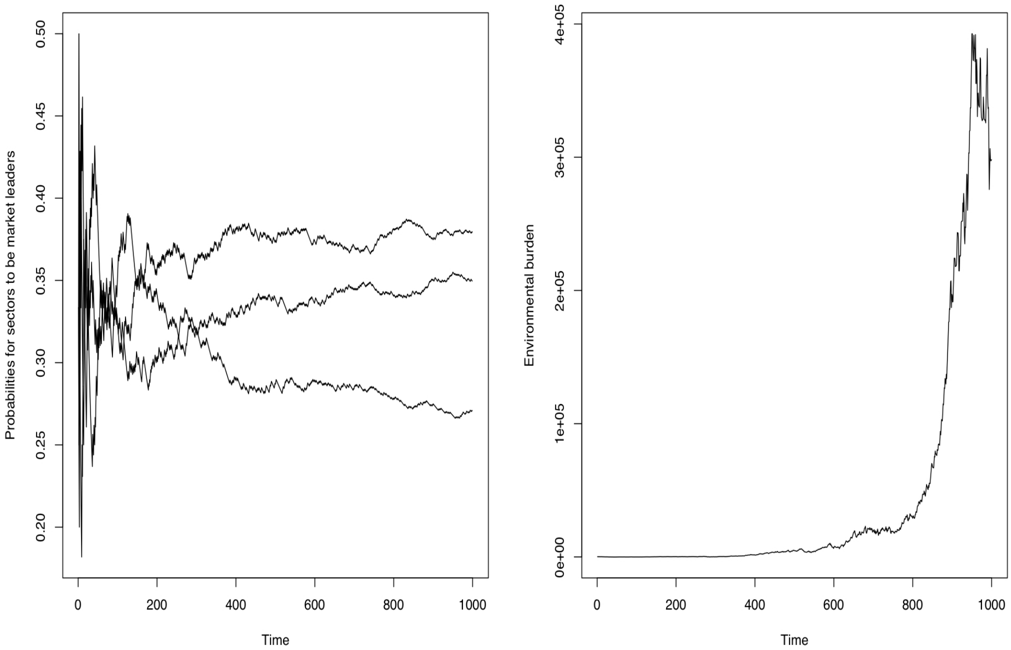

Figure 13: A realization of the simulation of the evolution of environmental burden for the path-dependency model without feedback.

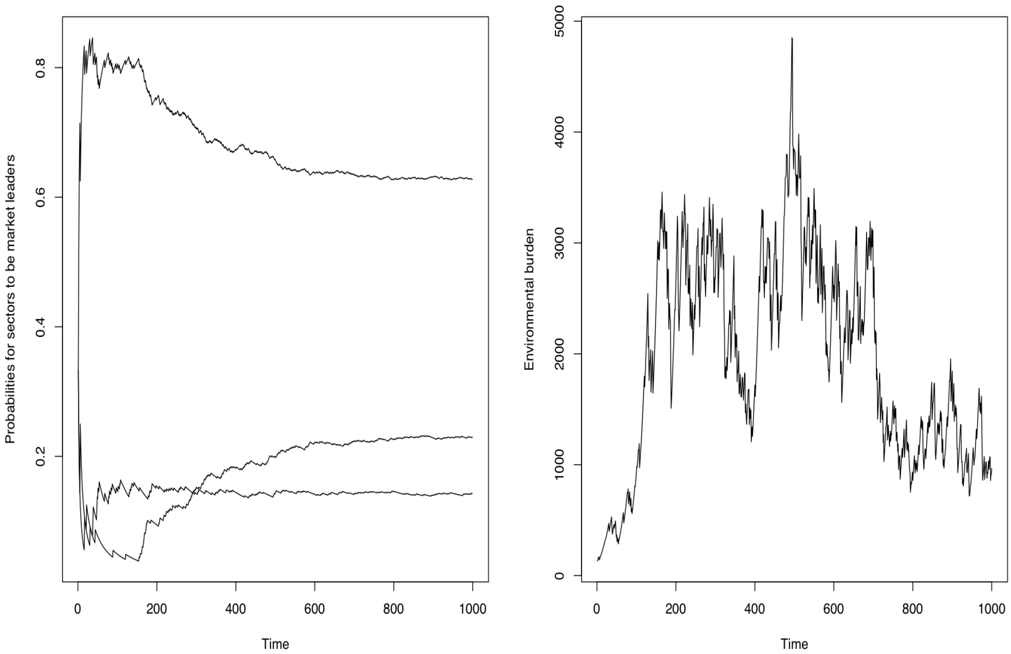

Figure 14: A realization of the simulation of the evolution of environmental burden for the path-dependency model with introduction of a feedback mechanism when the environmental burden is bigger than 3000.

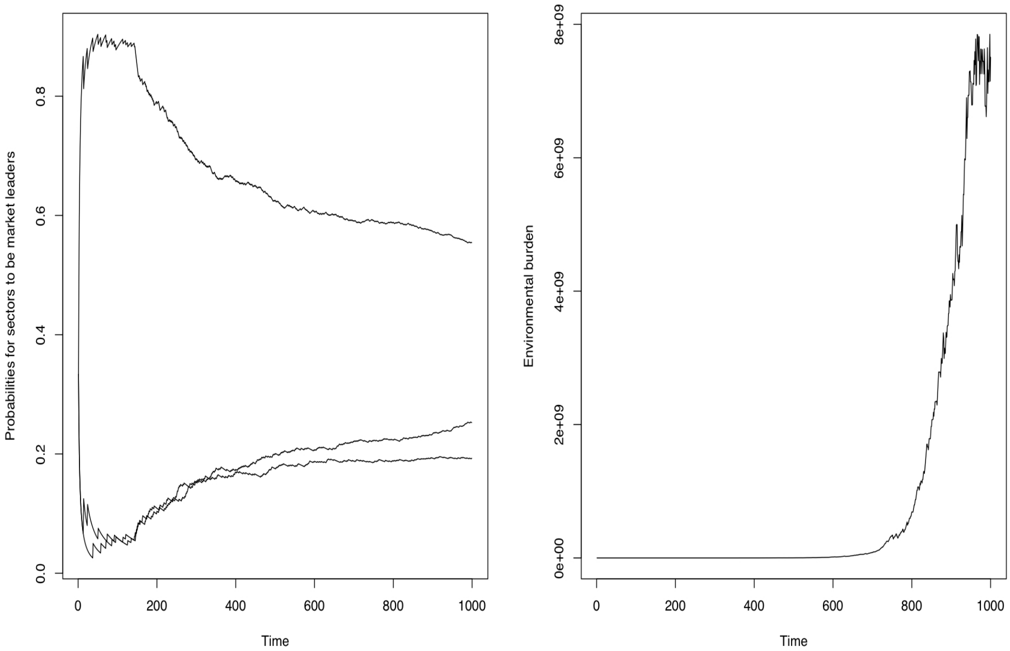

Figure 15: A realization of the simulation of the evolution of environmental burden for the path-dependency model with introduction of a feedback mechanism when the environmental burden is bigger than 3000.