How Elastic is Calorie Demand? Parametric, Nonparametric, and Semiparametric Results for Urban Papua New Guinea

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Abstract

This paper seeks further evidence on the elasticity of calorie demand with respect to household resources. The case presented is for urban areas of Papua New Guinea, where just over one-half of the population appear to obtain less than the recommended amount of dietary energy. The relationship between per capita calorie consumption and per capita expenditure in urban areas of Papua New Guinea is not consistent with the view that income changes have negligible effects on nutrient intakes. The unconditional calorie demand elasticity is approximately 0.6 for the poorest half of the population. Using parametric and semiparametric estimation to control for a wide range of other influences on calorie consumption does not materially reduce the size of the elasticity. Therefore, these results are not supportive of "growth-pessimism" and instead suggest that policies that increase urban household incomes will also act to reduce undernutrition.

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Inadequate nutrition is perhaps the most severe problem facing the poor. Therefore, a key question for any policy aiming to improve human development is whether it improves nutrition? The orthodox view in development economics has been that policies that increase the incomes of the poor have beneficial effects on nutrition. But recently a new literature has emerged suggesting that increases in income will *not* result in substantial improvements in nutrient intakes (Behrman and Deolalikar, 1987). The poor may increase food expenditures as incomes rise, but this extra spending goes on food attributes other than nutrients (Behrman, Deolalikar and Wolfe, 1988). Also, other factors, such as women's schooling, are claimed to be more important than incomes in determining nutrient demands (Behrman and Wolfe, 1984).

The key behavioural parameter in these studies is the elasticity of calorie demand with respect to household resources. Estimates of this elasticity range from 0.01 to 1.18 (Strauss and Thomas, 1995). The wide range is explained both by methodological factors and by the range of income levels in the countries studied, due to the likelihood that the elasticity varies with income (see below). The first methodological factor is whether the estimates are directly from calorie demand equations, or are indirect conversions from food demand equations. The estimates also are affected by whether the calories measured are those actually consumed (intake) or just those available to the household, whether household resources are measured by income or by expenditure, and (for rural households) the cropping season in which calories and income are measured. The recent literature on calorie demand elasticities claims that the high elasticities that were previously believed to exist are likely to be the result of either bad data or poorly designed estimation strategies (Behrman and Deolalikar, 1987; Bouis, 1994).

If changes in income do not result in substantial changes in nutrition it may increase "growth-pessimism" because of the wedge driven between affluence and a component of human development – having access to an adequate level of nutrients. A sense of indifference about short-term income shocks (e.g., following structural adjustment) may also result because of the assumption that affected households will just downgrade the quality, rather than the quantity, of their diets. The new evidence on calorie demand elasticities also sits uneasily with Sen's entitlement approach to famines; if calorie intakes of the poor are income unresponsive one would not expect entitlement failures to result in mass starvation (Ravallion, 1990).

Given the policy implications of the recent views on calorie demand, it is worth seeking further evidence on the elasticity of calorie demand with respect to household resources. In this paper, the case presented is for urban areas of Papua New Guinea. This is a setting with serious nutritional problems; almost one-half of the population obtain less than the recommended amount of calories, with the poorest decile getting only 54 per cent of the requirement (Gibson, 1995).[1] Papua New Guinea is also interesting because the economy has been subjected to a number of recent shocks, including droughts, structural adjustment, and a fall in the value of the currency by two-thirds since 1994. The resulting falls in real incomes have greatly affected the urban population, and it is reasonable to be concerned that nutrition has suffered since urban residents are highly dependent on imports of cereals and other foods.

In addition to policy relevance for Papua New Guinea, there are other benefits of studying calorie demand in urban areas. First, the number of undernourished people living in cities will soon exceed the number living in the countryside (Ruel and Garret, 1999), but most studies of calorie-income relationships have been restricted to rural areas.[2] Also, measurement error problems may be less severe because urban diets are based mainly on purchases rather than on self-produced items (although reliance on highly processed foods may make it harder to calculate calorie contents).[3] Problems in measuring quantities and values of self-produced foods may create errors on both sides of calorie demand equations (since own-food production is a component of income), causing an upward bias in the estimated effect of income on calories (Bouis and Haddad, 1992). Measurement error should be even less of a problem in our study because all members of respondent households kept detailed expenditure diaries and the enumerators also paid careful attention to transfers of food into and out of households. A final benefit of studying urban households is that the calorie-income relationship may be less subject to the seasonal variation that has been shown to exist in rural areas.[4]

The next section of the paper examines the previous literature on the relationship between income and calories. After describing the household survey data, we explain our various methods of estimating the relationship between calories and income. The main findings are then presented and the last section offers some conclusions.

Income and Calories: Previous Evidence

Strauss and Thomas (1995) summarise studies of income and expenditure elasticities of calorie demand and identify four themes. First, the largest estimates of nutritional responses to income changes come from *indirect* calculations of the calorie elasticity, based on (calorie) weighted averages of expenditure elasticities for broad food groups. This method assumes a constant conversion between expenditure on a food group and the quantity of calories obtained but if richer households buy more expensive calories within the broad food groups, the elasticity of calorie *quantities* with respect to income will be overstated. For example, Behrman and Deolalikar (1987) estimate an indirect elasticity of 0.77, which is 4.5 times higher than the directly estimated calorie elasticity (0.17).

The second theme is that the calorie elasticity is lower when household resources are measured by income rather than by expenditure. Measurement error bias is the likely cause because current incomes are more volatile than current expenditure, making them a more noisy measure of permanent income (Bhalotra and Attfield, 1998).

The third theme concerns the way that calories are measured. The data commonly available to economists refer to calorie *availability*, which are derived from the same household budgets used to produce estimates of total household expenditure. Having the dependent and an independent variable created from the same data creates the possibility of common errors. Unlike the usual case, in which measurement error causes bias of regression coefficients towards zero, correlated errors may increase the size of estimated elasticities (Bouis and Haddad, 1992). For example, a household may understate its food expenditures so the calculated calories will also be understated and it will appear that low levels of expenditure (as a proxy for income) correlate closely with low calorie consumption.

A further problem with calorie availability data is that they may not adequately control for *wastage* and *leakages*. Calorie consumption is overstated for households that give away or waste relatively more food or have relatively more visitors at meals, while it is understated for households that receive food gifts or that have members who are absent from many meals. Because households in the first group are likely to be rich and those in the second group poor, uncorrected leakages will cause the calorie elasticity to be overstated (Bouis, 1994).

The fourth theme is that elasticities measured at a single evaluation point, such as the mean expenditure level, may understate the elasticity that applies to much poorer households. Hence, if non-linearities are not accounted for, the elasticity relevant to the poorly nourished, who are the group of most concern to public policy, may be obscured (Ravallion, 1990).

The strategy for this paper is to undertake a careful set of empirical exercises that look at calorie demand. In the first part of our paper we will focus on producing estimates of calorie demand elasticities for different income groups (addressing the issue of non-linearities). We also want to see if these calorie demand elasticities are robust to different estimation techniques that address some of the main statistical issues raised by Strauss and Thomas (1995) and Subramanian and Deaton (1996), examining the effect when (a) the error term of the calorie demand equation is correlated with total expenditures; and (b) when upgrading the quality (and hence raising the cost) of calories is accounted for.

Data

The empirical work in this paper uses data from the Papua New Guinea Urban Household Survey, carried out in six provinces in 1985-87. Over 1300 households were surveyed but the available sample is smaller because of households with missing expenditure information (*n*=84) and the removal from the sample of non-private dwellings (*n*=149). After deleting a further 61 households because the roster of people present at each meal was not completed, a sample of 1033 households was left.

An important feature of the survey is that data were collected with income and expenditure diaries, rather than by the possibly less accurate recall method. Diaries were completed by all adults (and included questions on expenditures made by children) for a 14 day period (the customary pay cycle), with interviewers normally making daily checks on each household. In addition to food purchases and other recurring expenses, the diaries also recorded details on own-production of food, starting and ending food stocks, and transfers of food between households.

The diaries provide details of each household's food purchases, gifts, and own-family garden production for over 200 separate food items. The data used in this study were aggregated into 35 food groups. The aggregation, however, is unlikely to cause serious bias from unmeasured intra-group substitution (i.e., the problem raised by Behrman and Deolalikar, 1987) because we mainly aggregate across fresh fruit and vegetables, which are not important sources of calories. The cereal and root crop staples (rice, flour, sweet potato, taro, cassava, bananas and sago), and the main sources of dietary fats (coconuts, pork, dripping) remained as separate food items in the group of 35 foods.[5] One item where food quantities were not available was cooked meals eaten out of the home; calories from this source were derived as the average “price” each household paid for all other calories plus a 50 per cent premium to reflect processing margins (Subramanian and Deaton, 1996).[6]

One important feature of the survey was a roster of the people present at each meal during the diary-keeping period. These data complement the details on food gifts recorded in the diaries and allow an adjusted measure of per capita daily calorie availability to be computed. The unadjusted estimate of per capita daily calorie availability is divided by the ratio of the actual number of person-meals to the number of person-meals that would be expected given the household size. For example, residents in a household in which ten per cent more person-meals were consumed than would be expected (perhaps because there were guests present in the household for meals) have an adjusted calorie availability that is only 90.9 per cent (= 1/1.1) as high as the unadjusted calorie availability. Adjusting the calorie availability estimates in this way increases the apparent calorie consumption of the poorest quartile of households by three per cent and reduces the apparent consumption of the richest quartile by seven per cent . But even after this adjustment, and also taking account of differing requirements due to household composition, the poorest quartile have only 70 per cent of the recommended calories available to them (Table 1).

Two other features of the sample apparent in Table 1 suggest that this is an interesting setting in which to examine the calorie-income relationship. Incomes are relatively high by developing country standards – in purchasing power parity terms annual expenditures averaged US$2500 per person for the urban households in the sample (in 1985 prices).[7] This is 6.7 times higher than the average expenditure level for the rural households in Maharashtra studied by Subramanian and Deaton (1996) and 4.3 times higher than the mean expenditures of the Filipino households studied by Bouis and Haddad (1992).[8] Hence, calorie demand elasticities might be expected to be low if there is an inverse relationship between elasticities and income levels (Behrman and Wolfe, 1984).

Offsetting this possible effect of mean income levels, the high degree of inequality may cause a wider range of elasticities than is found in samples drawn from more homogeneous environments. For example, in purchasing power parity terms the expenditures of the poorest decile in urban Papua New Guinea are only 3.5 times higher than those of the poorest decile in rural Maharashtra (while mean expenditures are 6.7 times higher). In addition to the effects of inequality, two other factors may explain why the calorie availability of the poor in urban Papua New Guinea is no higher than that of the poor in environments that are generally much poorer. First, food budget shares are lower in urban Papua New Guinea than in rural Maharashtra or the Philippines because over a quarter of expenditure is committed to two essential non-food items: rent and transport.[9] Second, food expenditures do not buy as many calories in urban Papua New Guinea because of the high price of foods.[10] This high price reflects the lack of infrastructure for internal marketing – the capital city is not connected by road to any other major town or to any major agricultural hinterland – and the impact of transport costs and tariffs on imported food.

While Table 1 shows the substantial differences between the richest and poorest groups in urban PNG in terms of their calories and expenditure levels, there are also important differences in the composition of their diets. The poorest quartile get 40 per cent of their calories from rice, but rice provides only 29 per cent for the richest quartile. The locally produced, traditional staples (sweet potato, banana, taro, cassava and sago) provide a further 17 per cent of calories for the poorest quartile but only 11 per cent for the richest. This gap is partly made up by the rich getting 27 per cent of their calories from animal products, fats and oils, as compared to only 17 per cent from these sources for the poor, with the rich also getting a higher share of their calories from, and devoting a larger share of their food budget to, wheat products and meals consumed out of the home.

Finally, it is likely that there is an absence of credit institutions that could provide the poor with loans for consumption purposes. Although the survey did not collect information on personal loans or the use of bank accounts, savings and loans societies in Papua New Guinea are tied to particular employers. The survey data show that only 30 per cent of adults in the poorest quartile of households were in wage and salary employment, as compared to 56 per cent in the richest quartile, so it seems likely that the poor will have less access to credit.

Methods

Non-linearities may characterise the relationship between calories and income because the least well-nourished persons are likely to make the largest nutritional responses as their budgets shift (Ravallion, 1990). In other words, the poor may have much to gain from an increase in calorie intake while the rich have little to gain. Thus it is important to identify the full range of nutritional responses, rather than aggregating them into a single point estimate. To better understand the relationship between calorie demand and income, nonparametric regression may be an appropriate tool because it makes no assumptions about functional form, allowing the data to 'speak for themselves' (Delgado and Robinson, 1992).

Nonparametric regression estimates the function, $m(x)=E(y|x)$, by computing an estimate of the location of y within a specific band of x. If this band maintains a constant number of observations, the estimator is a "nearest neighbour" estimator while if it maintains a constant width it is a "kernel" estimator (Strauss and Thomas, 1995). We use a nearest neighbour estimator, known as LOWESS (Cleveland, 1979), because the distribution of income (measured by per capita expenditures--PCE) is skewed even after a log transformation. Thus, a kernel estimator may not give robust results (at least for the richer households where the data density is low) because the fixed width bands will have few observations in the upper tail. The details of the estimator are explained in Appendix 1.

Although nonparametric regression techniques help to explore non-linearities in the relationship between calories and income, they are restricted to bivariate relationships. Ideally, we would like to see the effect of income on calories after controlling for relevant covariates because otherwise the calorie elasticity may be biased. For example, if household size negatively affects both calories and per capita expenditures (because of scale economies and the lower calorie needs of children), the exclusion of household size would cause an upward bias in the estimated coefficient on per capita expenditures.

Previous studies have used two approaches to introducing other factors into calorie demand models. Subramanian and Deaton (1996) indirectly account for household size by splitting their sample into eight different household-size types and estimating nonparametric calorie-income regressions within each subsample. Strauss and Thomas (1995) use the nonparametric LOWESS estimator to explore the shape of the non-linearities in the calorie—income relationship and then use a parametric functional form (the log-inverse quadratic) that approximates the shape they find in their nonparametric work. The advantage of using the parametric approximation is that extra covariates can be added to the model.

In this paper we also search for a parametric specification that approximates the shape of our nonparametric calorie demand curve but we also use a new method of incorporating extra covariates into a nonparametric model – semiparametric estimation. A semiparametric estimator combines both nonparametric and parametric components:

$$y_i = z_i \boldsymbol{b} + q(x_i) + \boldsymbol{e}_i$$

where z_i is a $1 \times p$ vector of explanatory variables of known (or asssumed) functional form and x_i is the explanatory variable of unknown functional form (Robinson, 1988). Appendix 1 describes this estimation method in more detail.

Results

Nonlinearities in the Calorie-expenditure Relationship

Nonparametric Estimates

The first results reported are the nonparametric estimates of the regression of the logarithm of per capita calories, adjusted for meals fed to guests and meals received, on the logarithm of per capita expenditure (PCE). Figure 1 shows the locally weighted smoothed scatterplots between calories and expenditures for four different bandwidths: 100, 300, 500, and 700 observations. Each of these curves is based on the full sample of 1033 households, and the bandwidth refers to the number of observations used to form the smoothed scatterplot point for each household. Although an algorithm for the optimal choice of the smoothing parameter (and therefore number of nearest neighbours in the band) has been suggested by Cleveland (1979), the advantage of presenting several smoothed scatterplots is that it shows whether the main features of the results emerge, regardless of the level of smoothing chosen.

All four of the smoothed scatterplots in Figure 1 show that the relationship between calories and expenditures rises steeply at lower per capita per capita expenditure levels, but then flattens somewhat at higher levels. The changing slope is clearest in the scatterplot with a bandwidth of 700 observations because the finer level variation is suppressed. It appears that the slope of the regression function falls at a point near the median level of per capita expenditure, which is when predicted per capita calorie availability reaches about 2100 per day. However, the curve does not completely flatten out. In this respect, Figure 1 resembles the calorie availability – expenditure curves for Bukidnon in the Philippines presented by Strauss and Thomas (1995) and for Maharashtra presented by Subramanian and Deaton (1996). The interesting feature of the current results is that they are for urban households who are less poor than the Filipino and Indian households in the previous studies.

Figure 1 also shows standard errors for the nonparametric regression functions. These have been obtained by bootstrapping (Efron and Tibshirani, 1993). For each of the four nonparametric regression curves in Figure 1, we drew random samples with replacement (of size N=1033) from the residuals (i.e., the actual minus fitted values of log per capita calories). Each of these samples of residuals was added to the predicted value of log per capita calories (predictions based on the value of log PCE for each household), to give us 100 new samples of the dependent variable. The LOWESS regression was then re-estimated on each of these new samples, with the standard deviation over these 100 replications used as an estimate of the standard error for each point on the nonparametric regression curve.[11] The intuition behind this bootstrapping is that if we knew the population distribution we could obtain the sampling distribution of any statistic by simulation: draw random samples (with replacement) of size N=1033, calculate the statistic and make a tally of the values that the statistic takes for each sample. But, not knowing the true population distribution, bootstrapping instead uses the observed distribution of the sample in its place.

Figure 2 shows the slope of the curve in Figure 1 (the elasticity of calorie demand with respect to per capita expenditures) for the LOWESS regressions estimated with a bandwidth of 700 observations. For the poorest one-quarter of the population the calorie elasticity is approximately 0.60. In the second quartile the elasticity falls from 0.57 to 0.48, with a larger fall to 0.34 in the third quartile. The calorie elasticity then hovers around 0.30 for the richest one-quarter of the population. The fall in the size of the elasticity is similar to what Subramanian and Deaton (1996) find but the decline in the elasticity is less smooth, falling rapidly amongst the middle two population quartiles, which is the region where food energy requirements of approximately 2000 calories per person per day are achieved and then surpassed. The pattern in Figure 2 suggests that the constant elasticity given by the least squares coefficient of 0.42 (standard error 0.02) from the regression of log per capita calories on log PCE (estimated from the whole sample of 1033 observations) obscures the changing relationship between calories and income across the different parts of the sample.

Parametric Estimates

Regression results from traditional functional forms using parametric methods demonstrate the difficulties in capturing the changes in the calorie elasticity as income changes. Figure 2 shows the elasticity curve when per capita calories are regressed on the inverse of log PCE and its square. This parametric specification is used by Strauss and Thomas (1995) to approximate the shape of their nonparametric calorie elasticity curve but it does not give a good approximation to the nonparametric elasticity results in the current data from PNG. The log-inverse quadratic misses the rapid fall in the size of the calorie elasticity in the middle quartiles and overstates the elasticity for the poor and understates it for the rich. Interestingly, this deviation from the non-parametric curve is much less apparent in the calorie-expenditure curve; with the exception of the very poorest households, the predicted log calories using the parametric specification are within one per cent of the predictions from the nonparametric regression. Hence, it appears that one must examine the elasticities when deciding whether a parametric specification can replicate the patterns found with nonparametric regression.

The closest we come to isolating the changing relationship between per capita calories and expenditures in a parametric manner is with an income spline function. Initially, we tried four segments, each corresponding to a population quartile based on the distribution of per capita expenditures. Statistical tests, however, suggest that the first two segments can be collapsed into one ($p<0.84$). From the resulting model, the calorie elasticity for the first two quartiles is 0.62 (0.05); for the third quartile it is 0.41 (0.20); for the fourth quartile it is 0.24 (0.05), where standard errors are in the parentheses. A Wald test of linearity ($H_{0:}$ slope dummy variables for all quartiles equal zero) suggests significant structural differences in the calorie-expenditure relationship, with $\chi^2_{(4)}=24.2$.

Choosing the Covariates

With a suitable parametric functional form chosen (i.e., the income spline function), the next step in refining our characterisation of the income-expenditure relationship is to decide which variables to add to the model (to give us the specification of the semiparametric model—see next section below). Household size is likely to matter, as explained above. Demographic composition variables also may be important if there are differences in calorie consumption according to age and gender. The age and gender of the household head and education levels, especially for women, may affect nutrient intakes (Behrman and Wolfe, 1984), as may the ethnicity of the household head and the household's main economic activity. Because low-income consumers may have the largest nutrient response to price changes, food prices might be important to include as a way of ensuring that non-linearities are not just due to excluded price effects (Alderman, 1986). Cluster-level fixed effects are also candidates for inclusion because there may be unobserved community influences on eating patterns. Finally, although the households in the current sample are urban, many of them have food gardens and this may influence their calorie consumption.

Table 2 contains the results of regressing log calories on a log PCE spline function plus various sets of covariates (columns 1 to 4). Controlling just for household size in column (1) gives elasticities of calories with respect to per capita expenditure of 0.57 for the poorest two quartiles; 0.29 for the third quartile; and 0.13 for the richest quartile. These are somewhat smaller elasticities than when household size is excluded, with the reduction being largest at high expenditure levels. Thus, adding household size to the model increases the non-linearity in the calorie-income relationship. The results in column (2) are generated by a model that adds further covariates for characteristics of the household head, household demographic composition, education levels, and access to gardens. The added variables, however, only affect the estimates for the third quartile, where the calorie elasticity rises to 0.35. Among the new variables, the preponderance of negative signs on the four child demographic ratios confirms that children consume fewer calories than adults. The age of the household head also has a positive and significant effect. The ethnicity and gender of the household head, however, has no significant effect on calorie demand. The type of income earning activity of the household head also appears to have little impact on calorie demand, unless the household grows a garden, which negatively affects calorie consumption, a result that might reflect the fact that the crops grown by PNG urban residents are mostly vegetables, which have a lower calorie content than the cereals that non-gardening households would tend to buy.

Column (3) reports the results of adding the prices of seven major foods, which contribute two-thirds of available calories. Adding prices to the model causes only a small rise in the elasticity of calories with respect to per capita expenditures over all segments of the spline function. The small reduction in the non-linearity between calories and expenditures suggests that it is unlikely that excluded price effects are producing the non-linear relationship between calories and expenditures in Figure 2. However, this pattern may not hold in other settings, especially if resort is made to unit values (that is, expenditure divided by price) rather than the independently collected market prices used here.[12] The sign patterns of the price elasticities appear plausible, with increases in the price of cheaper sources of calories reducing calorie availability and increases in the price of more expensive sources of calories, especially sugar, increasing calorie availability.

Column (4) reports the results of adding 282 dummy variables, one for each cluster in the sample (and dropping prices, which do not vary within clusters). While the addition of the cluster effects does not attract a very large *F*-statistic, the calorie elasticity for the poorest half of the population falls to 0.51 and the elasticity for the richest quarter rises to 0.23. Excluded community effects appear to have exaggerated the non-linearity in Figure 2. The excluded community effects, however, do not eliminate the non-linearities; the within-cluster calorie elasticity for the poorest half of the sample is still two times higher than for richest quarter of the sample. Moreover, the overall responsiveness of calorie demand to income is not affected by the presence of the cluster effects: the coefficient on log PCE in a constant elasticity version of the column (4) equation is 0.38, which is slightly higher than the elasticity of 0.35 estimated without cluster effects. In fact, the most important result of Table 2 is that the income elasticity of calories is high in all of the equations, and it is especially high for the poor.

Semiparametric Estimates

Figure 3 shows the semiparametric estimates of the elasticity of calories with respect to per capita expenditure for the models using the covariates in columns 1, 3 and 4 of Table 2. The nonparametric elasticity curve is also presented for comparison. All of the semiparametric elasticity curves have the same basic shape as the nonparametric curve, although the addition of covariates results in estimated elasticities that are slightly smaller at all income levels (since the nonparametric curve in Figure 3 is higher at all points than any of the semiparametric estimates). Adding household size to the model reduces the size of the calorie elasticity by approximately 10 per cent for the poorest households, and by over 30 per cent for the richest households (the light solid line, Figure 3). Adding the rest of the covariates (demographics, economic activity, schooling, food prices) shifts the elasticity curve upwards slightly, especially at higher expenditure levels (the dark solid line, Figure 3). Adding cluster effects (and deleting prices) to get the ‘within-cluster’ model (the dashed line, Figure 3) causes calorie elasticity estimates to fall to approximately 0.5 for the poorest quarter of the population. However, it should be stressed again, that while this discussion has highlighted the differences between the nonparametric and semiparametric estimates, perhaps the most significant finding is that regardless of the estimating technique, the estimates for the poor are high. In other words, calorie consumption by urbanites in PNG positively responds to income changes at all levels of income, and the poor are especially responsive.

Instrumental Variables Estimates

The results presented thus far have been based on estimators that assume zero correlation between per capita expenditure and the error term. There are two possible reasons for questioning this assumption. The first is that household incomes, and hence expenditures, could be constrained by nutrition. If so, the coefficient on the per capita expenditure variable would be biased. Realistically, however, there are reasons to doubt this relationship in the current setting because of the low cost of purchasing the extra calories needed for labouring activity (Subramanian and Deaton, 1996). In PNG at the time of the survey, it cost just two per cent of the minimum daily wage to buy the 600 calories per day (in the form of rice) needed for a person to do active work as opposed to just surviving.[13]

Second, and perhaps most seriously, any random errors in measuring food expenditures are transmitted (by construction) both to calorie availability and total expenditures, resulting in correlated measurement errors. Bouis and Haddad (1992) suggest that for a linear model the upward bias from the correlated errors will typically outweigh the usual downward bias that results when an explanatory variable is measured with error. Subramanian and Deaton (1996) study this problem for a log-linear model and show that using nonfood expenditure as an instrumental variable (IV) for household total expenditure will give a lower bound to the true value of the calorie elasticity, whether or not correlated measurement error is present. The reason is that, conditional on the true value of income, a positive regression error implies that food expenditure is above its predicted value so nonfood expenditure must be below its predicted value. Hence, noise in the instrument is correlated with the regression disturbances (violating the requirements for an ideal instrument), so the IV estimates are biased downwards.

Table 3 contains OLS and IV estimates of the calorie elasticity for four different specifications of a constant-elasticity (log-log) model.[14] Two sets of IV estimates, one using nonfood expenditures as an instrument for total expenditures (as in Subramanian and Deaton, 1996) and one using household total income as an instrument are presented. Income should be a valid instrument because, as discussed above, the feedback from nutrition is likely to be small given the low cost of additional calories needed for physical activity. Measurement errors in income also should be uncorrelated with errors in expenditures because the two types of data were collected in separate sections of the survey and refer to different time periods.

The elasticities reported in the first row of Table 3 suggest that in the presence of correlated errors the lower bound elasticity for the bivariate relationship between per capita calories and per capita total expenditure is 0.31 (using non-food expenditures as an instrument); the upper bound is 0.42. Both lower and upper bounds fall by about 10 percentage points when household size is introduced as an additional covariate (row 2). The smallest estimate of the lower bound is 0.18, for the within-cluster model (column 2, row 4). However, this same set of covariates also gives the highest elasticity estimate (0.52) when household income is used as the instrument. Durbin-Wu-Hausman tests suggest that the IV estimates using nonfood expenditure as the instrument (column 2) are all significantly different from the corresponding OLS estimates.[15] But with the exception of the within-cluster model, when household income is the instrument (column 3), the IV estimates are not significantly different from OLS estimates.

Food Expenditures and Calorie Quality and Indirect Estimates of the Calorie Elasticity

In this final section, we illustrate that the high expenditure elasticity of calories holds even when changes in the quality and cost of calories are accounted for. Figure 4 contains the results of a nonparametric LOWESS analysis of the log of the price per calorie on the log of per capita expenditures. It is apparent that diets do shift towards costlier sources of nutrients as incomes rise because the richest households pay approximately three times more per calorie than their poorer counterparts.

The elasticity of the price per calorie with respect to per capita expenditure averages 0.35, and is somewhat higher for rich households. The elasticity of calorie quantity can be added to the calorie price elasticity to give the income elasticity of food expenditure. This food expenditure elasticity ranges from 0.92 for the poor to 0.69 for the rich, but the composition of the elasticity in terms of quantity and quality components varies with income level. Two-thirds of the extra food expenditures made by the poor go on increasing quantities of calories; only one third go on increasing calorie quality. For the rich, the ratios are roughly opposite.

Indirect estimates of the calorie elasticity, calculated from systems of food demand equations, do not show as large an upward bias as found by Behrman and Deolalikar (1987). Estimates of the total expenditure elasticities of demand for the 35 foods we use, reported by Gibson (1998), were combined with estimates of average calorie shares to yield an indirect estimate of the expenditure elasticity of calorie demand of 0.56. This indirect estimate is 1.3 times higher than the directly estimated elasticity from the least-squares regression of log per capita calories on log per capita expenditure. Although this bias is avoidable by directly estimating calorie demand equations, it is much smaller than the three- to four-fold error that Behrman and Deolalikar (1987) report. Even using a much more aggregated set of five foods (cereals; meat and fish; fruit, vegetables and nuts; root crops; and other foods), the indirectly estimated calorie elasticity is only 0.63. The difference from Behrman and Deolalikar's results is likely to be that at the lower income levels in rural south India, within-group substitution is strong, whereas in urban PNG most of the dietary substitution that occurs as households get richer is *between* the broad food groups.

Conclusions

The relationship between per capita calorie consumption and per capita expenditure in urban areas of Papua New Guinea is not consistent with the view that income changes have negligible effects on nutrient intakes. The unconditional calorie elasticity is approximately 0.6 for the poorest half of the population, most of whom have less than the recommended 2000 calories per day available to them. Using parametric and semiparametric estimation to control for a wide range of other influences on calorie consumption does not materially reduce the size of the elasticity. Our results are not supportive of “growth-pessimism” and instead suggest that policies that increase urban household incomes will also act to reduce under-nutrition.

These results also suggest that attention needs to be paid to any nutritional effects of real income shocks, such as those from the stabilisation programs and structural adjustments that Papua New Guinea is currently undergoing, especially because of the likelihood that the poor are credit-constrained. The estimated elasticity of 0.6 for the poorest half of the urban population suggests that their calorie availability may have declined by over 10 per cent during the period of falling real incomes since 1994. Given the existing levels of under-nutrition, such a decline almost certainly has had serious consequences. Some evidence for this decline in nutritional status comes from anthropometric measurements: for a subset of households in the sample used in this paper, children aged less than five years were weighed, with 15.1 per cent being below 80 per cent of the median weight for their age according to the reference standards of Jelliffe (1966).[16] But in a similar anthropometric survey carried out in urban areas in 1996, malnutrition appeared to have increased, with 19.9 per cent of children below 80 per cent of the median weight-for-age (Saweri, 2000).

Neither of these nutrition surveys gathered data on adult weights needed to evaluate the claim of Bouis (1994) that proportional differences in bodyweights across income groups are an upper bound indicator of differences in calorie intakes. This claim remains controversial because of variation in metabolic rates so that changes in calorie consumption are offset and do not automatically lead to changes in body weight (Subramanian and Deaton, 1996). Moreover, in urban PNG, less than one-half of adults (47 per cent) in the poorest quartile are economically active (i.e., working for wages or in formal or informal businesses), compared with over two-thirds of adults in the richest quartile.[17] Hence, the assumption of declining activity levels, which contributes to the predicted higher body mass of the rich, may not hold.

If our results characterise accurately the relationship between income and calories, policy makers still have to decide on the way they will respond to income shocks. Direct intervention in some cases, as suggested by Ravallion (1990), may be effective. Alternatively, improving the operation of credit and labour markets may provide the urban poor with ways to better smooth consumption and income. In this regard, the reform of urban minimum wage laws in 1992 may have helped to increase earning opportunities for the poor (Levantis, 2000).

In terms of methodology, the current results show that considerable non-linearities in the calorie-expenditure relationship may be revealed when a parametric structure is not imposed on the data. Also, the bias from using indirect methods to calculate the elasticity of calorie demand with respect to total expenditures appears less serious in these data than in some earlier studies.

Appendix 1

Nonparametric and Semiparametric Estimating Framework

Nonparametric Framework

For each point (x_i, y_i) on the scatterplot, the LOWESS estimator forms the smoothed point (x_i, $\hat{y}_i$) from a locally weighted regression of a first order polynomial. The weights come from a "tricube" function:

$$w_k(x_i) = \left[1 - \left(\frac{|x_k - x_i|}{\max \aleph(x_i)\, |x_j - x_i|}\right)^3\right]^3$$

which decreases for points further away from (x_i, y_i), becoming zero at the boundary of neighbourhood *À*(x_i). A new set of weights, d_i is then defined for each (x_i, y_i) based on the size of the residual y_i- $\hat{y}_i$. Larger residuals have smaller weights, to guard against outliers distorting the smoothed plots. New fitted values are computed as before, but with $w_k(x_i)$ replaced by $d_i w_k(x_i)$. The calculation of new weights and new fitted values can be repeated several times to get the robust locally weighted regression. Details can be found in Cleveland (1979).

Semiparametric Regression

The semiparametric estimator is based on the model described by Robinson (1988):

$$y_i = z_i b + q(x_i) + e_i \qquad E(e_i \,|\, z_i, x_i) = 0 \qquad (i = 1,2,\ldots,n) \tag{1}$$

where y_i is the logarithm of per capita calories for the ith household, z_i is a $1 \times p$ vector of explanatory variables of known (or asssumed) functional form, b is a $p \times 1$ vector of regression coefficients, and x_i is a $1 \times k$ vector of explanatory variables of unknown functional form. Equation (1) can be rewritten as

$$y_i - E(y_i \,|\, x_i) = (z_i - E(z_i \,|\, x_i))b + e_i \tag{2}$$

suggesting that $q(x)$ can be estimated in a three-step procedure. First, the unknown conditional means, $E(y_i \,|\, x_i)$ and $E(z_i \,|\, x_i)$ are estimated using a nonparametric estimation technique. Second, these estimates are substituted in place of the unknown functions in equation (2) and ordinary least squares is used to estimate b from

$$y_i - \hat{E}(y_i \,|\, x_i) = \left(z_i - \hat{E}(z_i \,|\, x_i)\right)b + e_i^* ,$$

with these estimates denoted $\hat{b}^*$. Noting that equation (1) can be rewritten as

$$y_i - z_i b = q(x_i) + e_i \tag{3}$$

the third step is to insert the $\hat{b}^*$ into equation (3) so that $q(x)$ can be estimated by a nonparametric regression of $\left(y_i - z_i \hat{b}^*\right)$ on x. This final nonparametric regression should identify the relationship between calories and household resources, taking account of the other covariates that entered via the parametric part of the model. Examples of this approach can be found in Anglin and Gencay (1996) and Bhalotra and Attfield (1998).

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Table 1: Per capita expenditures and calorie availability

	Real per capita total expenditure (kina/fortnight)[a]	Food share of total expenditure (%)	Per capita daily calorie availability[b]	Adjusted per capita daily calorie availability[c]	Calories as percentage of requirements[d]
Expenditure quartile					
Poorest	15.66	56.3	1481	1525	70.4
II	27.97	53.5	2148	2189	99.0
III	44.98	50.2	2842	2755	121.9
Richest	103.01	38.8	3614	3370	140.4
ALL	47.90	45.1	2524	2463	109.4

Source: Papua New Guinea Urban Household Survey, 1985-87

[a] 1985 prices (Kina 1.00 = US$1.00 in that year).

[b] Derived from food expenditures, with allowances for self-produced foods, net gifts of food (excluding meals), and net food stock changes (not measured for minor foods).

[c] Adjusted for meals fed to non-residents and meals received in other households.

[d] Based on recommended allowances in *Nutrition for Papua New Guinea*, PNG Department of Health, 1981.

Table 2: OLS estimates of calorie availability regressions

	(1)		(2)		(3)		Within cluster (4)	
	β	|*t*|	β	|*t*|	β	|*t*|	β	|*t*|
ln PCE	.566	(10)	.566	(10)	.586	(11)	.506	(8.6)
ln PCE * Q3 Dummy	-.281	(1.4)	-.214	(1.1)	-.173	(.9)	-.150	(.7)
ln PCE * Q4 Dummy	-.433	(6.0)	-.433	(5.8)	-.409	(5.5)	-.277	(3.3)
ln household size	-.222	(11)	-.183	(7.3)	-.163	(6.1)	-.179	(5.7)
rf15+			.030	(.4)	.051	(.6)	.040	(.4)
rm714			-.083	(.9)	-.066	(.7)	-.123	(1.1)
rm06			-.001	(.0)	.021	(.2)	.123	(1.1)
rf714			-.191	(1.8)	-.190	(1.8)	-.288	(2.4)
rf06			-.078	(.7)	-.048	(.4)	-.063	(.5)
Expatriate head			.068	(1.0)	.048	(.7)	.015	(.2)
Highlands head			-.014	(.4)	-.009	(.3)	-.036	(.8)
Female head			-.080	(1.2)	-.089	(1.4)	-.101	(1.4)
Age of head			.002	(1.7)	.002	(1.8)	.003	(2.0)
Wage job			.008	(.2)	.023	(.7)	.067	(1.8)
Formal business			.059	(1.4)	.090	(2.1)	.083	(1.6)
Informal business			.058	(1.4)	.055	(1.3)	.037	(.8)
Female school years			-.004	(1.0)	-.006	(1.4)	-.005	(1.0)
Male school years			-.003	(.9)	-.003	(.8)	-.003	(.7)
Has a garden?			-.118	(4.8)	-.063	(1.3)	-.203	(.7)
ln price of:								
Bread and biscuits					.088	(.3)		
Rice					-.053	(.1)		
Flour					-.753	(1.3)		
Banana					.125	(1.7)		
Coconut					-.108	(.9)		
Sweet potato					-.168	(1.6)		
Sugar					1.090	(1.8)		
$\bar{R}^2$	.451		.468		.479		.548	

Note: Models also contain an intercept and intercept dummies for the third and fourth population quartiles. Variables beginning with *r* are demographic ratios, so that e.g., rf714 is the ratio of females aged 7-14 to total household members. The omitted group is male adults. The omitted ethnic group is household heads from the lowlands. The omitted economic activity group is household heads who are unemployed. The within cluster regression contains 282 dummy variables for clusters. The *F*-test for the exclusion of the cluster effects is 1.64 with 282 and 729 degrees of freedom.

Table 3: OLS and IV estimates of calorie demand elasticity

Covariates	OLS Estimates	Instrumental Variables estimates: ln *g* as instrument[a]	Instrumental Variables estimates: ln *y* as instrument[b]
ln PCE	0.42	0.31	0.41
	(0.017)	(0.019)	(0.025)
		[R^2=0.86]	[R^2=0.47]
ln PCE, ln *n*	0.33	0.20	0.30
	(0.018)	(0.020)	(0.030)
		[R^2=0.88]	[R^2=0.53]
ln PCE, ln *n*, demographics, economic activity, schooling, food prices	0.38	0.20	0.40
	(0.023)	(0.026)	(0.055)
		[R^2=0.90]	[R^2=0.60]
ln PCE, ln *n*, demographics, economic activity, schooling, cluster effects	0.38	0.18	0.52
	(0.028)	(0.033)	(0.079)
		[R^2=0.93]	[R^2=0.76]

Notes: Standard errors in ( ). R^2 from the first stage regression in [ ].

[a] ln *g* is the logarithm of per capita non-food expenditures.

[b] ln *y* is the logarithm of per capita income.

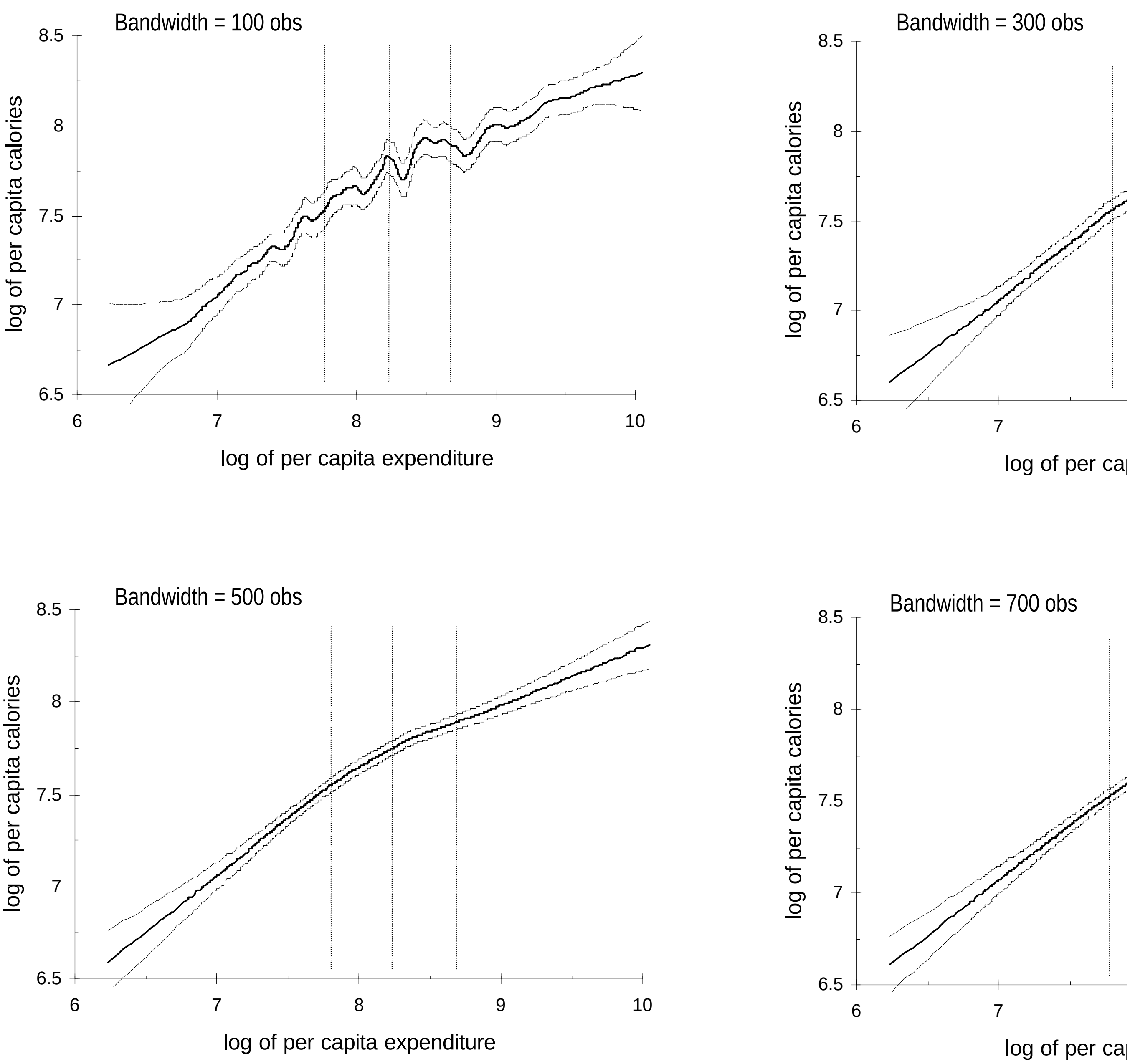

Figure 1: Regression function for log per capita calories on log per capita expenditure: L(

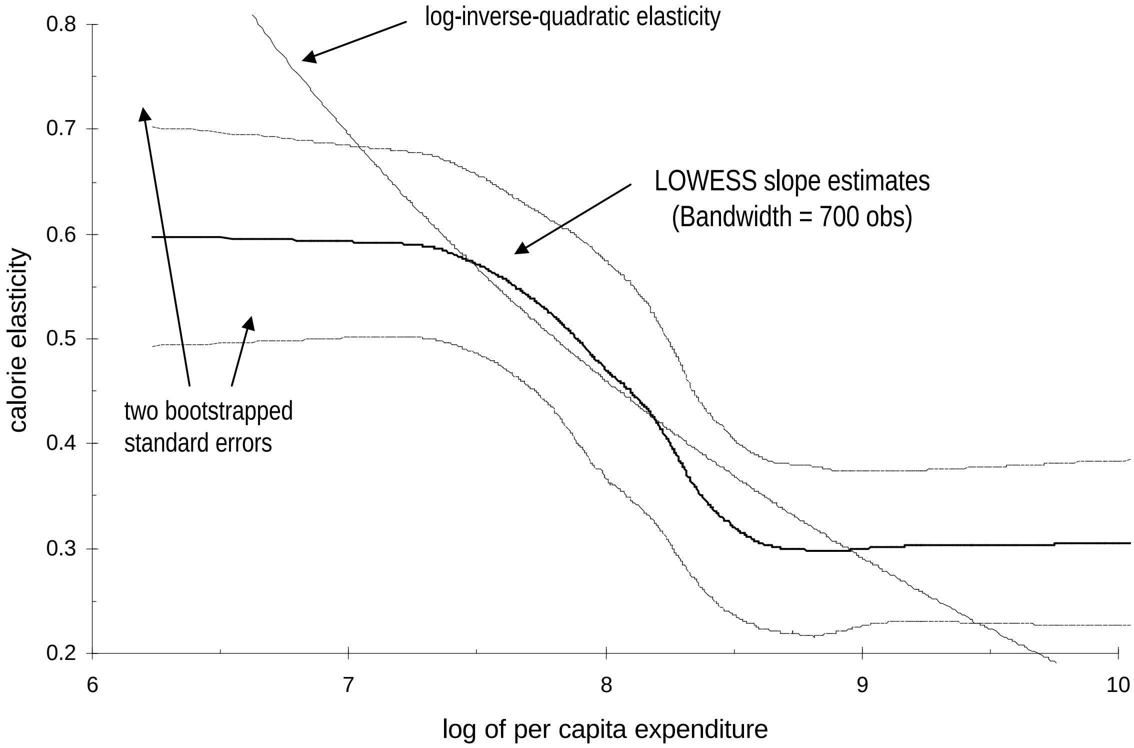

Figure 2: Elasticity of calories with respect to per capita expenditure

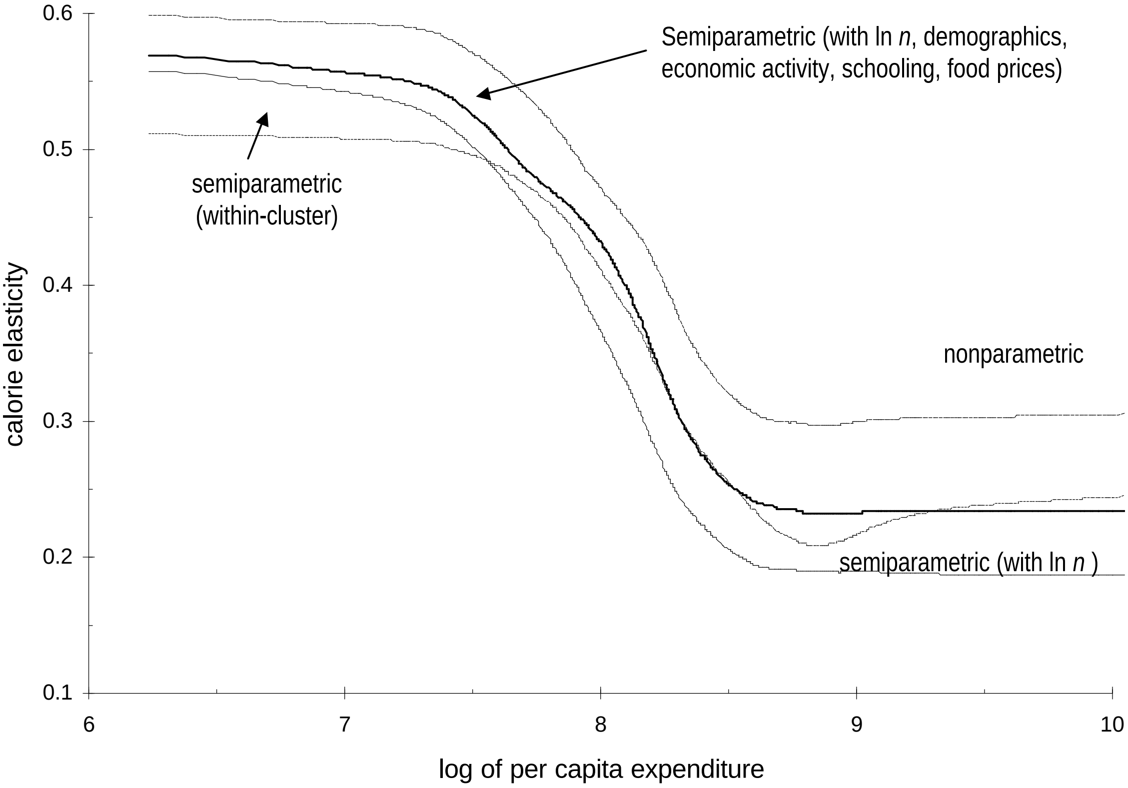

Figure 3: Nonparametric and semiparametric calorie elasticities: LOWESS estimates (Bandwidth=700 obs)

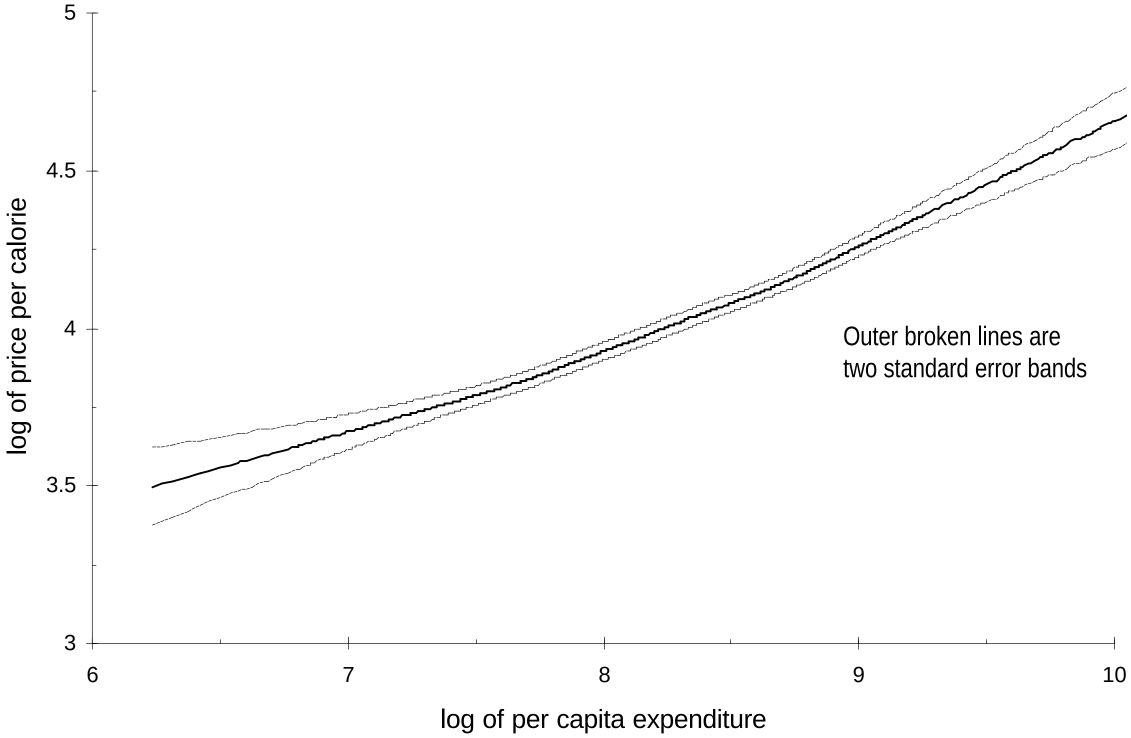

Figure 4: Regression function for log calorie price on log per capita expenditure

Endnotes

[1] A referee has noted that controversy surrounds the definition and use of nutrient requirements (Payne and Lipton, 1994). Rather than being precise dietary energy requirements, there may instead be adaptive ranges within which some individuals can substantially reduce energy needs as a response to energy stress without incurring significant risk to survival. We are unaware of evidence from urban Papua New Guinea showing that people of the same body size and composition may need different amounts of energy for the same lifestyles. However, there is evidence from rural PNG of energy expenditures exceeding energy intakes (Hipsley and Kirk, 1965; Yamauchi, 2000).

[2] An exception is the studies in the special issue of *World Development* (vol. 27, no. 11, 1999) devoted to food security and nutrition in urban areas.

[3] In urban PNG, self-produced items average five per cent of the value of food consumption, ranging from seven per cent in the poorest quartile to three per cent in the richest quartile. Highly processed items, which include "other cereals", "processed meat", "spreads and sugared food", and "processed foods not elsewhere specified" comprise five per cent of the average food budget, varying from four per cent in the poorest quartile to six per cent in the richest.

[4] In the urban data used here, allowing the calorie-income elasticity to vary across the four quarters of the year does not attract statistically significant *F*-statistics ($p<0.55$).

[5] More disaggregated data (58 food groups) were available for one province. When these were used, the correlation with the estimates from the 35 food group data was 0.999. The elasticity of per capita calorie availability with respect to per capita expenditure was 0.598 using the 35 food groups, and 0.596 using the 58 food groups. The Pacific Islands Food Composition Database was used to compute the calorie quantities from the food quantity data.

[6] The fraction of food expenditure on cooked meals eaten out of the home is similar for the poorest three quartiles, at between 4.6 and 4.9 per cent, but for the richest quartile it is higher, at 9.2 per cent. But sensitivity analyses with the premium for processing margins did not reveal significant effects on the calorie-income elasticity. For example, changing the processing premium from 50 per cent to 100 per cent caused the calorie elasticity for the richest quartile to drop from 0.24 to 0.23.

[7] The ratio of the purchasing power parity to the official U.S. dollar exchange rate was 0.491 for Papua New Guinea in 1985 (Summers and Heston, 1992).

[8] This comparison relies on applying the ratio of the purchasing power parity to the official exchange rate in 1985 (0.379 for India and 0.303 for the Philippines) to the official exchange rates for 1983 for India (Rs10.98 per US$) and for 1984/85 for the Philippines (16.7 pesos per US$). The mean expenditures in Maharashtra were Rs115 per month and in the Philippines were 46.3 pesos per week.

[9] The poorest quartile in the sample spend 21.2 per cent of their budgets on rent, while for the richest quartile it is 21.3 per cent. Transport expenses account for 5.2 per cent of household budgets for the poorest quartile and 11.8 per cent for the richest quartile.

[10] Rice is the cheapest source of dietary energy in urban Papua New Guinea, costing US$0.35 per 1000 calories at the time of the survey (in PPP terms). In contrast, the average price of rice in rural Maharashtra is reported by Subramanian and Deaton (1996) as US$0.17 per 1000 calories and some of the cheaper sources of calories cost only one-half the price of rice.

[11] The bootstrapping did not take account of the two-stage sample design, where approximately 300 census enumeration areas, containing 50 households on average, were first selected, and at the second stage households within these areas were selected. The difficulty is with the variable number of households (between two and ten) selected from each enumeration area, to ensure self-weighting. It would be very complex to replicate this variable cluster size in a resampling experiment. Ignoring the two-stage sampling should not understate the standard errors greatly because the average number of households selected per cluster was only 3.8, and Deaton and Subramanian found only a small design effect using a sample where 10 households were selected from each cluster.

[12] Deaton (1988) shows that unit values are correlated with household expenditures due to the tendency of richer households to buy higher quality foods. In contrast, the prices used here are monthly average market prices, reported as part of the urban Consumer Price Index. According to ANOVA on the log prices, three-quarters of the total variation in prices is across towns and one-quarter is across months.

[13] A referee has asked why the poor do not eat more rice, given the low cost of calories from this source. Case study research amongst the urban poor in PNG has identified the blandness of the diet, with rice eaten in a plain boiled state, as one factor causing substitution towards costlier nutrients (Morauta, 1984). Differences in

incomes and preferences within households are also likely to be relevant, because the expenditure diaries show that men allocate a significantly smaller share of their food budgets to rice than do women.

[14] Instrumental variables estimation of a spline model was also attempted but the results did not seem to be consistent with the other estimates. Using nonfood expenditure as the instrument and ln PCE as the only covariate gave estimated elasticities of 0.058, -3.285, and -0.077 for the first two, the third, and the fourth quartiles. As Strauss and Thomas (1995) suggest, interactions with functional form may wreak havoc with IV estimators. Moreover, the properties of the estimator with nonfood expenditure as the instrument have only been worked out for a log-linear structure, rather than a non-linear function.

[15] These tests are based on the added-variable approach, with the residuals from the first stage regression of log PCE on the instrument(s) added to the second stage model and a *t*-test on the coefficient on these added residuals indicates whether IV and OLS results differ significantly (Davidson and MacKinnon, 1993, pp.232-242). When non-food expenditure was used as the instrument, these *t*-values (with one degree of freedom) were between 14.3 and 18.9, depending on the other covariates used in the model.

[16] These data also highlight the differences between the well-off and the poor: for households in the richest quartile, only 9.5 per cent of children were underweight, while for the two poorest quartiles 17 per cent of children were underweight.

[17] This low level of economic activity appears to be due to the high urban minimum wages and the strict regulations on petty trading which have stifled the development of the urban informal sector (Levantis, 2000).