International Consumption Patterns for Proteins and Fats: Intra-distributional Mobility and the Role of Income Elasticity

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Abstract

Stochastic kernels are used in this paper to investigate intra-distribution dynamics in the world per capita intakes of proteins and fats. The analysis of actual transitions over the last 40 years indicates that lagging countries improved their position relative to the leading. Long-run (steady-state) distributions have been obtained using estimated intake change models. These distributions have been compared to "virtual" ones revealing that the income elasticity of demand or equivalently the rate of growth in per capita income does have a strong influence on the dispersion of intakes at the steady-state.

Key Words: *Nutrient Intakes, Stochastic Kernels*

JEL Classification: Q1, D12, C14

Introduction

The dynamic evolution of dietary patterns in different parts of the world has attracted considerable attention in the economic research since the early 1980s. Blandford (1984), Wheelock and Frank (1989), Herrmann and Roder (1995), Uhl (1991), Connor (1994), and Gil et al. (1995), compared the dietary patterns in developed countries and they found that diets were getting increasingly similar; Grigg (1995) analyzed the factors (e.g. economic, environmental, cultural) influencing the spatial variation in the world protein consumption; Fousekis and Lazaridis (2005) investigated the dynamics of the world caloric (energy) intakes. They found that despite the higher availability of food at a global level, the differences between low- and high-intake countries are still considerable making, thus, convergence in the foreseeable future unlikely. Policy makers have also a keen interest in the evolution of the international nutrient consumption patterns since both under-nutrition in low-income countries and over-nutrition in the more affluent ones accounts for a significant proportion of deaths and chronic disease all over the world (The World Health Report, 2002).

The overwhelming majority of the empirical studies regarding convergence in per capita food consumption (or in per capita nutrient intakes) have been based on the so called Barro's regression in which the change in consumption over a period of time is regressed on an initial consumption level and other variables which are assumed to affect consumption growth. A negative and statistically coefficient of the initial consumption level in such regression is taken to imply convergence. As shown by Quah in a flurry of papers (e.g. Quah, 1993a, 1993b, 1996a, 1996b, 1997), however, Barro's regressions are not quite informative about convergence or divergence. For Quah, ques-

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tions related to persistence (here, tendency of countries to retain their rank in the cross-section nutrient intake distribution), mobility (here, low intake countries become high intake ones and the opposite), convergence (here, all countries attain very similar intake levels) and club formation (here, countries catching-up with one another but only within particular groups) can be properly addressed by developing a probability model of transitions, that means, by developing the law of motion for the entire cross-section intake distribution.

In this context, the objective of the present paper is the analysis of intra-distribution dynamics for two nutrients, namely, proteins and fats. While most of the earlier empirical studies relied on data from few Western or OECD countries the present work relies on data from 103 countries around the world. The empirical investigation is based on stochastic kernels.[1] Moreover, given that for economists income elasticity is considered to be a very important determinant of demand for nutrients, the paper follows an approach proposed recently by Fingleton and Lopez-Bazo (2003) to examine the effect of income elasticity on the shape of the long-run intake distributions.

The paper is structured as follows. Section 2 contains the analytical framework (transition density functions and simulation of the long-run intake distributions). Section 3 involves the specification and estimation of the intake change models. Section 4, presents the actual intake dynamics for the period 1961 to 2001 and investigates the effect of income elasticities. Section 5 offers conclusions.

Analytical Framework

Transition Density Functions

Let R be a vector of the intake ratios of a given nutrient in each country relative to the highest intake (leading) country, and f_t (R=x) and f_{t+k} (R=x) be the probability density of R=x in periods t and $t+k$, respectively. The relationship f_t and f_{t+k} can be expressed as

$$f_{t+k}(R=\mathrm{y}) = \int_0^1 g_k(R=\mathrm{y}/R=\mathrm{x}) f_t(R=\mathrm{x})\mathrm{dx} \tag{1}$$

where g_k is the stochastic kernel (transition density), that means the density of $R=\mathrm{y}$ in period $t+k$ conditional on $R=\mathrm{x}$, k periods before (Durlauf and Quah, 1999; Quah, 1996a). A transition density provides the likelihood that a country which occupies a certain part of the cross-section distribution of R will transit to another part of it in k periods summarizing, thus, the whole information about the intra-distribution dynamics. The non parametric estimation of a transition density is described in Quah (1996a). The first step, involves a bivariate kernel density estimation of the joint density function of t and $t+k$ at the points x and y. The second step, involves integration of the joint density over the values of R in $t+k$ to obtain the marginal density at period t. The third step, involves division of the joint density by the marginal density at t to yield a consistent estimate of the stochastic kernel.

Persistence, mobility, convergence, and club formation can be then read off the graph of the transition density and the associated contour plot. For example, if the probability mass is located along the positive diagonal this points to low mobility (or strong persistence). On the other hand, clockwise kernel shifts indicate a tendency for convergence in distribution with low (high) intake countries in *t* having a high probability of experiencing an improvement (deterioration) of their relative position in *t+k*. In the extreme case, the probability mass is located along a parallel to the *R* values at *t* indicating that nutrient intake levels in all countries are likely to converge to very similar levels in period *t+k*, irrespective of their position in *t*. Finally, peaks in the kernel (separated by valleys with vanishing probability mass) indicate the existence of what Durlauf and Johnson (1995) termed as "basins of attraction" which encourage the formation of convergence clubs.

Just as stochastic kernels can quantify how the distribution of *R* evolves over time, they can also describe how a set of conditioning factors alter that distribution (Quah, 1996a and 1997; Fingleton and Lopez-Bazo, 2003). This can achieved by comparing an unconditional (long-run) distribution with a conditional ("virtual") distribution obtained by imposing restrictions on the parameters of an intake change model. In case that the probability mass lies along the positive diagonal one may conclude that the conditioning factor in question (e.g. income elasticity) has no influence whatsoever on the shape of the long-run intake distribution. The opposite will be true in case that conditioning shifts the stochastic kernel about the positive diagonal.

Simulating an Equilibrium Intake Distribution

The intake change (denoted by $\hat{C}$) between periods *t* and *t+k* may be expressed as

$$\underset{(n\times 1)}{\hat{C}} = \underset{(n\times m)}{(X)}\underset{(m\times 1)}{(b)} + \underset{(n\times 1)}{(G)}\underset{(1\times 1)}{(b_G)} + \underset{(n\times 1)}{\varepsilon} \tag{2}$$

In (2), *G=1-R* stands for the *n* start-of-the period intake gaps, *X* is a matrix of *n* observations from *m* factors (other than *G*) which are hypothesized to influence intake growth, b and b_G are parameter vectors, and ε is a disturbance term. With b_G positive (suggesting that laggards grow faster than leaders) there is a stable long-run equilibrium in which the expected rate of intake growth is exactly the same across all countries, meaning that

$$E(\hat{C}-\hat{C}^*)=0 \Rightarrow (X)(b)+(G^e)(b_G)-(X^*)(b)=0 \tag{3}$$

where $\hat{C}^*$ is the equilibrium intake growth rate for the leader, G^e are the equilibrium intake gaps, and *X** is a matrix with the same dimensions as *X* but containing identical rows which are each equal to the leader's row in *X* (Fingleton and Lopez-Bazo, 2003). From (3) follows that

$$(G^e)(b_G)=(X^*)(b)-(X)(b) \Rightarrow G^e=(X^*-X)(b)/b_G\ , \tag{4}$$

suggesting that the vector of the equilibrium intake ratios (the simulated long-run intake distribution), denoted by R^e, may be obtained as

$$R^e=1-G^e\ . \tag{5}$$

The results in this section set the basis for conditioning analysis. The simulated equilibrium distribution is the unconditional one. Changing the coefficients of model (2) and utilizing relations (4) and (5) yields the desired conditional distributions.[2]

Specification and Estimation of the Intake Change Model

The empirical intake change model is specified here as

$$\hat{C} = b_0 + b_I \hat{I} + \sum_i b_i D_i + b_G G + \varepsilon \ , \tag{6}$$

where $\hat{C}$ is the change in the daily per capita intake for proteins or fats, $\hat{I}$ is the change in real per capita income, G is the start-of-the period gap, and D_i are continent dummies. As it stands, model (6) is an Engel function for nutrients in differential form modified for continent influences (captured by the dummies) and for catching-up effects (captured by G).[3] The coefficient of $\hat{I}$ is the intake elasticity with respect to income. A positive coefficient of the G variable will indicate the presence of catching-up effects in the sense that initially low-intake countries have exhibited higher rates of intake growth compared to the initially high-intake ones. A positive (negative) coefficient of a continent dummy will indicate that countries in the respective continent have experienced higher (lower) intake growth rates relative to the control continent.[4]

The data for the empirical analysis come from two sources, namely, the FAOSTAT (FAO, 2006) and the Penn World Table 6.1 (2004). The FAOSTAT provides information on daily per capita intakes for proteins and fats, while the Penn World Table provides information on real GDP per capita. Data on both nutrient intake as well as on real per capita income are available for 103 countries (41 from Africa, 13 from North and Central America, 11 from South America, 17 from Asia, 17 from Europe, and 4 from Oceania) over the period 1961-2001.[5] The top 5 and bottom 5 countries in the intake distributions are presented in the Appendix.

For the estimation, the start-of-the period intake level of each country has been set equal to its average in 1961-63, while the end-of the period intake level has been set equal to its average in 1999-2001.[6] Accordingly, G has been computed from the average intakes in 1961-63, $\hat{C}$ has been computed as the growth rate in intakes between 1961-63 and 1999-2001, and $\hat{I}$ as the growth rate in real per capita income between 1961-63 and 1999-2001.[7] For both proteins and fats, the estimation of the full model (6) yielded a number of coefficients associated with continents dummies which were statistically insignificant at any reasonable level. Therefore, the initially estimated models were subjected to redundant variables likelihood ratio tests (LRT). The application of these tests has led to two preferred models presented in Tables 1 and 2.[8] The adjusted coefficients of determination are 0.35 for proteins and 0.51 for fats, which are quite satisfactory given that the estimations rely on cross-sectional data. The Rasmey reset tests support strongly the selected specification for proteins, while for fats the selected specification cannot be rejected at the 5 percent level. The coefficients of income growth for both nutrients are statistically significant at the 1 percent level or less and so it the case for the coefficients of the G variable (something that points outs to the presence of catching-up effects).

Distribution Dynamics and the Role of Income Elasticity

As mentioned in Section 2, the analysis of distribution dynamics requires estimation of joint density functions. This has been implemented here as suggested by Wand and Jones (1995). In particular, for points x and y in the start-of-the period and the end-of-the period, respectively, the estimate of the joint density function is

$$\hat{f}(x,y)=\frac{(\sum_s \varphi((x-x_s)/h_x)\varphi((y-y_s)/h_y)}{nh_x h_y}, \tag{7}$$

where φ stands for the Gaussian kernel, n for the number of observations, and h_x and h_y for the Sheather and Jones (1991) bandwidth parameters. The estimations (which are available upon request) have been carried out using S-Plus routine *kde2d* from the library of Venables and Ripley (1999).

Table 1. The Preferred Intake Change Model for Proteins

Explanatory Variables	**Parameter Estimate**	**Standard Error+**
Constant	-0.244*	0.065
G	0.750*	0.113
$\hat{I}$	0.117*	0.049
D_1	-0.095**	0.044
D_5	0.136**	0.042

R^2 (Adjusted)	0.342

	Value of the Test Statistic	**p-value**
Ramsey Reset Test		
1 fitted term	0.01	0.993
2 fitted terms	0.01	0.998

+: Heteroscedasticity Robust; *(**) Statistically significant at the 5 (10) percent level or less.

Table 2. The Preferred Intake Change Model for Fats

Explanatory Variables	**Parameter Estimate**	**Standard Error+**
Constant	-0.187*	0.072
G	0.856*	0.101
$\hat{I}$	0.263*	0.062
D_1	-0.207*	0.069
D_3	-0.101	0.061

R^2 (Adjusted)	0.504

	Value of the Test Statistic	**p-value**
Ramsey Reset Test		
1 fitted term	3.591	0.068
2 fitted terms	4.787	0.091

+: Heteroscedasticity Robust; *(**) Statistically significant at the 1 (5) percent level or less.

Figure 1a presents the stochastic kernel of the actual transitions for protein intakes, while Figure 1b presents the associated contour map. The start-of-the period intake ratios are denoted by R1962 (because they have been obtained by averaging intakes in 1961-63) and the end-of-the period intake ratios are denoted by R2000 (because they have been obtained by averaging intakes in 1999-2001). There is a clockwise shift in the kernel most notable at the very low (less than 0.4) R1962 ratios as well as at the R1962 ratios between 0.7 and 0.8, suggesting that countries which initially had ratios lower than 0.4 or between 0.7 and 0.8 enjoyed a higher probability of improving their position in the proteins intake distribution relative to the rest. Also the probability mass is quite thin about the R1962 ratio of 0.7. It appears that countries with start-of-the period R ratios just above 0.7 jumped to ratios close to 0.9 and separated themselves from countries with start-of-the period ratios just below 0.7 which showed no improvement in their relative position. Although there are no very distinct peaks, the vanishing probability mass in the neighborhood of the R1962 ratio of 0.7 provides some indication of club formation. The dispersion, however, within each of the two clubs is considerable (and this is in line with the absence of very distinct peaks).

Figure 1c shows the stochastic kernel relating the R2000 distribution to the simulated/equilibrium distribution (denoted by RE), and Figure 1d shows the associated contour map. There is a notable clockwise shift in the kernel for the whole range of the R2000 values meaning that the long-run (steady-state) distribution is likely to be more concentrated than the end-of-the period one. Despite the increased concentration, the probability mass does not lie along a parallel to the horizontal axis suggesting that in the long-run the intakes are not likely to converge to very similar levels but each country will approach its own-steady state level which may well be different from those of the rest.

The effect of income elasticity on the long-run intake distribution can be determined by adjusting the coefficient of $\hat{I}$ in the intake growth model downwards or upwards, while setting all other coefficients equal to their estimated values (Fingleton and Lopez-Bazo, 2003). Here, somewhat arbitrarily we set the coefficient of $\hat{I}$ equal to 50 percent of its estimated value (that is, 0.058 instead of 0.117). Figure 1e presents the stochastic kernel relating the equilibrium distribution with the “virtual” distribution (denoted by RI), and Figure 1f the associated contour map.[9] There is a very clear clockwise shift in the kernel suggesting that the income elasticity has a very strong influence on the dispersion of the long-run intake distribution. Lower (higher) income elasticities work towards lower (higher) concentration.[10] With the lower income elasticity a club appears to be forming at about the 0.9 RE value.

Figure 2a presents the stochastic kernel of the actual transitions for fats, and Figure 2b the associated contour map. In contrast with proteins, the clockwise shift in the kernel for fats is most notable at the relatively high R1962 ratios. The probability mass is vanishing around the start-of-the period 0.6 ratio with countries on the right jumping to ratios as high as 1 and countries on the left failing to improve their position or even experiencing a deterioration of it. Again, the vanishing probability mass provides an indication of club formation. As it is the case with proteins, however, there is considerable dispersion within each club (something which is reflected in the presence of twin peaks both above as well as below the 0.6 ratio).

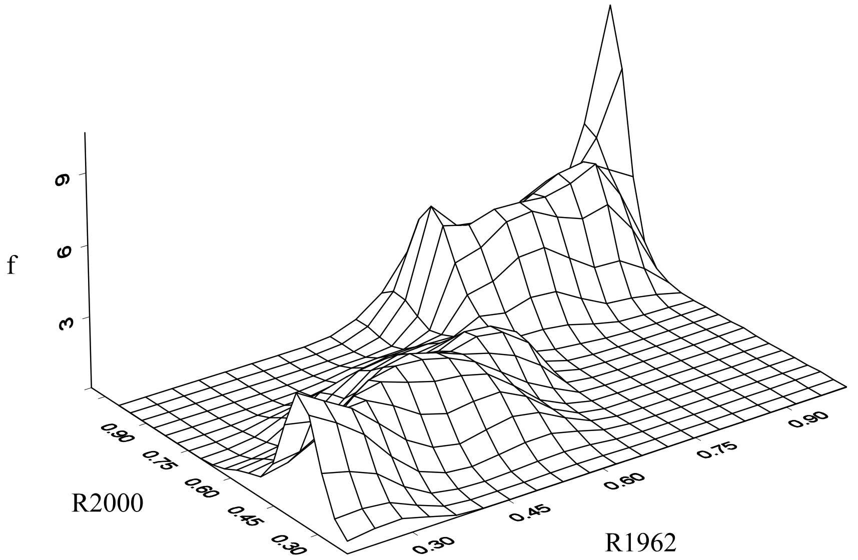

Figure 1a. *Proteins: Stochastic Kernel for the Actual Transitions*

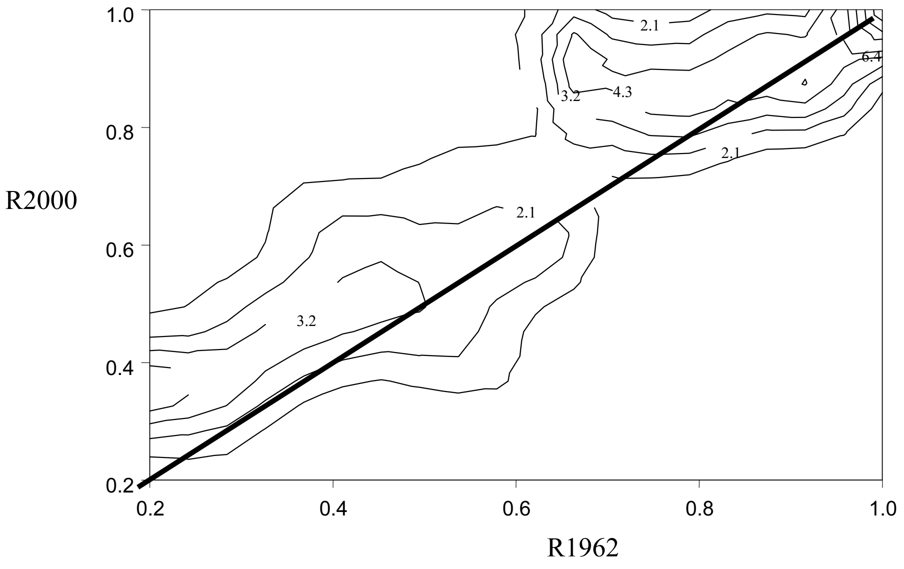

Figure 1b. *Proteins: Contour Map for the Actual Transitions*

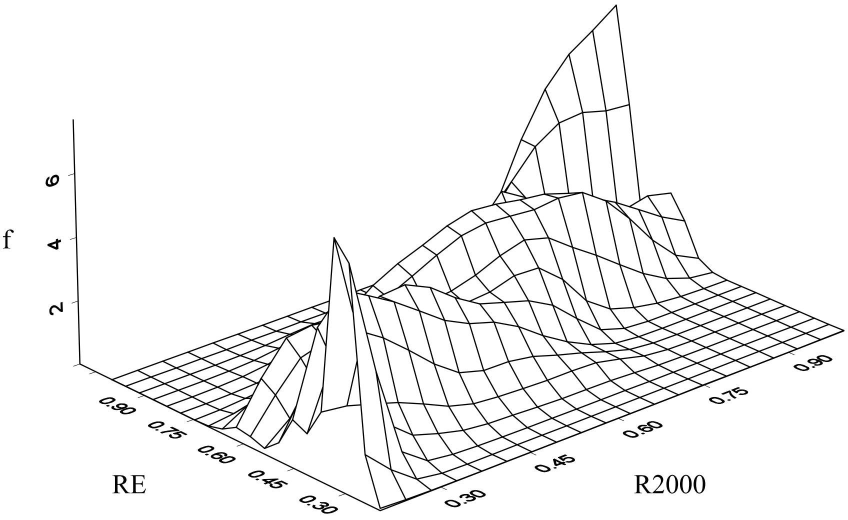

Figure 1c. *Proteins: Stochastic Kernel for the End-of-the Period and the Equilibrium Distribution*

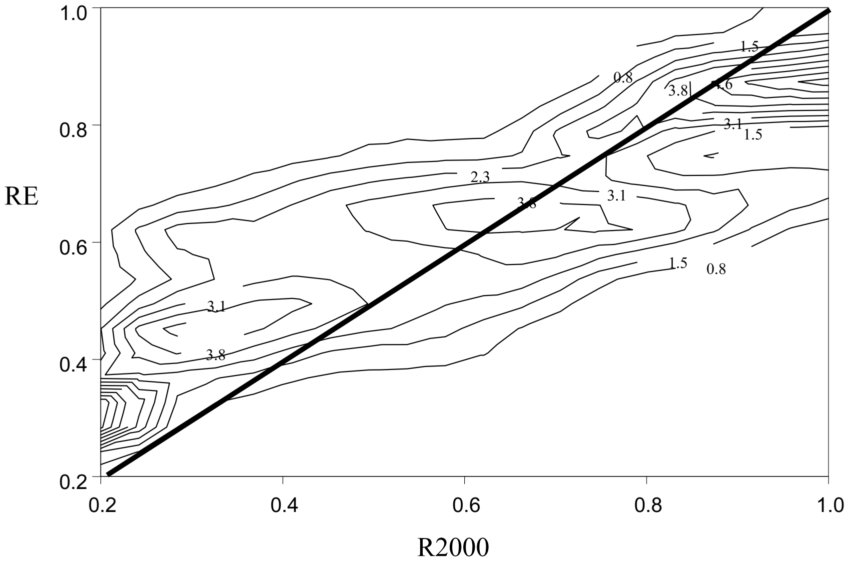

Figure 1d. *Proteins: Contour Map for the End-of-the Period and the Equilibrium Distribution*

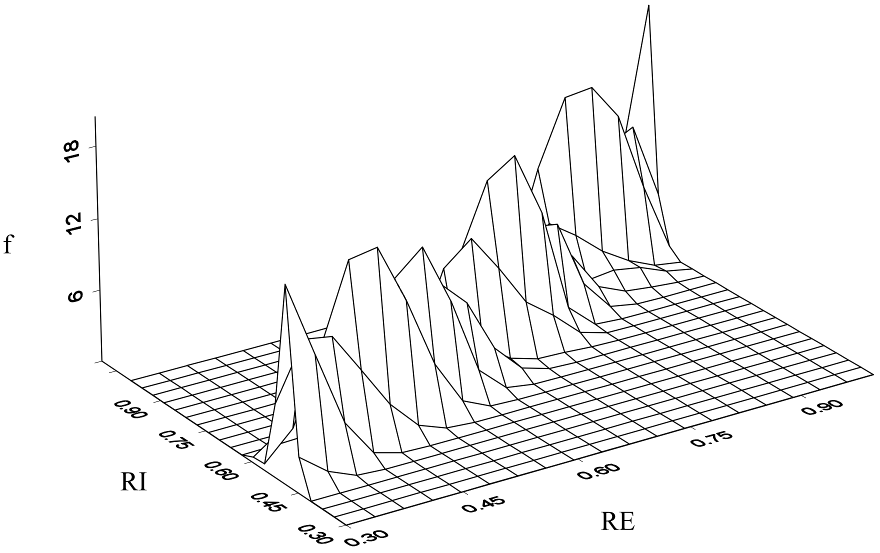

Figure 1e. *Proteins: Stochastic Kernel with Conditioning for Income Elasticity*

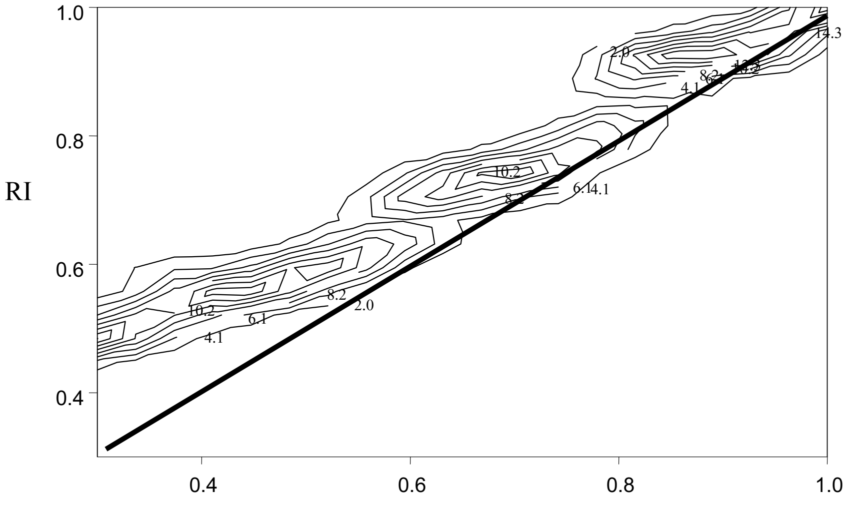

Figure 1f. *Proteins: Contour Map with Conditioning for Income Elasticity*

Figure 2c shows the stochastic kernel relating the R2000 distribution to the simulated/equilibrium distribution, and Figure 2d shows the associated contour map. The long-run distribution of fat intakes will be more concentrated than the end-of-the period one. Again, because the probability mass does not lie along a parallel to the horizontal axis long-run convergence to very similar intake levels is not likely.

Figure 2e shows the stochastic kernel relating the equilibrium distribution with the "virtual" (conditioned) distribution, and Figure 2f shows the associated contour map. For the conditioning, the income elasticity has been set again to 50 percent of its estimated value. As expected, there is a very clear clockwise shift in the kernel suggesting that the income elasticity does has a strong influence on the dispersion of the long-run intake distribution. There is no indication for club formation with the lower income elasticity.

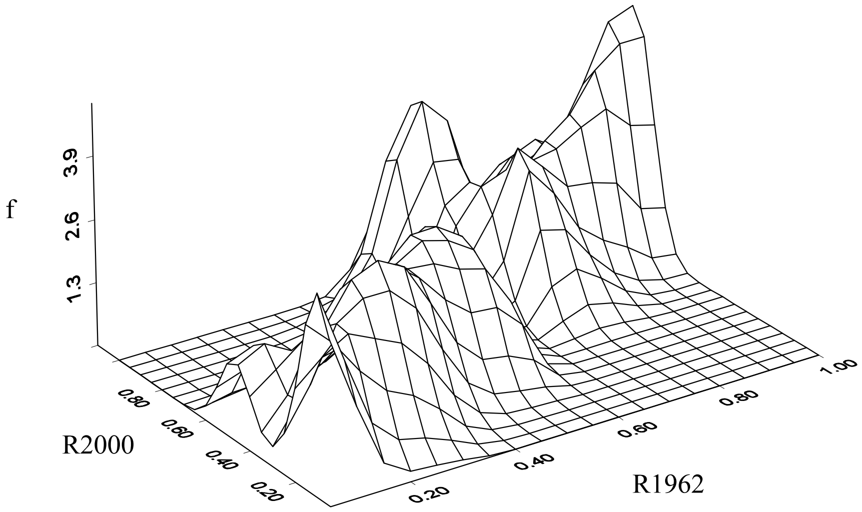

Figure 2a. *Fats: Stochastic Kernel for the Actual Transitions*

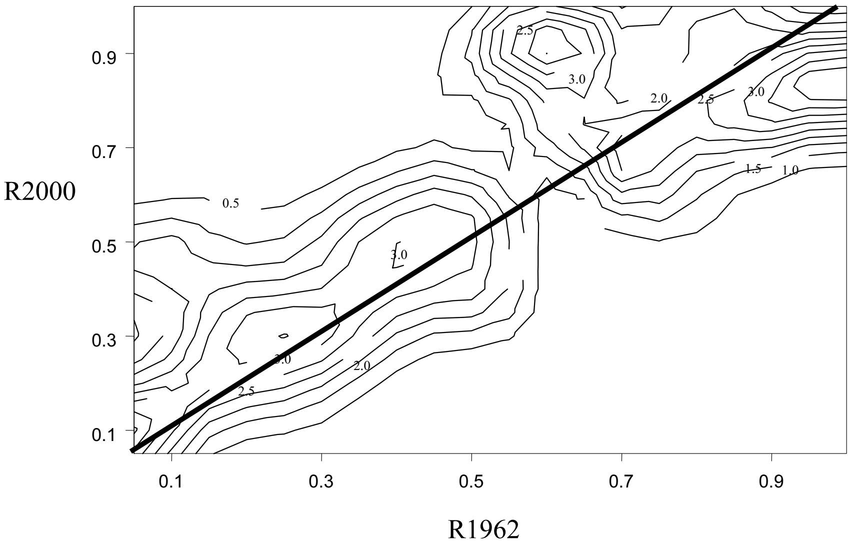

Figure 2b. *Fats: Contour Map for the Actual Transitions*

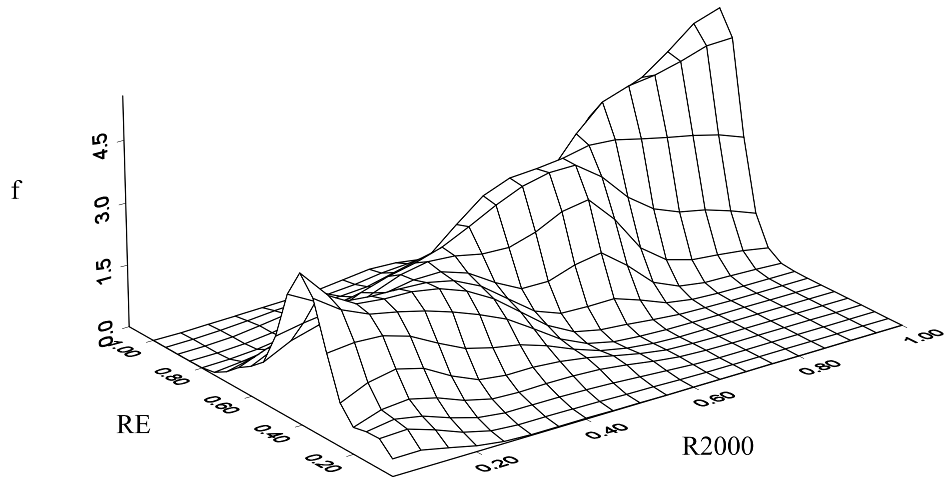

Figure 2c. *Fats: Stochastic Kernel for the End-of-the Period and the Equilibrium Distribution*

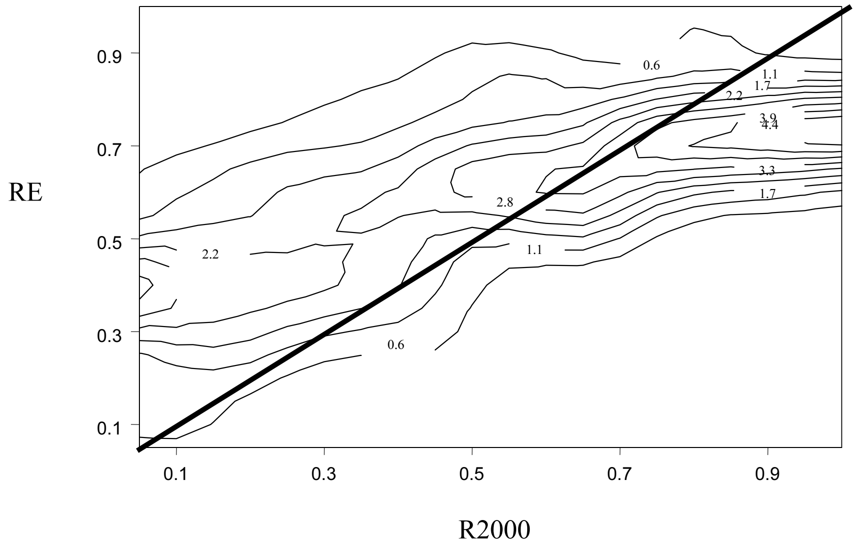

Figure 2d. *Fats: Contour Map for the End-of-the Period and the Equilibrium Distribution*

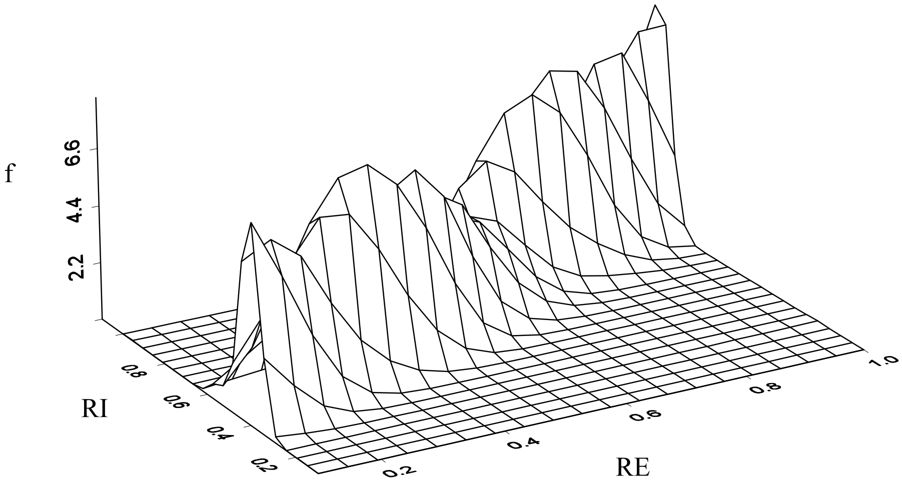

Figure 2e. *Fats: Stochastic Kernel with Conditioning for Income Elasticity*

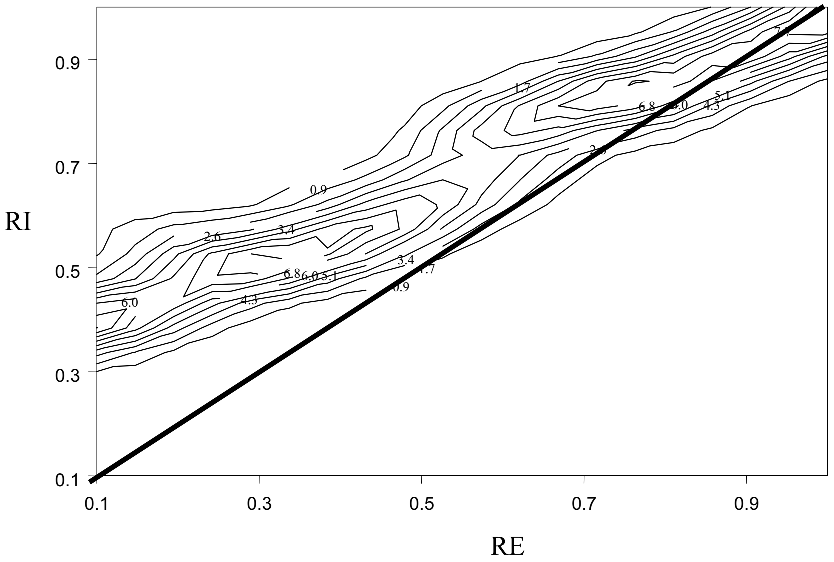

Figure 2f. *Fats: Contour Map with Conditioning for Income Elasticity*

Conclusions

Stochastic kernels have been are used in this work to investigate intra-distribution dynamics in the world per capita intakes of proteins and fats. The analysis of actual transitions from the period 1961-63 to the period 1999-2001 suggested that for both nutrients laggards have improved their position relative to the leaders. This should be largely attributed to two forces. First, is the substantial increase in food availability at the global level over the last 40 years as a result of improvements in agricultural productivity and a better functioning of the food processing and distribution sector. Second, is the fact that the per capita intakes of the selected nutrients in the leading countries reached their upper asymptotes by the early 1980's. Since then, several of them have experienced reductions in intakes reflecting the higher awareness about the detrimental effects of nutrient excess and imbalance. In addition, the analysis of actual transitions provided some evidence of club formation for proteins and fats but with substantial dispersion within each club.

Long-run/steady-state distributions of nutrient intakes have been simulated using a recently proposed approach and were found to be more concentrated that those in the 1999-2001 period. The relevant stochastic kernels, however, indicated that convergence of intakes at very similar levels is not likely. The long-run distributions have been compared with "virtual" ones revealing that the magnitude of income elasticity or equivalently the rate of growth in real per capita income has a strong influence on the dispersion of an equilibrium distribution of intakes.

For economists, income is a very important determinant of the demand for nutrients. But, it is not the only one. Environmental, cultural, and religious factors and even international trade and tourism can also play a role in dietary patterns. In the estimated intake change models some (although not all) continent dummies were found to be statistically significant. This is an agreement with the notion that factors beyond income growth may affect changes in nutrient intakes. The use of continent dummies, however, is admittedly a rather crude way of capturing the influence of those factors. Future research may use more sophisticated ways providing, thus, richer insights into the forces behind the evolution of nutrient intake patterns in the world.

Notes

[1] Fousekis and Lazaridis (2005) relied on a large cross-section of caloric (energy) intakes and analysed the intra-distribution dynamics through a transition probability matrix (Cox and Miller, 1965). Such matrices, however, are not very well suited for the study of distributions involving continuous variables like nutrient intakes since the estimation results may depend on the choice of the discretizing grid (Quah, 1993b). In contrast, the stochastic kernels by being the counterparts of transition matrices where the number of states tend to infinity provide robust results with regard to mobility, stratification, and convergence (Quah, 1997; Durlauf and Quah, 1999).

[2] The dynamics of an evolving cross-section distribution can be investigated considering either differences or ratios of variables. The choice between the two depends largely on the notion of the long-run cross-section distribution that a researcher has in mind. If she(he) thinks that each country in the long-run will attain a fixed level of intake it is appropriate to consider differences in intake levels. If, however, she(he) believes the long-run cross-section distribution is the one in which not the absolute but the relative positions of all countries will be fixed it is appropriate to consider intake ratios. The overwhelming majority of researchers work with the latter notion in mind (e.g. Johnson, 2001; Quah, 1997; Fingleton and Lopez-Bazo, 2003).

[3] Other factors such as food prices may influence growth in nutrient intakes. However, price information is unavailable. We note that most of the empirical studies at a national level (e.g. Naya, 1994; Variyam et al., 1996) and all empirical studies at an international level (e.g. Gil et al., 1995; Herrmann and Roder, 1995; Angulo et al., 2001) do not include prices in nutrient demand equations.

[4] The continent dummy variables are: D1 for Africa, D2 for North and Central America, D3 for South America, D4 for Asia, D5 for Europe, and D6 for Oceania. Asia is treated as the control continent.

[5] The analysis of distribution dynamics is conducted here in terms of nutrient intake levels. The intake level, however, is just one among a number of possible indicators of food consumption patterns. Others can be the shares of certain food items in the food budget, the shares of given nutrients taken from given food items, on even the income elasticities of demand, as in the study of Angulo et al. (2001). Because different variables may have different implications, the results of any empirical study should be always interpreted with the indicator employed in mind.

[6] Nutrient intakes in low-income countries may be subject to random shocks because of adverse weather conditions, civil wars, etc. The three-year averages have been used to reduce random noise.

[7] When equation (6) is estimated from cross-sectional data leads to a common to all countries income elasticity of demand for intakes. Given, however, that the objective of this study is to assess how an increase (decrease) in the elasticity of demand for all countries in the sample simultaneously affects the shape of the long-run distribution, working common ("average over the sample") demand elasticity is not overly restrictive.

[8] The estimation results from the two full models are available upon request. For proteins, the p-value of the test statistic for the hypothesis that D2, D3, and D6 are simultaneously redundant is 0.885; for fats the p-value that of the test statistic for the hypothesis that D2, D5, and D6 are simultaneously redundant is 0.662.

[9] Alternatively, one could set the coefficient of $\hat{I}$ equal to 150 percent of its estimated value. The kernel in that case will be (almost) the mirror image relative to the positive diagonal of that in Figure 1e.

[10] Complying, thus, with *a priori* expectations. To explain it we use here a very simple example. Let two countries with initial daily per capita protein intakes of 100 (leading country) and of 50 (lagging country), respectively. Let also the *income effect* (income elasticity multiplied by income growth) in both countries be 0.02. Then in one period, the daily per capita intake in the first country will increase to 102 and in the second country will increase to 51 (the difference in intakes will be 51). Let now that the income elasticity decreases to 50 percent of its initial value, while the rate of growth in income remains the same. Then in one period the intake in the first country will become 101 and in the second will become 50.5 (the difference in intakes will be now reduced by 0.5). With the smaller income elasticity the lagging has improved its position relative to the leading one. From the example it is obvious that what matters for the dispersion is the magnitude of the income effect. One could get exactly the same results by holding the income elasticity constant and reducing the growth rate for all countries by 50 percent.

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APPENDIX

Countries at the top and the bottom of the intake distribution

A. Proteins*

1961-1963		1999-2001	
Top	**Bottom**	**Top**	**Bottom**
Iceland 120.2	Comoros 31.6	Iceland 120.7	Congo Dem. Rep. 24
Australia 106.7	Central Afr. Rep. 32.6	Portugal 119.7	Mozambique 37.7
Argentina 104.7	Papua N. Guinea 33.1	Greece 119.2	Congo Rep. 41.9
France 103.3	Indonesia 34.8	France 117.3	Comoros 42.3
Ireland 101.8	Mozambique 35.4	Ireland 115.4	Central Afr. Rep. 43.6

B. Fats*

1961-1963		1999-2001	
Top	**Bottom**	**Top**	**Bottom**
UK 137.6	Rwanda 10.5	France 166.7	Burundi 10.4
Iceland 135.6	Burundi 12.2	Austria 163.3	Rwanda 16.9
Switzerland 134.4	Korea Rep. 14.6	Belgium 160.1	Congo Dem. Rep. 23.6
Denmark 132.3 103.3	Bangladesh 15.5	Italy 155.5	Bangladesh 26.3
Netherlands 129.1	China 16.8	Spain 152.6	Malawi 28.5

*, daily intakes in grams.