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Abstract

The relationship between calorie and nutrient (fat, protein, and carbohydrates) intake as a function of income is explored using data for 171 countries over two time periods 1990-1992 and 2003-2005. Three types of analysis are employed: i) nonparametric, ii) panel regressions, and iii) quantile regressions. Engle curves for calories, fat, and protein are approximately linear in logs with carbohydrate intakes exhibiting diminishing elasticities as incomes increase, becoming negative around $US7500 and above. Other nutrient and calorie elasticity estimates are positive statistically significant. Elasticities range from 0.10 to 0.25, with fat having the highest elasticities. The estimated elasticities for the quantile regressions are similar across the 0.25, 0.50 and 0.75 quantiles, but with moderate evidence that countries in the higher quantiles have lower elasticities than those in the lower quantiles. There has been a small but significant shift in the elasticities across the two periods.

Keywords: Calorie and Nutrient Consumption, Food and Nutrition Policies, Income Elasticities, Nonparametric Regression, Panel Data, Quantile Regression.

JEL codes: C11, C14, C21, C23, O10, O47, Q18

1. INTRODUCTION

"For the first time since 1970, more than one billion people, about 100 million more than last year and around one-sixth of all of humanity, are hungry and undernourished worldwide" Food and Agriculture Organization (2009).

"Obesity has reached epidemic proportions globally, with more than 1 billion adults overweight, at least 300 million of them clinically obese, and is a major contributor to the global burden of chronic disease and disability" World Health Organization (2004).

The number of undernourished people in the world increased from 854 million in 2006 to an estimated 1.02 billion in 2009, representing the greatest amount of hungry people in nearly half a century (FAO 2009). The FAO (2009) contends that while the current economic crisis plays a role in the global escalation of hunger, surging domestic food prices and deteriorating household incomes are especially to blame. Paradoxically, the growing international prevalence of hunger and starvation resulting from energy and nutrient deficiencies continues amidst global concern regarding the rapidly increasing prevalence of chronic diseases resulting from overweight and obesity. As of 2005, an estimated 1.6 billion adults over age fifteen were overweight and 400 million were obese (WHO 2006). Although the spread of obesity was confined historically to the developed countries, emerging trends indicate the growth of overweight and obesity in the developing world (Seidell 2000; Prentice 2005; Hossain et. al 2007; Misra and Khurana 2008). In fact, in many developing countries, both childhood malnutrition and adult obesity are concurrently observed within households resulting in a "dual burden of disease" (Doak et. al 2004; Caballero 2005; Prentice 2005).

A potential key determinant of food consumption is income. Therefore, studies on the relationship between income and nutrient intake receive considerable attention. Reutlinger and Selowsky's (1976) influential work sparked a prolific literature on estimating the income elasticity for calorie intake using an Engel curve approach. Knowledge of these elasticities is a critical component in the design of policies to combat malnutrition in poor countries and to improve diets in both rich and poor countries. For example, a large elasticity suggests a policy designed to increase the income of the poor and promote economic growth is an effective long-term strategy. Conversely, a small elasticity suggests limited scope for income-enhancing economic policies. Just as important, knowing how calorie and nutrient elasticities change with income becomes necessary in light of the obesity epidemic. The process of economic development spurs a "nutrition transition" in which diets high in carbohydrates are replaced with more varied diets high in fat (Popkin 1994). If calorie-income elasticities show no indication of decreasing at higher incomes, then there is a stronger need for public programs to influence diets in developed and developing countries.

The debate regarding the relationship between nutrient intake and income has high prominence in the development literature. Historically, the "conventional wisdom" of the World Bank and other institutions in the development arena was that deficient energy intake and hunger can be assuaged through income growth (World Bank 1980, 1981). However, a series of articles emerged in the 1980s casting doubt on the role of income (Wolfe and Behrman 1983; Behrman and Wolfe 1984; Behrman and Deolalikar 1987). In a notable study, Behrman and Deolalikar (1987) obtain an insignificant income elasticity using household data from rural Indian villages and conclude that increases in income do not result in meaningful improvements in nutrient intakes. The role of income in nutrition continues to spawn serious investigation, with contrasting results appearing throughout the literature. While the positive relationship between nutrient intake and income is reinforced in some studies, other studies find either small or insignificant income elasticities. Moreover, some studies argue that the relationship is linear (Bhargava 1991), while other studies uncover important nonlinearities in the income-calorie relationship (Gibson and Rozelle 2005; Skoufias 2003). Finding a nonlinear relationship is important as it suggest the impact of income on calorie intake is affected by the actual level of calorie intake. For example, high calorie consumers may not be as greatly affected by a marginal increase in income as low calorie consumers and as such will have a smaller elasticity.

With the evidenced mixed, the debate continues regarding the true relationship between nutrient intake and income and the appropriate economic policies for combating hunger and malnutrition. Also left unclear is the extent the nutrition transition is expected to occur in the developing economies, which involves not only a worsening in diet quality across the developing world but also a likely global epidemic from diet related chronic disease. The role of income in nutrition is clearly important for developing countries. However, as people in developed countries consume calories at increased levels, asking if further increases in income are likely to aggravate problems associated with obesity also becomes important. The primary objective of this paper is to assess the relationship between income and nutrient intake in an international sample of developing and developed countries. In particular, the analysis utilizes a large cross-sectional sample of 171 developing and developed countries across two different time periods (1990-1992 and 2003-2005). Most studies tend to focus on a particular country in a single year using household data. While such an approach is insightful, estimates from an aggregate Engel curve using international data on nutrient intake and income provides a global perspective and generalizes results beyond the country level.

The paper proceeds as follows. The second section reviews the recent literature. The third describes the data and outlines the econometric methods. The fourth section discusses the empirical results. The final section concludes.

2. THE INCOME ELASTICITY OF CALORIE INTAKE

While estimates of the income elasticity are abundant, the true approximate magnitude is a controversial topic owing to the wide range of estimates. Bouis and Haddad (1992) provide a good review and, though not up to date, find elasticity estimates in the range of

0.01 to 1.18, some statistically significant and others not. In one of the earliest studies using cross-country data to estimate an aggregate Engel curve, Reutlinger and Selowsky's (1976) obtain a statistically significant but small income elasticity estimate of around 0.17, suggesting that nutritional status cannot be improved through income-enhancing economic policies alone. In addition to the studies conducted by Behrman and associates (see, Behrman, Deolalikar, and Wolfe (1988), for a summary), a number of other papers claim that income is not the most salient factor in malnutrition, such as Reutlinger and Alderman (1980), Sahn (1988), Ravallion (1990), Bouis and Haddad (1992), and Bouis (1994).

Even though a substantial literature warns against an income-focused policy, the role of income is still considered important by many development institutions. According to the latest FAO (2009, p.36) report on the growing concern of food insecurity, the recent "diminished economic access to food because of higher prices was compounded by lower incomes." While a number of early papers substantiate the conventional wisdom of the World Bank before the "revisionist" papers emerged in the 1980s (Pinstrup-Andersen and Caicedo 1978; Ward and Sanders 1980), more recent studies also counter the revisionist regime (Subramanian and Deaton 1996; Dawson and Tiffin 1998; Tiffin and Dawson 2002; Abdulai and Aubert 2004). Table 1 provides a summary of recent studies since the review in Bouis and Haddad (1992). The estimated elasticities are of moderate magnitude (between 0.2 and 0.5) and most authors conclude that improving income is crucial to combating malnutrition. Different approaches partly explain the variation in estimates.

One difference is how the Engel curve and resulting income elasticity is estimated. Generally two methods are followed in the literature. The first method uses micro-level data obtained from household surveys to estimate the elasticity via an indirect approach (using food expenditure data to estimate a model of demand and then convert food elasticities into nutrient elasticities) or a direct approach (using food diaries based on dietary intake recall data to estimate the nutrient elasticities directly). The second method uses aggregate data on average per-capita dietary energy supply derived from national food balance sheets. Aggregate studies also follow one of two approaches. The first approach employs annual time series data for a specific country. The second approach uses cross-sectional data on a number of countries in a specific year (panel data approaches are also possible). Both approaches provide meaningful avenues to explore the relationship between energy intake and income.

This paper follows an aggregate approach which provides an international perspective. Although the empirical literature has grown considerably, most of the focus is on single-country analyses. There is a need for cross-country comparisons, particularly in light of dual international efforts relating both to nutrient excess and nutrient deficiency. The WHO (2004) global strategy on diet, physical activity, and health focuses on improving the quality of diets across developing and developed countries in order to assuage obesity and prevent diet-related chronic diseases. Meanwhile, the International Alliance Against Hunger (IAAH 2004), a global partnership of international organizations, works to eradicate hunger and malnutrition. Such efforts point out the need to complement single-country studies with more broad-based empirical evidence derived from cross-country econometric analysis.

Another important difference between studies is that some assume a specific parametric relationship between income and calorie intake, while some generalize the relationship using nonparametric estimators, which allow for potential nonlinearities. For example, a higher income elasticity of calorie intake ought to be expected for poor households since they may have insufficient income to pay for adequate nutrition. Nonparametric regression procedures allow for such a possibility and mitigate problems of statistical bias resulting from a misspecified parametric form. Some studies investigate the potential for nonlinearities and find they are not present (Subramanian and Deaton 1996; Abdulai and Aubert 2004). Other studies using nonparametric methods, however, suggest the income elasticity is better described by a curve rather than a line (Roy 2001; Gibson and Rozelle 2002; Skoufias 2003). These studies conclude that nonlinearity is an important characteristic in the relationship between income and calorie intake.

In addition to using a parametric panel estimator to test for time-effects in the income-nutrient relationship, this paper also uses a nonparametric estimator, which lets the relationship be both non-linear and non-monotonic. Calorie intakes between poor households and rich households can respond differently to income. This paper also employs quantile regression. Since the effect of income may differ across the distribution of calorie intake, particular segments of the intake distribution are of great interest, especially from a public health and nutrition policy perspective. Concerns regarding obesity and hunger solicit special attention to the tails of the intake distribution, where dietary excess and deficiency occurs, rather than at the means. Since most previous studies rely on a form of ordinary least squares (either parametric or nonparametric), the marginal effects of income derived from these studies are assumed to be the same over the distribution of calorie intake. Quantile regression relaxes this assumption and allows for heterogeneous responses of calorie intake to income. Despite the strong appeal of quantile regression, very few studies employ them. The few that do use either focus on food intake rather than calorie or nutrient intake (Variyam et. al 2002; Gustavsen and Rickertsen 2006; Boukouvalas et. al 2009) or focus only on the nutrient intake for one country only (Fousekis and Lazaridis 2005; Skoufias et. al 2009; Shankar 2010).

Even if a reasonably sized and statistically significant income-calorie elasticity is found, the role of income in nutritional status is still unclear since people may shift the composition of their nutrient consumption as income changes (Behrman and Deolalikar 1989). As incomes rise, expenditure on food may increase because more expensive food is being purchased but the nutrient content of these foods may not increase proportionately (Pitt 1983; Behrman, Deolalikar, and Wolfe 1988). Improvements in income can trigger increases in food expenditures or total calorie intake, but this may not coincide with a diet more rich in nutrients (Brinkman et. al 2010; Behrman and Deolalikar 1987). Households tend to increase the variety of their diet based on features other than nutrient content, such as taste and quality, as they substitute away from cheaper sources of calories towards more expensive ones. Conversely, studies that uncover a small or zero elasticity do not necessarily imply that a change in income does not affect nutrition. For example, a drop in income may result in unchanged calorie intake, but the consumption of vital nutrients may fall as household substitute towards cheaper and less nutritious foods. Regardless of the size of the elasticity for calories, there is little room for conclusions regarding the consumption of important nutrients, such as proteins, fats, and carbohydrates (Skoufias 2009).

The existing evidence on income elasticities for nutrient intake from single-country studies reveals considerable differences. Pitt and Rosenzweig (1985) use farm household data from Indonesia and find a negative income-calorie elasticity (-0.03), but small and positive elasticities for protein (0.02), fat (0.03), and carbohydrates (0.01). Berhman and Deolalikar use household data from India and obtain a mean income elasticity of 0.17 for calories and of 0.06 for protein. This paper decomposes calorie intake into three key nutrients: proteins, fats, and carbohydrates. In so doing, this paper provides the first income elasticity estimates of key macronutrients for an international cross-country sample. Obtaining income elasticity estimates that break down total calorie intake into individual nutrients is important from a policy perspective. Economic growth may increase total calorie intake, reducing problems related to hunger and malnutrition, but may also result in a greater proportion of fat in the diet, causing higher rates of obesity and diet-related chronic diseases. The income-calorie elasticity alone is not enough to guide policy makers. Understanding the general composition of the diet and the consumption of particular nutrients becomes crucial in this context.

In addition to the problem of deficient calorie and nutrient intake is the problem of excessive intake which causes overweight and obesity. The World Health Organization (2006) projects that by 2015 nearly 2.3 billion adults will be overweight and over 700 million will be obese. As developing countries experience economic growth, overweight and obesity are on the rise in low- and middle-income countries, particularly in urban areas (WHO 2006). High income countries tend to obtain most of their dietary energy supply from fat (Drewnowski 2003). The analysis in Drewnowski and Popkin (1997) reveals a global convergence towards a diet deriving a higher proportion of energy from fat across a sample of developed and developing countries. As countries develop, the urbanization process relocates people out of rural areas and into more urban settings (Bleich at. al 2008). Rural populations typically engage in more physical activity and eat more varied diets, while urban populations usually eat spend more time in sedentary activity and eat less varied and more processed food (Popkin 1999, 2004; Webb 2010). Also worrying is the trend that the nutrition transition is occurring at lower levels of income than previously thought (Drewnowski 2003; Popkin 2010). As pointed out in Popkin and Ng (2007, p.200), "even poor nations had access to a relatively high-fat diet by 1990 when a diet deriving 20% of energy (kilocalories) from fat was associated with countries that have a GNP of only $750 per capita". Such figures are cause for concern and Drewnowski and Popkin (1997) warn about the possibility that a diet containing close to 30% of energy from fat could become the global norm.

3. DATA AND METHODS

Aggregate data on average per capita dietary energy supply are derived from national food balance sheets obtained from the FAO Statistics Division. A cross-sectional sample of 171 developing and developed countries across two different time periods (1990-1992 and 2003-2005) is constructed (please refer to Table A1 in the appendix for the list of countries). Dietary energy consumption per person is defined as the amount of food, in kilocalories per day, for each individual in the total population. The measure is based on food available for human consumption computed as the residual from the total food supply less waste and other uses, such as from industry or agriculture. Income data, sourced from the International Financial Statistics of the International Monetary Fund, is the Gross Domestic Product (GDP) for each country in billions of 2005 U.S. dollars. To convert these values to GDP per capita, population data is used from the Penn World Tables.

Three main estimation methods are employed in this paper. All three are Bayesian. First, there is the nonparametric approach outlined in Chapter 10 of Koop (2003). The second is a linear (in parameters) panel regression that can be estimated using the framework outlined in Chib and Greenberg (1995). And, finally the recently developed method for estimating quantile regressions (the Bayesian Exponentially Tilted Empirical Likelihood, BETEL method) outlined in Lancaster and Sung (2010). When using the panel approach, alternative models are evaluated using the Bayesian Deviance Information Criteria (DIC) outlined in Spiegelhalter et al. (2002). A full description of each of the methods can be found in the references above, therefore, the coverage here is succinct.

The Nonparametric Approach

The motivation for using a nonparametric approach is that the relationships between calorie or nutrient consumption and income may be highly non-linear and plausibly non-monotonic. Nonparametric flexibility allows the examination of whether simple functional forms are viable. Therefore, this approach is employed first before investigating the relationships using a parametric approach. The nonparametric method assumes:

$$y_i = f\left(x_i\right) + e_i$$

where y_i is the average consumption in country i of calories or one of the nutrient groups, and x_i is per capita income in country i. Alternatively y_i and x_i may be logged values of these variables. The error term e_i is assumed to be independently and identically normally distributed. As outlined in Koop (2003), the nonparametric relationship can be modelled by estimating $f(x_i)$ at each point value of x_i. Crucially, the estimation of the nonparametric relationship requires a smoothing parameter η to be estimated. This parameter is analogous to a bandwidth selection using classical kernel estimation. Within the Bayesian approach to estimation, this parameter can be estimated by maximizing the marginal likelihood of the relationship or through cross-validation. The former method is used, for which readers are referred to Koop (2003). When using the nonparametric approach, the models are estimated for the two periods separately. Thus, there are two sets of nonparametric regressions.

The Panel Approach

For the panel approach, the models investigated are of the form (or special cases of)

$$y_{it} = \alpha_t + \beta_{1t} x_{it} + \beta_{2t} x_{it}^2 + \beta_{3t} x_{it}^3 + e_{it}$$

where $e_{it} \sim N(0, \sigma^2)$, $E(e_{it}, e_{jt}) = 0$ for all $i \neq j$ and $E(e_{it}, e_{jt*}) = \rho\sigma^2$ for all $t \neq t^*$. Also, y_{it} denotes the dependent variable (calories or nutrients or logs of these variables) for country i at time t and x_{it} is per capita income (or log values) for country i at time t. Since there are only two time periods, the values of t are one and two. By allowing the relationship to be cubic, the model deals with functions that have variable second derivatives whereby the function may be convex and concave over alternative regions of the variable space. The imposition of restrictions are investigated, such as $\beta_{it} = \beta_{it*}$ (no time effects) and/or $\beta_{2t} = 0$ and/or $\beta_{3t} = 0$, in which case the function may become quadratic or linear (or linear in logs). The Bayesian approach further allows imposition and investigation of whether inequality restrictions are consistent with the data. For example, in the cubic relationship the hypothesis might be that $\beta_{3t} < 0$ since one might expect that consumption of calories or nutrients would not increase at an accelerating rate as incomes rise. Finally, take note that an alternative panel approach assumes that $\beta_{jt} = \beta_{jt*}$ for all j along with $e_{it*} = e_{it} + z_i$ where z_i is a normally distributed country effect. This "within country/between time" regression is also estimated.

The Quantile Approach

Unlike the previous two approaches, the BETEL does not have an explicit functional form for the likelihood. Instead, the empirical likelihood is constructed by optimizing an entropy measure for any given value of the parameters. The empirical likelihood is multiplied by some relatively diffuse priors to obtain the posterior distribution of the parameters, and then this can be mapped using a Metropolis-Hastings algorithm. The BETEL approach can be used more generally than for quantile regressions. The moment conditions are derived from the condition that (for two variables y_i and x_i)

$$\Pr\left(y_i < \alpha(\tau) + \beta(\tau)x_i \mid x_i\right) = \tau$$

The parameters $\alpha(\tau)$ and $\beta(\tau)$ represent the intercept and slopes for the τ^{th} quantile. Like the nonparametric regressions, quantile regressions are run separately for each time period.

4. RESULTS AND DISCUSSION

Discussion of the results proceeds sequentially examining the nonparametric results first, followed by the results of the panel regressions, followed by the quantile results. As stated above, the nonparametric regressions were run for each of the variable pairs separately over the two periods (1990-1992 and 2003-2005). Only the results for the latter period are presented, since the nonparametric plots are almost the same between the two periods. First, Figure 1 examines the raw nutrient shares modelled as a function of the raw per capita variable. The middle line is the fitted (mean) nonparametric relationship, with the two outside lines containing the 95% confidence intervals for the mean. As can be seen from the plots, the relationships between shares of nutrients and per capita income appears to be non-linear, with poorer countries having relatively high levels of carbohydrates as a proportion of their diet (top left hand corner of Figure 1). As incomes increase, however, the shares of carbohydrates decrease with a small rise in proteins but a much larger rise in fats. In the poorest countries, about 80% to 85% of the diet is in the form of carbohydrates and only around 10% in fats. As incomes increase though, there is a rapid switch to fats, levelling off at around a 50% share in carbohydrates and a 38% share in fats, with the remainder being proteins. The warnings made by Drewnowski and Popkin (1997) about the possibility that a diet containing close to 30% of energy from fat could become the global norm has in fact become the norm for many countries already. This trend is particularly worrying since changes in diets are typically irreversible. For example, while increasing income is associated with diets higher in fat, economic downturns are not associated with a return to healthier eating (Drewnowski 2003).

The second set of nonparametric plots in Figure 2 are the log calorie and nutrient intakes regressed against log per capita income (the relationships between the raw data were also examined, and these were highly nonlinear and not presented here). What is interesting about the fitted curves using the log data is that for each of the variable pairs the nonparametric curves are quite linear. In other words, the data are consistent with being linear in logs, and therefore have constant elasticities. There is some evidence of a slightly lower slope at very low levels of per capital income for total calories, fats, and proteins. Perhaps surprisingly, however, the increases in consumption of these quantities towards the upper end of the income range do not appear to level off. This implies that as per capita incomes rise, a given percentage increase in per capita incomes continues to give the same percentage increase in calories, along with increases in fats, proteins, and carbohydrates. Also evident is that the carbohydrate line is much flatter, meaning that increases in incomes are not leading to the same increases in carbohydrates as for fats and proteins. This is consistent with the previous nonparametric results using the nutrient shares.

In view of the nonparametric results, the linear in log specifications represent plausible empirical characterizations of the relationships between calories/nutrients and per capita income. This hypothesis is explored further using parametric methods. As outlined in the methods section, a set of panel regressions are specified, where the variables have been logged prior to estimation. Before presenting parameter estimates, alternative specifications including only a quadratic term and excluding a cubic or quadratic term are investigated first. No other restrictions are imposed at this stage, with further restrictions investigated subsequently. The DIC for each of the models is computed, with the preferred model being the one with the lowest DIC. The results are presented in Table 2. The models with the lowest DIC are highlighted in bold, and the linear (in variables) specification is preferred for total calories, protein, and fats. However, the quadratic model is preferred for carbohydrates. Results conclude that the panel results are in concordance with the nonparametric results. Evidence suggests total calories, protein, and fats have approximately constant elasticities over per capita incomes. This is not the case, however, for carbohydrates. The restrictions on the parameters across the time periods are investigated in Table 3 to test if the relationships differ across the two periods (1990-92 and 2003-05). For these comparisons the linear models are used, even for carbohydrates. As seen from the results in Table 3, while there is evidence that the constants in the models can be restricted across the two periods, none of the models support constant elasticities across the two periods, suggesting that there have been other changes in consumption patterns other than those driven by incomes.

Table 4 presents the elasticity estimates using the Panel approach. Again, the linear model results are given in Table 4. As mentioned above, the quadratic model is preferred for carbohydrates, therefore carbohydrates are discussed further below. The estimates in Table 4 reveal that while the DIC does not support constant elasticities over the two periods, the differences in elasticities across the periods is very small. The calorie elasticity is around 0.09

for both periods and both periods have 95% elasticity confidence intervals that would be contained within the interval (0.072,0.104). Both protein and fat elasticities are significantly larger than the calorie elasticities (at around 0.14-0.15 and 0.23-0.24, respectively), whereas the carbohydrate elasticity is much smaller (at around 0.02-0.025). This is consistent with the previous results regarding nutrient shares. Overall, the results suggest that a 10% increase in per capita incomes will lead to around a 1% rise in calorie consumption, but with the larger components being an increase in fat consumption, followed by protein consumption, with a very small increase in carbohydrate consumption. As noted, however, the carbohydrate elasticity does not appear to be constant. To further investigate carbohydrate consumption the income elasticity is estimated at each level of income. These are plotted in Figure 3 for the two time periods, which again are very similar. The basic picture that emerges is that the carbohydrate elasticity is around 0.10 for very low levels of income, decreasing at a decreasing rate from there on, but remaining positive until around $US7500 per year. Beyond this point carbohydrate consumption has a negative elasticity.

The results for the quantile regressions are presented in Table 5. Again, these are linear in log specifications for each of the variables. Table 5 reports the upper 75%, the median, and the lower 25% percentile elasticity estimates. In all cases, for all quantiles, the results are very similar to the estimated elasticities from the panel results. Of central interest is whether there seems to be a divergence between the different percentile values. As can be seen by Table 5, these are very small. A large divergence between the lower and the upper percentiles would mean that countries with a higher consumption (for a given level of per capita income) are responding differently to those with a lower consumption (for a given level of per capita income). For example, if for calories the β 0.25 was much smaller than β 0.75 then countries with lower consumption of calories or nutrients would be less responsive to income changes than those with relatively high consumption of calories. This arguably would be the most worrying scenario, since increased incomes would be having the least effect on those with the lowest consumption, and increased incomes would be having the highest effect on those with the highest income. From Table 5, however, the opposite tends to be true. For both periods, the majority of the variables have non-decreasing or increasing elasticities moving down the percentile groups. Therefore, those consuming relatively small amounts of calories or nutrients (for a given level of income) tend to be the most responsive to changes in the levels of income. As noted though, the divergence between the quantiles is very small indeed.

5. CONCLUSIONS

Hunger and undernutrition is primarily responsible for millions of deaths every year, mostly in children (Victoria et. al 2008). Around 178 million children suffer from chronic undernutrition, which causes both physical and mental growth stunting, and over 2 million children die each year as a result of insufficient dietary intake (Black et. al 2008). At the other end of the spectrum, developed and developing countries alike face problems with obesity and high levels of consumption of nutrients, such as saturated fat, which have been shown to lead to a higher incidence of problems such as hypertension, heart disease, strokes, diabetes, cancer, and obesity. Understanding the relationship between calorie intake and income is crucial to developing strategies towards combating chronic diseases associated with both nutrient deficiency and nutrient excess. The dual burdens of hunger and obesity, require special attention to the tails of the nutrient intake distribution. Given the historical difficulty in coordinating effective international action against hunger and undernutrition, in addition to the escalating global obesity epidemic, there is a continued need for research on effective policy instruments to combat these dual burdens (Morris et. al 2008).

This paper examined the relationship between calorie/nutrient intakes and per capita incomes using a two-period panel of 171 countries. The literature is extended in two ways. First, the relationship between income and average calorie intake is disaggregated into important nutrient components (carbohydrates, proteins, and fats), which permits the relationship with income to differ between each nutrient. Most of the literature on nutrition and income focuses entirely on total calorie intake. While the income elasticity of calories infers how the total level of energy is affected by income, it reveals nothing about how income affects diet composition. The few studies that do estimate nutrient-income elasticities (Pitt and Rosenzweig 1985; Behrman and Deolalikar 1987; Behrman and Wolfe 1987; Skoufias et. al 2009) confine their analysis to a single country. Second, this study employs three different estimators (nonparametric, parametric, and quantile) for a robust interpretation of the income-nutrient relationship. A nonparametric estimator allows the relationship between income and calorie/nutrient consumption to be non-linear and non-monotonic. The parametric panel estimator permits estimation of both 'within-country' and 'between-time' effects and allows for testing of changes in the relationship over time. The quantile estimator lets the marginal effect of income on calorie/nutrient intake be different over the intake distribution. In other words, the impact of income may be different between rich and poor countries, which consume calories at different levels, so improvements in income may not impart equal benefits. While some studies use both parametric and nonparametric estimators, few utilize quantile regression.

Calories, fats, and proteins are found to have positive significant income elasticities. The data on these variables are also consistent with having constant elasticities across the income range. Carbohydrate consumption has high positive elasticities only at low income levels, becoming negative at high incomes. Quantile regressions yields similar elasticity estimates to the nonparametric and panel approaches at both the upper and lower quantiles, but there is evidence to suggest that higher consuming countries had slightly lower elasticities than for those in the lower quantiles (for both calories and nutrient components). Findings have both positive and negative implications. First, in line with the majority of previous studies, the small but positive income elasticities suggest income growth will increase calorie consumption and increase all nutrient consumption for low income countries (below US$7500). However, elasticity estimates fall below the majority of existing estimates.

In terms of overall calorie consumption, a 10% rise in incomes is required for 1% rise in calorie consumption. Thus, rather large increases in income are needed for improvements in the nutrition status of people in poorer countries. The implications for higher income countries are perhaps no less important. Findings suggest that this overall rise in calorie consumption as incomes rise holds also for rich countries. Thus, for countries that are already consuming well beyond the recommended calorie levels, further increases in income will lead to even larger consumption of calories. Moreover, the consumption of fat has the largest elasticity at around 2.5 that of overall calorie consumption, meaning the larger component of increased calorie consumption will be in terms of fats. While these elasticities may seem small, in the absence of any other change in behavior, extrapolating current income growth predicts significant cumulative increases in calorie consumption that would exacerbate existing problems associated with obesity.

Development strategies aimed at improving economic growth may prove to be insufficient at alleviating hunger and may at worst exacerbate problems of poor diet and obesity in both developing and developed countries. Even in the absence of targeted food policies, the global economic crisis will likely worsen the quality of diets internationally. In response to falling incomes, households are likely turn to fatty and calorie-dense, but nutrient poor and inexpensive processed foods. As the composition of diets change towards more fatty foods, countries across the globe will experience deteriorating nutrient status and health. Global efforts to improve diets require the coordinated design and implementation of policies that can address the dual public health problems of nutrient excess and deficiency.

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Table 1. Summary of recent studies

Author	Year	Data Level	Data Type	Timeframe	Country	Elasticity
Bhargava	1991	Individual	Panel	1976-1977	India	0.13
Grimard	1996	Household	Cross-sectional	1984-1985	Pakistan	0.40-0.50
Subramanian and Deaton	1996	Household	Cross-sectional	1983	India	0.40-0.55
Dawson	1997	Aggregate	Cross-sectional	1992	41 DCs	0.07
Dawson and Tiffin	1998	Aggregate	Time-series	1961-1992	India	0.34
Roy	2001	Individual	Panel	1976-1978	India	<0-0.15
Dawson	2002	Aggregate	Time-series	1961-1998	Pakistan	0.19
Gibson and Rozelle	2002	Household	Cross-sectional	1985-1987	Papua New Guinea	0.18-0.59
Tiffin and Dawson	2002	Aggregate	Time-series	1961-1992	Zimbabwe	0.31
Skoufias	2003	Household	Cross-sectional	1996, 1999	Indonesia	0.01-0.45
Abdulai and Aubert	2004	Household	Panel	1998-1999	Tanzania	0.49
Aromolaran	2004	Household	Cross-sectional	1999-2000	Nigeria	0.19
Skoufias et. al	2009	Household	Cross-sectional	2003-2004	Mexico	<0-0.07
Babatunde et. al	2010	Household	Cross-sectional	2006	Nigeria	0.18

Table 2. DIC for Functional Forms

	Calories	Carbs	Protein	Fats
Cubic	-1180.25	-1109.16	-966.52	-738.66
Quadratic	-1178.46	**-1109.56**	-967.91	-738.32
Linear	**-1180.93**	-1102.93	**-969.28**	**-741.57**

Table 3. DIC for Restrictions Across Periods for Linear Models

	Calories	Carbs	Protein	Fats
Unrestricted	-1180.93	-1102.93	-969.28	**-741.57**
Constant Elasticities	-1178.20	-1103.60	-969.27	-733.40
Constant Intercept	**-1182.60**	**-1104.83**	**-971.27**	-739.89
Constant All Parameters	-1151.22	-1090.24	-947.37	-716.88

Table 4. Elasticity Estimates from Linear Panel Regression

	Calories		Carbs		Protein		Fats	
	Mean	Stdv	Mean	Stdv	Mean	Stdv	Mean	Stdv
2003-05	0.086	0.006	0.020	0.007	0.140	0.009	0.230	0.014
1990-02	0.092	0.006	0.025	0.007	0.148	0.009	0.241	0.014
	Mean	Stdv	Mean	Stdv	Mean	Stdv	Mean	Stdv
Diff	0.074	0.030	0.026	0.036	0.162	0.041	0.209	0.060

Table 5. Elasticity Estimates from Quantile Regression

2003-05	Calories		Carbs		Protein		Fats	
	beta	stdv	beta	stdv	beta	stdv	beta	stdv
$\tau = 0.75$	0.083	0.009	0.016	0.007	0.130	0.012	0.197	0.020
$\tau = 0.50$	0.088	0.007	0.020	0.009	0.140	0.007	0.229	0.016
$\tau = 0.25$	0.089	0.010	0.026	0.010	0.152	0.011	0.257	0.024
1990-92	beta	stdv	beta	stdv	beta	stdv	beta	stdv
$\tau = 0.75$	0.093	0.008	0.019	0.007	0.137	0.012	0.217	0.018
$\tau = 0.50$	0.094	0.007	0.019	0.010	0.147	0.010	0.264	0.021
$\tau = 0.25$	0.094	0.008	0.028	0.007	0.156	0.014	0.274	0.027

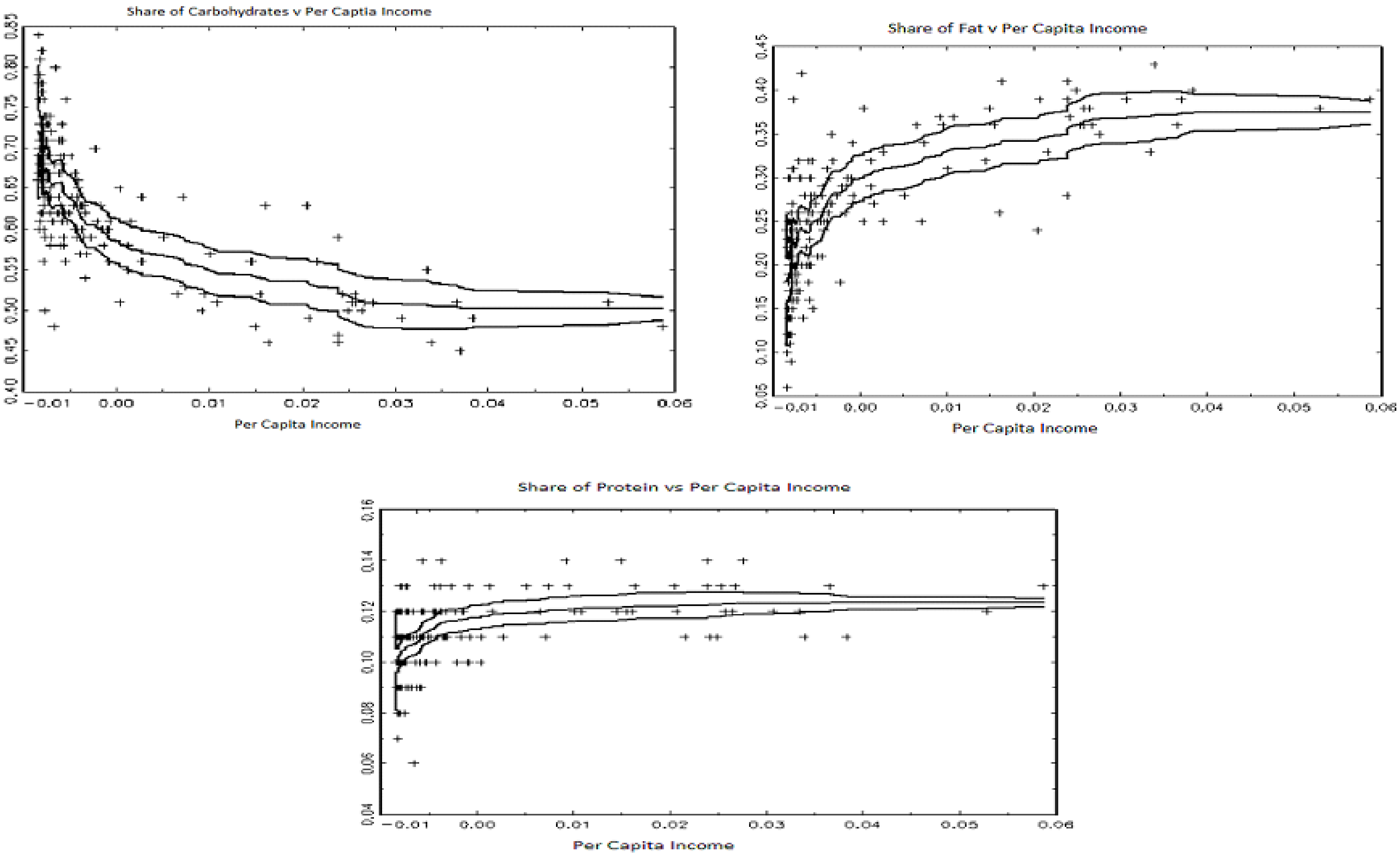

Figure 1. Nutrient Shares versus Per Capita Income

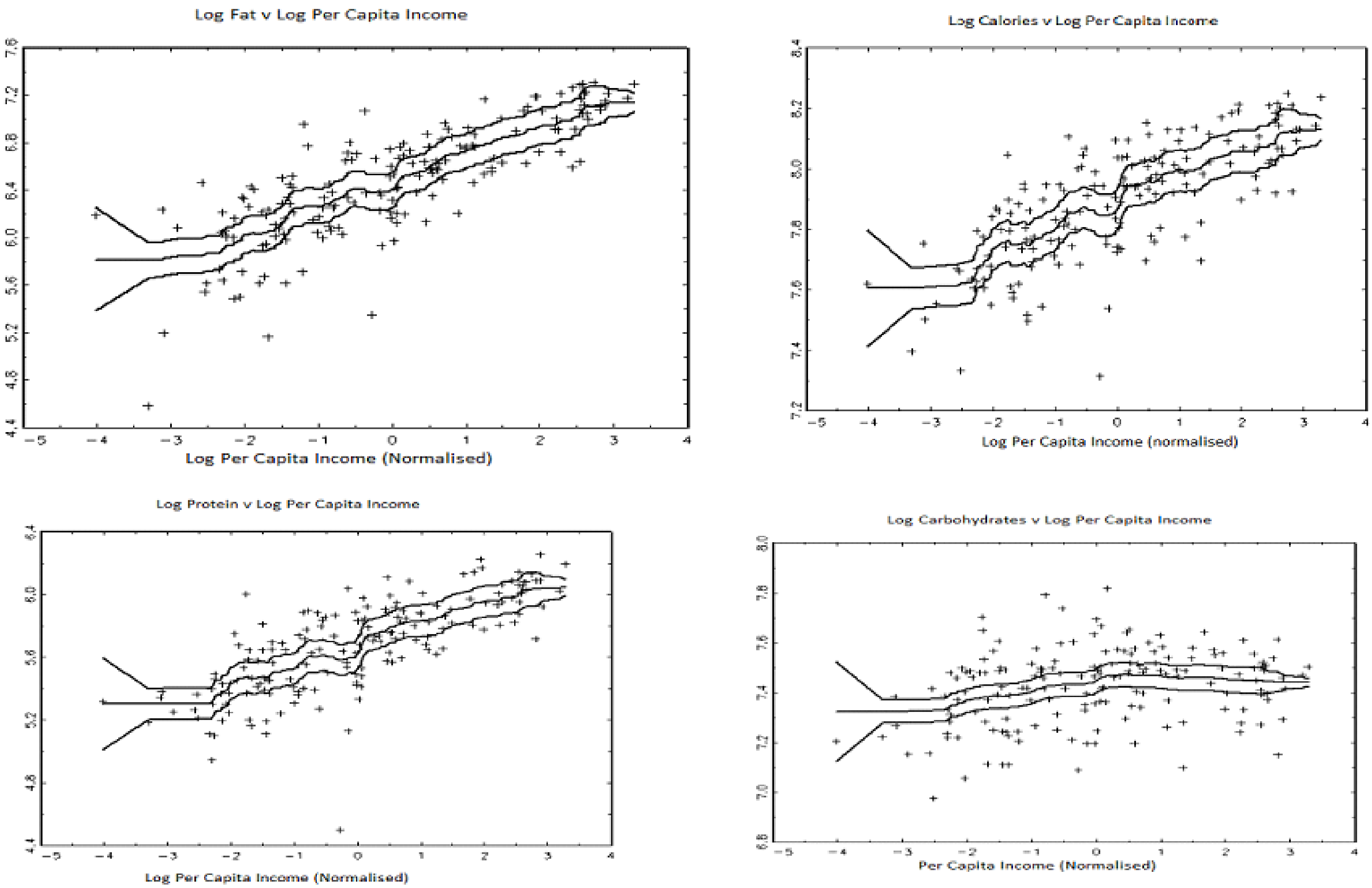

Figure 2. Log Nutrient Consumption versus Per Capita Income

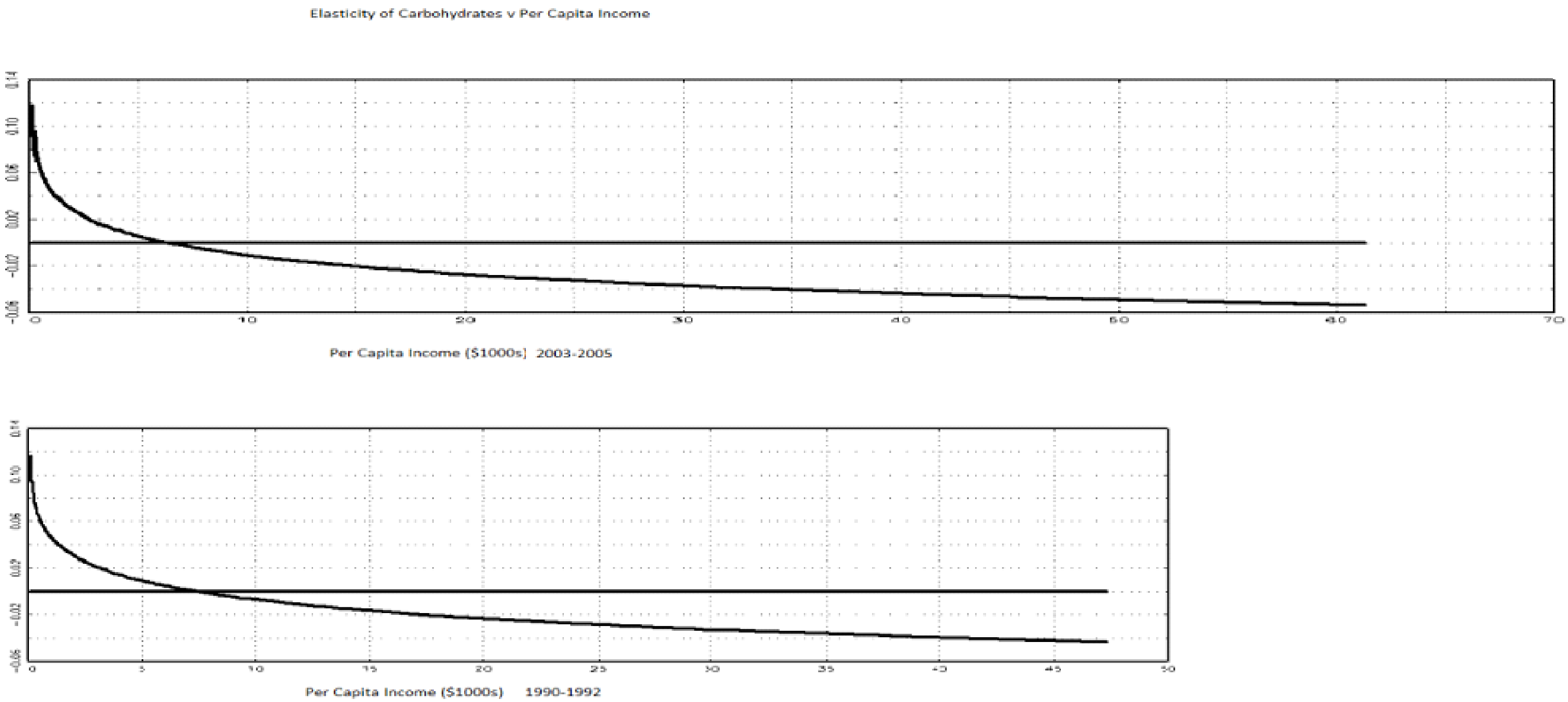

Figure 3. Carbohydrate Income Elasticity

Table A1. List of Countries

Albania	Denmark	Laos	St. Lucia
Algeria	Djibouti	Latvia	St. Vincent & Grenadines
Angola	Dominica	Lebanon	Samoa
Antigua and Barbuda	Dominican Republic	Lesotho	Sao Tome and Principe
Argentina	Ecuador	Liberia	Saudi Arabia
Armenia	Egypt	Libyan Arab Jamahiriya	Senegal
Australia	El Salvador	Lithuania	Serbia & Montenegro
Austria	Eritrea	Luxembourg	Seychelles
Azerbaijan	Estonia	Madagascar	Sierra Leone
Bahamas	Ethiopia	Malawi	Slovakia
Bangladesh	Fiji	Malaysia	Slovenia
Barbados	Finland	Maldives	Solomon Islands
Belarus	France	Mali	South Africa
Belgium	French Polynesia	Malta	Spain
Belize	Gabon	Mauritania	Sri Lanka
Benin	Gambia	Mauritius	Sudan
Bermuda	Georgia	Mexico	Suriname
Bolivia	Germany	Mongolia	Swaziland
Bosnia and Herzegovina	Ghana	Morocco	Sweden
Botswana	Greece	Mozambique	Switzerland
Brazil	Grenada	Myanmar (Burma)	Syrian Arab Republic
Brunei Darussalam	Guatemala	Namibia	Tajikistan
Bulgaria	Guinea	Nepal	Thailand
Burkina Faso	Guinea-Bissau	Netherlands	Togo
Burundi	Guyana	New Caledonia	Trinidad and Tobago
Cambodia	Haiti	New Zealand	Tunisia
Cameroon	Honduras	Nicaragua	Turkey
Canada	Hungary	Niger	Turkmenistan
Cape Verde	Iceland	Nigeria	Uganda
Central African Rep.	India	Norway	Ukraine
Chad	Indonesia	Pakistan	United Arab Emirates
Chile	Iran	Panama	United Kingdom
China	Ireland	Paraguay	Tanzania
Colombia	Israel	Peru	USA
Comoros	Italy	Philippines	Uruguay
Congo, Rep. of	Jamaica	Poland	Uzbekistan
Costa Rica	Japan	Portugal	Vanuatu
Côte d'Ivoire	Jordan	Rep. of Korea (S. Korea)	Venezuela
Croatia	Kazakhstan	Republic of Moldova	Viet Nam
Cuba	Kenya	Romania	Yemen
Cyprus	Kiribati	Russian Federation	Zambia
Czech Republic	Kuwait	Rwanda	Zimbabwe
Dem. Rep. of the Congo	Kyrgyzstan	St. Kitts and Nevis	