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Does Income Really Matter? Nonparametric and Parametric Estimates of the Demand for Calories in Tanzania

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Abstract

This study employs both nonparametric and parametric methods to examine the influence of household expenditure and other demographic variables on household consumption of calories in Tanzania, using recent survey data. Under each estimation strategy we employ, we find significant and positive relationship between household expenditure and calorie consumption. Even with an estimation strategy that ensures consistent estimates in the presence of measurement error, the calorie-expenditure elasticity is 0.46, a finding that is consistent with the traditional view that, increases in household income will improve calorie intake and help alleviate inadequate nutrition.

1. Introduction

Low nutrient intake of poor households continues to be central in the discussion of poverty in both developed and developing countries. In spite of the progress made in improving nutrient availability in the last decade, a substantial proportion of poor households in developing countries still have inadequate access to food. The average per capita daily calorie supply in developing countries increased from 2,140 in 1970 to 2,716 in 1996-98, while the number of malnourished people declined from about one billion in 1970 to 800 million in 1996-98. The estimated 800 million undernourished are chronically poor and will not be able to achieve food security even if the average availability of food goes up, unless effective long-term policies are put in place to raise the incomes of the poor (Aziz, 2001).[1]

The concern about undernutrition in developing countries has led to an expanding empirical literature on the determinants of undernutrition. Quite prominent in this empirical literature is the relationship between calorie consumption and income. Although the subject is quite important, theoretical positions are quite different and the empirical assessments of the issue have led to little agreement among authors. Theoretically, one point of view suggests that productivity of workers depends on their wages through the nutrition that their earnings enable them to purchase. According to this line of argument, which is attributable to Leibenstein (1957), Mirrlees (1975) and Stiglitz (1976), competition will not press wages down beyond a certain point because a lower level of wages would not provide workers with enough consumption to enable them work effectively. Empirical studies along this line include those of Strauss (1986) for Sierra Leone, Sahn and Alderman (1988) for Sri Lanka, and Bouis and Haddad (1994) for the Phillipines.

In contrast to the argument advanced above, many scholars have taken nutrition to be conditioned by income and by the demand for food. The argument is that hunger and malnutrition would be eliminated by economic growth. Despite appreciable debate about the response of households to changes in income in low-income countries, the empirical evidence appears mixed. Strauss (1984) and Subramanian and Deaton (1996) have estimated elasticities of demand for calories that are quite high, thus lending support to the notion of increasing calorie demand with economic growth. On the other hand, Behrman and Deolaliker (1987), Bouis and Haddad (1992) and Bouis (1994) report estimates of elasticities that are close to zero, suggesting that, increases in income will not lead to substantial improvements in calorie intake. They argue that even among the very poor, as income rises households tend to substitute for taste and non-calorie nutrients, resulting in a flat calorie-income curve.

Although the different approaches employed in the various studies account partly for the differences in the magnitudes of the elasticities, the results suggest little agreement on the responsiveness of calorie intake to income growth, leaving the debate unresolved. What is clear from the literature is the fact that very few studies have empirically examined the determinants of calorie demand in Sub-Saharan Africa (Strauss, 1984; Sahn, 1994). This is in contrast to the myriad of empirical work on household calorie demand in Asia and South America.

This paper therefore contributes to the empirical literature using a unique data set on households in Tanzania. The country belongs to the group of low-income poor countries, with a GDP of 240$ per capita in 1999. The World Health Organization's Basic Health Indicators show that widespread malnutrition and undernutrition prevails in the country. A better understanding of the factors, which might be associated with undernutrition, should aid policy makers in creating nutrition policies. We use panel data from rural and urban areas of Dar es Salaam and Mbeya to examine the influence of household total expenditure and demographic factors such as household size, education, age and gender of the household head on calorie

[1] Undernutrition actually relates to inadequate food intake. It is important to note that where the quantity of food or calorie intake is reduced, then so is intake of micronutrients.

intake. Two broad approaches have been used to estimate calorie-demand relationships. The indirect approach estimates food demand/expenditure systems for a small number of food groups and then converts the resulting food-income elasticities using constant calorie-to-food conversion factors. The direct approach simply estimates a reduced-form Engel equation of the demand for calories. This requires information on quantities of each food consumed to calculate nutrient intakes, which are then used to estimate the relationship with income or expenditure. Strauss and Thomas (1995) and Alderman et al. (1997) argue that potential bias due to aggregation can be avoided by direct estimation. Hence, the direct approach is employed in this study.

First, we examine the cost of calories and how the patterns of demand and calorie demand change with total expenditure. Second, we use nonparametric estimations to explore the shape of the relationship between calories and expenditure, as well as calories and household size. We then employ panel data techniques to investigate the impact of the other covariates on calorie intake. To the extent that household expenditure is mostly measured with error, we employ an empirical strategy suggested by Griliches and Hausman (1986) to obtain a consistent estimate of the calorie-expenditure elasticity.

2. The Data and Summary Statistics

The data for the present analysis come from a panel of households from rural and urban Tanzania. The sample consists of 496 households in two regions of the country, with extensive food and expenditure and socioeconomic data on over 2,689 adults and children, interviewed three times at four-month interval, between 1998 and 1999. A two-stage random sampling technique was used to select 500 households from Dar es Salaam and Mbeya regions in Tanzania. In a first-stage, secondary data was used to obtain general information on the distribution of household income in both urban and rural areas of the two regions. In a second stage, households were randomly chosen to ensure adequate representation of high, medium and low income households. Urban areas are generally classified into wards, while villages constitute the rural areas. Hence, ten households were selected from each ward in urban areas, and twenty households from each village in rural areas. The design and data collection was carried out in collaboration with the Sokoine University of Agricultural in Morogoro. Information from the selected households was gathered through a questionnaire. Respondents were asked to recall how much they consumed of each of all food items over the last 30 days and to report expenditures in shillings as well as physical quantities when appropriate. Meals away from home were also included. Four households fell out of the analysis as a result of incomplete information, leading to a final sample of 496 households.

The survey items included household consumption quantities, prices and total expenditure data on food and nonfood commodities, and demographic characteristics for each sampled household. Consumption from own production and consumption from receipts in kind were valued at prices then prevailing locally. Other information collected in the survey included household land-ownership the age, sex, marital status, and educational level of family members, the occupation of the household head, household religion, and access to piped drinking water and electricity. The average household consists of about six people. The average per capita household expenditure is 27,212 Tanzanian shillings per person per month; the corresponding means for the bottom and top deciles are 5,679 shillings and 85,591 shillings, respectively.[2] Households spent about 51.6% of their total expenditure on food items, with nonfood items constituting the rest of the 48.4%.

We calculated calorie intakes from the basic data using the USDA Nutrient Database for Standard Reference (Release 13). The full detail of reported food consumption is employed,

[2] The prevailing exchange rate during the survey was 670 Tanzanian shillings to a U.S. dollar. The minimum wage in Tanzania at the time of the survey was 30,000 shillings per month.

with weights converted to calories using the calorie content factors. In computing the calorie consumption, it is assumed that total of food consumed g is made up of individual groups of food j. These individual groups of food are taken to be homogenous, so that a kilogram of food j has a constant calorie available k_j no matter who buys it (Subramanian and Deaton, 1996). Total calories Y is then given by the $Y = \sum_{g}(\sum_{j \in g} q_{gj} k_{gj})$, where q_{gj} is the total quantity of food. Given that no information is available on leakages from food fed to guest, plate waste, loss in cooking and other food preparation and feeding of animals, the resulting calorie variable is calorie availability rather than intake (Bouis and Haddad, 1992).

Table 1 provides a budget allocation profile of the households. Also presented in the Table are the calorie sources and how much each calorie costs if purchased via each of the various foods. Columns 1-3 show the food expenditure patterns, expressed as shares of the budget. These values are computed from the budget shares of each of the 1,488 observations, averaged over the whole sample in column 1 and then over the top and bottom deciles of per capita household total expenditure in columns 2 and 3, respectively (Subramanian and Deaton, 1996). Columns 4-6 show the distribution of calories over the various food groups. The last row shows that per capita daily calories are 2,270 on average and 1,414 and 3,040 in the two extreme deciles, respectively. The average of 1,414 for the low decile is significantly below the average for developing countries as a whole, indicating that much needs to be done to improve the calorie intake of poor households.

Cereals, roots, and pulses is the largest source of calories for Tanzanian households, with 69.2% on average. This food group is particularly important in covering energy needs of poor households, since the calorie share of cereals, roots, and pulses amounts to 83.2% of total calorie availability of the bottom 10% of the households in the study. However, as is evident in the Table, the significance of this group as a source of calories declines with increasing income. The meat, fish and eggs group is less important in providing calories to households. It provides 9% on average, 16.4% for high income households and only 3.6% for the poorest income group.

Columns 7-9 show how many Tanzanian shillings of expenditure on each food group were required to generate 1,000 calories. On average households spent 164 shillings per 1,000 calories, with the poorest decile paying 90 and the richest 247 shillings per 1,000 calories. Cereals, roots, and pulses provide cheap calories to all households, particularly to the poorest income group. On the other hand, meat, fish, and eggs; fruits and vegetables, as well as milk and milk products are expensive sources of calories. The observed increase in price of calories from low to high income households is due to a shift in consumption to more refined and processed products as income increases, suggesting that households do not only increase their availability of calories with growing income, but also tend to purchase more expensive goods, which are of higher quality.

3. Econometric Specification and Results

3.1. Nonparametric estimations

In analyzing the calorie-expenditure relationship, an issue of major concern is potential nonlinearity. As indicated by Strauss and Thomas (1995), among the poor, calorie intakes are likely to respond positively to expenditure, but as expenditure increases the elasticity will decline, possibly to zero, or even become negative at high enough expenditure levels. A number of studies that have included quadratic terms in expenditure or income have found a concave relationship (e.g., Sahn, 1988).

Nonparametric smoothing techniques represent a set of flexible tools for analyzing unknown regression relationships. They allow data to search appropriate non-linear forms that best describe the available data, and also provide useful tools for parametric non-linear modeling and helpful diagnostics.For our estimation, we employ the local regression technique known as LOWESS (Cleveland, 1993). The superiority of the local regression techniques over kernel and other methods has been shown by Fan (1992). The LOWESS approach is a nearest neighbor type estimator that works as follows. At any given point x, a linear regression of the logarithm of calories per head on the logarithm of per capita expenditure is run using αn neighbors, where $0 < \alpha \leq 1$ and n is the total number of observations. The optimal α is determined by generalized cross validation. Tricube weights are chosen to be largest for sample points close to x and to diminish with distance from x. If we let $\Delta_i(x) = |x_i - x|$ be the distance from x to the x_i, and $\Delta_{(q)}(x)$ be the distance from x to the nearest neighbor not considered in estimation i, then the neighborhood weight given to the observation (x_i, y_i) for the fit at x is

$$w_i(x) = T\left(\frac{\Delta_i(x)}{\Delta_{(q)}(x)}\right). \tag{1}$$

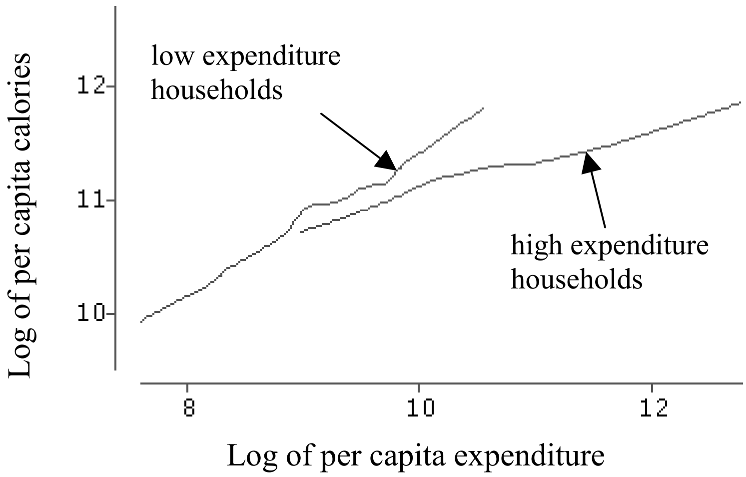
where T(u) is the tricube weight function given as:

$$T(u) = \begin{cases} \left(1 - |u|^3\right)^3 & for\,|u| < 1 \\ 0 & otherwise. \end{cases} \tag{2}$$

For x_i such that $\Delta_i(x) < \Delta_{(q)}(x)$, the weights are positive and decrease as $\Delta_i(x)$ increases. For $\Delta_i(x) \geq \Delta_{(q)}(x)$, the weights are zero. An evenly spaced grid of 128 points in the distribution of log per capita expenditure was chosen and local regressions for each point calculated.

Figure 1 presents the nonparametric estimates of the relationship between household per capita calorie consumption and per capita expenditure, our two main variables of interest. The bandwidth is 0.8, with lower bandwidths exhibiting similar shapes as the one in Figure 1.

Figure 1. Calorie-expenditure curves for low and high expenditure groups: Non parametric estimates



We partition the sample into low-expenditure and high-expenditure households to examine how the calorie consumption of the two groups respond to changes in household expenditure.[3] Although the curve for low-expenditure households is steeper than the one for

[3] The soft-core poverty border for Tanzania suggested by Ferrera (1996) was used to partition the households into the two groups. Correcting for inflation resulted in a poverty line of 188,888 Tanzanian Shillings per capita per annum. About 38% of the households fell below this poverty line.

high-expenditure households, both curves show increasing calorie consumption with household expenditure. The steeper curve for low-expenditure households suggests that the response of this group of households is much higher than their counterparts in the high-expenditure category. No non-linearity is observed for both expenditure groups.

Another relationship of major interest is that between calorie availability and household size. At constant per capita expenditure, households with a higher proportion of children are likely to consume less calories. As Subramanian and Deaton (1996) have argued, even if only all-adults households are compared, it is not obvious that in a household with twice as many members and twice the resources, household members will each choose to consume as many calories. However, shared public goods, or economies of scale within the household, might release resources that would permit more consumption of food and thus calories.

Figure 2: Calories and per capita expenditure for households of different sizes

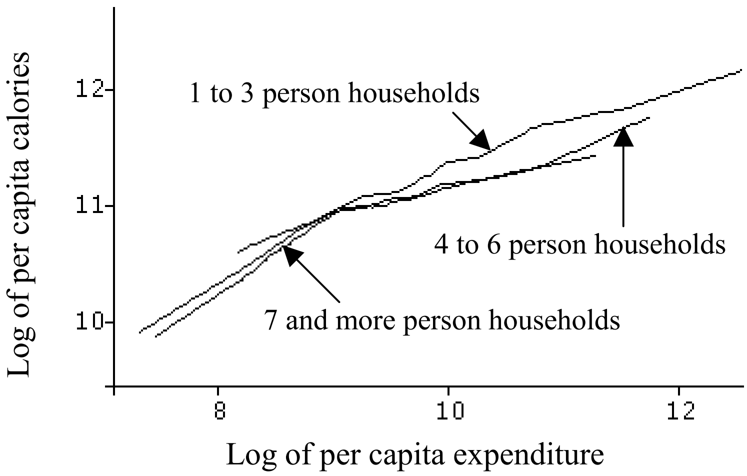


Figure 2 presents the relationship between log calorie availability and log per capita expenditure for various household sizes. This is also estimated using the nonparametric approach described earlier. Given the low sample size and limited number of households with 1 and 2 members, only three groups of household sizes are estimated. Despite the fact that some of the curves cross and touch, the relationship reveals that the highest curve pertains to one to three person households and the lowest to those households with more than six persons.

3.2. Parametric estimations

The bivariate nonparametric estimations of the previous section do not fully consider the effects of factors that may influence calorie consumption and are related to total expenditures. An important determinant of household per capita calorie consumption is household composition: adults tend to consume more calories than children. Level of food prices tend to influence user cost of nutrition and hence calorie availability. Similarly, seasonal factors affect food availability and consumption in a developing country like Tanzania. Other factors also need to be considered. For example, in several parts of Sub-Saharan Africa, market prices of foodgrains tend to be higher in urban than rural areas which in turn affects calorie availability. Furthermore, the energy needs of households engaged in agriculture may be higher, since agricultural labor tends to be more physically demanding than many nonfarm activities.

Controlling for the effects of these covariates requires a suitable parametric approach. Following other research in this area (Sahn, 1988; Bouis and Haddad, 1992; Subramanian and Deaton, 1996), and given the panel nature of our data, the calorie consumption function is specified as:

$$Y_{it} = X_{it}\beta + Z_i\gamma + \varepsilon_{it} \tag{3}$$

where Y_{it} denotes the total calorie available to household i in round t; X_{it} is a vector of time-varing observable variables; Z_i represents a vector of time-invariant observable variables; β and γ are vectors of coefficients associated with time-varying and time-invariant observable variables respectively, and ε_{it} is an error term summarizing the influence of all other omitted variables. Specifically, the variables denoted by X_{it} are per capita household expenditure, household size, market prices of maize and rice, fraction of household members in various age groups, and age of household head in months. The variables denoted by Z_i are education level of household head and dummy variables indicating region of residence, religion of household, round of survey to capture seasonal effects, household participation in nonfarm work, self-employment in agriculture, and presence of electricity. The dummy representing region of residence is used to control for whether the household is located in Dar es Salaam or Mbeya region, while the urban dummy represents rural or urban location of the household.

We control for household-effects by assuming that ε_{it} is composed of two main sources of variation such as

$$\varepsilon_{it} = \alpha_i + \eta_{it} \tag{4}$$

The first term α_i, the latent household effect captures the time-invariant household specific heterogeneity that can arise from the omission of some key variables, such as tastes. It is assumed to be a random variable that is distributed independently across households, with variance σ_α^2. The disturbance η_{it} is assumed to have a zero mean and constant variance σ_η^2, uncorrelated over time and uncorrelated with all included regressors. Failure to account for the household effects can be viewed as a specification error that is likely to bias the estimate of the effect of household expenditure on calorie consumption.

The standard method of sweeping out the household effects is by transforming variables to deviations from their household-specific means. As pointed out by Hausman and Taylor (1981), the ordinary least squares (OLS) coefficient estimates from the transformed data (known as within groups or fixed effects estimators) have two important defects: Firstly, all time-invariant variables are eliminated by the transformation so that γ in equation (3) cannot be estimated. Secondly, under certain circumstances, the within-groups estimator is not fully efficient since it ignores variation across individuals in the sample. Bouis and Haddad (1992) also note that the within estimator is biased in the presence of measurement error or behavioral endogeneity. For the present study, all the problems listed above are of significance, since we are also interested in capturing the effects of time-invariant variables such as seasonal factors, household location and other demographics, as well as labor variables.

Hence, we employ the Hausman and Taylor (1981) random effects estimator that treats unobserved effects as randomly distributed across households. The Hausman-Taylor estimator differs from conventional random effects generalized least squares (GLS) estimators by making use of additional information concerning a priori assumptions on which included right-hand-side variables will be correlated (endogenous) and uncorrelated (exogenous) with the unobserved effects. Besides dealing with potentially endogenous time-invariant unobserved household effects as well as the time-varying endogeneity of observables, the Hausman-Taylor (H-T) approach also allows the time-invariant explanatory variables (which are swept out from the within estimations) to be included in the regression estimations.

To show the necessary condition for the H-T approach, we substitute (4) into (3) to obtain

$$Y_{it} = X_{it}\beta + Z_i\gamma + \alpha_i + \eta_{it} \tag{5}$$

The a priori information that the H-T approach uses involves distinguishing between columns of X and Z in equation (5) which are asymptotically uncorrelated with α_i, from those which are not. Thus, if we consider $X_{it} = [X_{1it} \vdots X_{2it}]$ of dimensions $[TN \times k_1 \vdots TN \times k_2]$; $Z_i = [Z_{1i} \vdots Z_{2i}]$ of dimensions $[TN \times g_1 \vdots TN \times g_2]$. If the k_1, g_1 vectors can be assumed to be uncorrelated with α_i, while the k_2, g_2 vectors are assumed to be correlated with α_i, consistent estimation of equation (5) is possible if the columns of X_{1it} provide sufficient instruments for the columns of Z_{2i}. A necessary condition for this is clearly that $k_1 \geq g_2$; that there be at least as many exogenous time-varying variables as there are endogenous time-invariant variables.

For our analysis, we assume that X_1 contains local market prices of rice and maize, both assumed uncorrelated with α_i. Z_1 is assumed to contain the religion, region of residence of the household, and gender of household head, while Z_2 contains the dummy representing whether the household is employed in farm activities or not, which is allowed to be correlated with α_i. As indicated earlier, for identification of an efficient estimator, it is necessary that $k_1 \geq g_2$. Basically, the H-T approach uses the means of the X_1 variables as instruments for the Z_2 variables. The variables used in the analysis are described in Table 2.

Table 3 presents the results of the estimation of the calorie consumption function. Following Subramanian and Deaton (1996), we treat household size and structure as exogenous variables. A double-logarithmic specification was used in the results presented in Table 3. For comparison, we present estimates from OLS, fixed effects and the Hausman-Taylor appraoch. The fixed effects results show that all the time-invariant variables are eliminated by the data transformation. The *t*-values given are calculated with Whites's (1980) formula that accounts for non-parametric forms of heteroscedasticity. Consistent with the nonparametric estimation, the logarithm of per capita expenditure has a positive and significant effect on calorie consumption. The point estimates of the per capita expenditure coefficient, which are the calorie-expenditure elasticities are 0.529, 0.647 and 0.586 for the OLS, fixed effects and H-T approach, respectively. The magnitude of the fixed effects estimates appear to be in line with the observation made earlier that when there is commonality in measurement error, this bias may be exacerbated by use of panel techniques. These results are very much in the traditional camp and provide no support for the notion that calorie consumption will not increase with higher standard of living, that the calorie elasticity is zero.

Many of the other variables also have well-determined effects on calorie consumption. All the coefficients of the age category variables turn out to be negative and mostly significant, supporting the notion that children consume less calories than adults. Seasonal differences in production and marketing also tend to influence the availability of calories. The significant and positive signs of the coefficients for rounds one and two of the survey show that relative to the lean season, households have more calories available during the farming and postharvest seasons. The negative and significant coefficients of the prices of maize and rice also indicate that higher prices for these food products lead to lower household availability of calories.

Variables describing the residence and religion of the household also appear to matter. The coefficient of the urban variable is negative and significant, indicating that households residing in urban areas have less calorie available to them than their counterparts in the rural areas. Although household incomes and expenditures are generally higher in urban areas, the lower prices of food products in the rural areas appear to be positively impacting on the availability of calories in these areas. Also significant and negative is the coefficient of the Dar es Salaam variable, indicating that relative to their counterparts in Mbeya region, households located in Dar es Salaam have less calories available to them.

Consistent with the results from the nonparametric estimates of Figure 2, the coefficient of the variable for household size is negatively significant, indicating that calorie consumption declines with increasing household size. However, the level of education, age of household head and gender of the household head, as well as participation in nonfarm activities do not appear to influence the availability of calories.

3.3. Accounting for measurement error

In estimating the calorie-expenditure relationship, total household expenditure is employed. However, total expenditure is the sum of food expenditure and nonfood expenditure, each of which is certainly measured with error. Food expenditure is the sum of a large number of components, the same components that, appropriately scaled, make up the estimate of total calorie availability. The total expenditure used in the analysis is most probably measured with error, and the error of measurement is positively correlated with the composite error term in the regression, itself partly determined by the measurement error in calories (Subramanian and Deaton, 1996).[4]

Given the presence of measurement error in total expenditure *TE*, equation (5) can be respecified as

$$Y_{it} = \beta_0 + \beta_{te} TE_{it}^{*} + \delta A_{it} + \gamma Z_i + \alpha_i + \eta_{it} \tag{6}$$

where $TE_{it} = TE_{it}^{*} + w_{it}$; the vector A_{it} contains the other time-varying variables and the measurement error w_{it} has mean zero and i.i.d. over households and time. The model can then be rewritten in terms of the observed total household expenditure as

$$Y_{it} = \beta_0 + \beta_{te} TE_{it} + \delta A_{it} + \gamma Z_i + \alpha_i + \eta_{it} - \beta_{te} w_{it} \tag{7}$$

Since the w_{it} component of the composite error term in equation (7) is negatively correlated with observed total expenditure, within-household (or first difference) estimates of β_{te} are downward biased. However, Bouis and Haddad (1992) argue that this standard downward attenuation bias from the measurement error in total expenditure will be typically outweighed by the upward bias from the correlated errors arising from leakages due to food fed to guests, leaving a net upward bias. The direction of the net bias is therefore an empirical issue that we investigate here.

Supposing the calorie demand equation (5) was estimated, eliminating fixed effects by taking differences from sample averages, the so-called within estimate (ξ_w) will be obtained, whereas estimation of a first-differenced version delivers ξ_Δ estimates

$$Y_{it} - Y_{it-1} = \beta_{te}(TE_{it} - TE_{it-1}) + \delta(A_{it} - A_{it-1}) + (\eta_{it} - \eta_{it-1} + \beta_{te} w_{it} - \beta_{te} w_{it-1}) \tag{8}$$

The estimation of ξ_w and ξ_Δ in equations (7) and (8) results in correlation between the right-hand-side variables and the disturbance term. However, Griliches and Hausman (1986) demonstrate that by combining information given by these two (inconsistent) estimates, a consistent estimate (ξ) can be constructed according to

$$\xi = \frac{2\,\xi_w\, Var(\widetilde{X}) - \frac{T-1}{T}\,\xi_\Delta\, Var(\Delta X)}{2\,Var(\widetilde{X}) - \frac{T-1}{T}\,Var(\Delta X)} \tag{9}$$

where $\widetilde{X}_{it} = X_{it} - (1/T)\sum_{t=1}^{T} X_{it}$, and $\Delta X_{it} = X_{it} - X_{it-1}$. If ξ_w and ξ_Δ do not differ significantly, then this is an indication that there is no measurement error. We can test for the equality of these two estimates by constructing a *t*-statistic, since the difference between ξ_w and ξ_Δ has an (asymptotically) normal distribution.

In columns 1 and 2 of Table 4, the within-household estimates reported in Table 3 and those of the first-differenced estimates of equation (8) are reported. The third column provides a *t*-test of equality of these two estimates. The point estimates for per capita expenditure are 0.647 and 0.503, respectively. The *t*-statistics indicate that with the exception of the per capita expenditure variable, the differenced estimates are not much different from those of the within

[4] This correlation between the measurement errors in the dependent and independent variables means that this is not a standard errors-in-variables problem.

estimates. As Bouis and Haddad (1992) have argued, in the presence of measurement errors, the within-household estimates tend to overstate the effects of total expenditure on calorie availability.

In order to obtain a consistent estimate of the total expenditure coefficient, we employ the instrumental variable estimation strategy suggested by Griliches and Hausman (1986).[5] The natural instruments here are lags of per capita expenditure, which are highly correlated with the first difference of current total expenditure, but uncorrelated with the composite error term under the assumption that the measurement error is independently distributed. In this case, all lags of per capita expenditure dated $t - 2$ and earlier are valid instruments. This is the specification that appears in column 3 of Table 4. The results in this column are computed by the generalized method of moments (GMM) estimator developed by Hansen (1982) and White (1982). This estimator is efficient and allows for conditional heteroskedasticity in the errors. The coefficient of the instrumental variable estimator is 0.459, which is much lower than the within-household estimate of 0.647. The Hansen's chi-square test of overidentifying restrictions yielded a statistic of 1.93 with a p-value of 0.362, thus supporting the validity of the instrument. What is clear from these results is that the estimate of 0.459 is very far from zero, thus reinforcing the previous conclusion that improving the standard of living will increase calorie consumption.

4. Summary and Conclusions

This paper employs both parametric and nonparametric estimation techniques to investigate the relationship between household calorie consumption and per capita household expenditure and other demographic variables. The parametric and nonparametric analysis both indicate a positive and strong relationship between per capita expenditure and calorie consumption. Although the positive effect of expenditure is robust to a variety of estimators, the estimated magnitude is sensitive to the econometric specification. Even with an estimation strategy that ensures consistent estimates in the presence of measurement error, the calorie-expenditure elasticity is 0.46.

This finding of a significant and positive effect of expenditure on calorie availability lends support to conventional wisdom that income growth can alleviate inadequate calorie consumption. The results provide no support to the notion that calorie consumption will not increase with higher standard of living, that the calorie elasticity is zero. We therefore conclude that economic growth that is broad-based and accompanied by increases in income for the very poor can reduce undernutrition in a developing country like Tanzania. Our data tabulations in Table 1 reveal that the average per capita daily calorie consumption is 2,270. However, disaggregating by expenditure decile shows that the average daily calorie consumption are 1,414 and 3,040 for the lower and upper deciles of per capita expenditure, respectively. This indicates that policies aimed at increasing calorie supply without a simultaneous increase in incomes of nutrient-deficient consumer groups may entail large nutritional waste and could be ineffective.

In spite of our relatively high expenditure elasticity, it is important to note that the extent to which calorie consumption will change with increasing income will depend on the consumption behavior of households. If households choose to substitute more expensive sources of calories for cheaper ones, their calorie consumption and overall nutrition may increase appreciably. Our analysis reveals that, on average households spent 164 shillings per 1,000 calories, with the poorest decile paying 90 shillings per 1,000 calories and the top decile 247 shillings per 1,000 calories. This observed increase in price of calories from low to high

[5] We note that the use of lags of per capita expenditure as instruments also provides some additional assurance against the possibility of reverse causation from current calorie to current expenditure.

income households is due to a shift in consumption to more refined and processed products as income increases, suggesting that households do not only increase their consumption of calories with growing income, but also tend to purchase more expensive food products, which are of higher quality.

The negative and significant influence of food prices on calorie consumption also suggest that lower food prices could improve calorie intake. In addition to this effect, lower food prices could also lead to increased real incomes of poor households, particularly urban workers. However, since lower food prices may have negative effects on farmers‘ incomes and food production, a policy intervention in that area may not be appropriate. In the long-run, income-augmenting policies may therefore be more effective in influencing consumption behavior and improving nutrition than cheap food policy. Overall, our findings clearly point to the fact that higher standard of living will increase calorie consumption in Tanzania. Nutrition policies should therefore include targeted measures to improve the incomes of poor households.

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Table 1: Expenditure Pattern, Calorie Consumption, and Prices per Calorie, Mbeya and Dar es Salaam Regions 1998/1999

	Food expenditure shares			Calorie Share			Price per Calorie (TSh per 1000 Calories)		
	Mean All (1)	Bottom 10% (2)	Top 10% (3)	Mean All (4)	Bottom 10% (5)	Top 10% (6)	Mean All (7)	Bottom 10% (8)	Top 10% (9)
Cereals, Roots, and Pulses	43.3%	57.9%	31.0%	69.2%	83.2%	53.4%	98.94	59.70	142.32
Meat, Fish, and Eggs	20.4%	14.5%	27.1%	9.0%	3.6%	16.4%	397.16	353.04	413.96
Fruits and Vegetables	17.6%	13.3%	18.5%	5.1%	5.1%	4.9%	644.79	240.81	960.45
Milk and Milk Products	7.2%	4.8%	10.5%	2.2%	1.1%	3.6%	665.60	433.59	744.28
Edible Oils	7.1%	5.7%	8.8%	8.4%	3.7%	13.6%	145.00	136.64	159.96
Other food	4.3%	4.0%	4.1%	6.2%	3.2%	8.1%	109.32	110.00	116.86
Total Food (Calories)				2,270	1,414	3,040	164.09	89.96	246.74

Note: Mean refers to mean over the whole sample, bottom 10% to mean over households in the bottom decile of per capita household expenditure, and top 10% to mean over households in the top decile of per capita household expenditure. Shares of calories and of expenditures are calculated on an individual household basis and are averaged over all appropriate households. Calorie prices are averages over consuming households (Subramanian and Deaton, 1996).

Table 2: Variable definitions

LPCCAL	=	logarithm of household total calorie availability per month and capita
LPCE	=	logarithm of per capita expenditure per month
LPMAIZE	=	logarithm of price of maize
LPRICE	=	logarithm of price of rice
URB	=	one if the household is located in an urban area, otherwise zero
DAR	=	one if the household resides in Dar es Salaam region, otherwise zero
FARM	=	one if the household is engaged in farm activities, otherwise zero
NONFARM	=	one if the household participates in nonfarm activities, otherwise zero
DMUS	=	one if the household is Muslim, otherwise zero
RD1	=	one for first round of survey, zero otherwise
RD2	=	one for second round of survey, zero otherwise
HSIZE	=	total number of household members
DEMU5	=	percent of SIZE less or equal to 5 years of age
DEM611	=	percent of SIZE that are greater than 5 years and less or equal to 11 years of age
DEM1217	=	percent of SIZE that are greater than 11 years and less or equal to 17 years of age
DEMGT18	=	percent of SIZE that are greater than 17 years of age
DWOMEN	=	one if household is headed by a women, zero otherwise
AGEHD	=	age of head of household in years
EDUHD	=	education of head of household in years
DELEC	=	zero-one dummy for presence of electricity for house

Table 3: Calorie availability-expenditure estimates[a]

	Specification					
	OLS		Fixed Effects		Hausman-Taylor	
Variable	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	7.7871	25.87			7.9895	17.77
LPCE	0.5296	31.00	0.6473	28.92	0.5862	10.90
HSIZE	−0.1295	−6.86	−0.1054	−2.26	−0.1379	−2.52
DEMU5	−0.1142	−2.79	−0.0422	−2.57	−0.0954	−1.98
DEM611	−0.0963	−2.32	−0.2187	−2.06	−0.1742	−2.13
DEM1217	−0.0377	−1.75	−0.0975	−1.14	−0.1879	−1.01
DWOMEN	0.0476	0.23			−0.1014	−1.26
AGEHD	0.0015	1.09	0.0027	0.85	0.0041	−1.13
EDUHD	−0.0132	−1.16			−0.0288	−0.34
LPMAIZE	−0.0376	−1.92	−0.0768	−2.25	−0.0634	−2.10
LPRICE	−0.1174	−2.61	−0.1408	−2.53	−0.1323	−2.67
RD1	0.0887	4.04			0.1027	4.61
RD2	0.0381	2.02			0.0494	2.60
DAR	−0.1496	−5.836			−0.2971	−7.09
URB	−0.1122	−6.20			−0.0764	−5.17
NONFARM	0.0210	1.00			0.0359	1.24
FARM	0.0462	2.24			0.0852	2.46
DMUS	0.0443	2.59			0.0666	2.67
Adjusted R^2	0.42		0.48		0.31	
No of observations	1492		1492		1492	

[a] Heteroskedasticity-consistent *t*-values are reported.

Table 4: Calorie availability-expenditure estimates[a]

	Specification		
Variable	F.E. (OLS) [ξ_w] (1)	F.D. (OLS) [ξ_Δ] (2)	G–H ξ (3)
LPCE	0.6473 (28.92)	0.5028 (21.56)	2.396 [0.4587][b]
HSIZE	−0.1054 (2.26)	−0.0881 (2.14)	−1.156
DEMU5	−0.0422 (2.57)	−0.0599 (3.66)	0.782
DEM611	−0.2187 (2.06)	−0.2630 (1.95)	0.3058
DEM1217	−0.0975 (1.14)	0.0846 (1.02)	0.546
LPMAIZE	−0.0768 (2.25)	−0.1132 (2.71)	−0.6391
LPRICE	−0.1408 (2.53)	−0.1182 (2.34)	−1.3745

[a]The estimates in the first and second columns are the fixed effects or within (ξ_w) and first-differenced (ξ_Δ) regressions, respectively. If the two estimates differ significantly, then this may be taken as evidence of measurement error in the independent variable. The numbers in the third column are *t*-statistics testing this hypothesis.

[b]Consistent estimate described by Griliches and Hausman (G-H) (1986).