Household Characteristics and Calorie Intake in Rural India: A Quantile Regression Approach*

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Abstract

The present paper investigates the nutrition demand pattern for rural households in India. The non-parametric approach of quantile regression is applied to characterize the entire distribution of calorie consumption. This technique has an advantage over the traditional ordinary least square technique. It relaxes the assumption of a constant effect of the explanatory variables over the entire distribution of the dependent variable. These effects are allowed to vary over the entire distribution of dependent variable i.e., in this case the distribution of calorie consumption. The results show that indeed, the responsiveness of calorie consumption to various factors differs across different levels of calorie consumption. A comparison of the quantile regression results with OLS results suggests conclusions and policy suggestions based on OLS results are unlikely to be ideal. Some further light is also shed on the debate on calorie income elasticity as the magnitude is observed to be different for the undernourished and the over nourished households.

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1 Introduction

Access to adequate food and proper nutrition is one of humanity's basic needs. One fifth of the population of developing countries i.e., around 800 million people, were reported to be suffering from chronic undernutrition by the FAO (1992). Malnourishment creates a vicious circle - without regular adequate food an individual is not able to live a healthy and active life. Without such a life the individual will be unable to efficiently produce or procure food or perform well in the labour market. Thus, it is very important to provide people with adequate food availability or in other words "food security". Food security is broadly defined by the Food and Agriculture Organization of the United Nations (FAO) as access to enough food for a healthy, active lifestyle. Although national food security is important it is only effective if measures are taken at the household level. At that level "food security" is defined as 'access to food that is adequate in terms of quality, quantity, safety and cultural acceptability for all household members' (FAO 1992). In economics, the importance of health and nutrition has been widely accepted. Health and nutrition have both demand and supply side effects. On the demand side, people require health and nutrition to stay fit as they derive satisfaction from feeling healthy. Health and nutrition have an effect on the fertility and mortality of the population which has a direct effect on development of the economy. On the supply side, health and nutrition affect individual productivity, thereby having an effect on human-capital formation. These factors affect the efficient functioning of an economy. Thus a healthy nutritional population status is vital for economic growth. There is great interest around the world in improving nutrition in developing countries though measures such as price subsidies and income generation policies. In order to actually "improve nutrition" it is important to define the meaning of an adequate and balanced diet for different groups of individuals within a society and design economic policies in a manner which caters to their needs. "A large variation exists in defining 'adequate' nutrition, ranging between 1400 and 2800 Kilo Calories (Kcal) and is therefore subject to value judgement" FAO (1992). In India, the Indian Council of Medical Research (ICMR) sets up the Nutrition Advisory Committee and recommends the "dietary allowances" of the various nutrients for the various age groups within the population. As per the ICMR report a daily energy intake is recommended of 2400 Kcal per person in rural areas and 2100 Kcal per person in urban areas. For the entire population, the basic minimum energy consumption on the basis of the recommended dietary allowance is 2200 Kcal per capita per day. To give a general idea about the calorie consumption pattern and income distribution in India, Table 1 presents the distribution of per capita calorie consumption and per capita expenditure for rural households. The data is based on two rounds of the National Sample Surveys conducted in 1987-88 and 1993-94 [1].

The table exhibits a wide variation in the per capita calorie consumption (PCC) of households at different quantiles of the calorie consumption distribution. In 1987-88, the mean per capita calorie consumption suggests an average individual is adequately nourished. However a closer look at the table suggests that what is true for the average household might not be true for the entire population. Households in rural India, in the less than the 50^{th} percentile range are undernourished according to the ICMR recommendation of a daily intake of 2400 Kcal per person. Those at the 50^{th} percentile have a per capita calorie consumption close to the recommendation at 2438.66 Kcal. In 1993-94 the calorie distribution pattern was different . The 2400 Kcal/day mark was achieved by households at the 25^{th} percentile, suggesting nutritional standards in India improved in the post reform period[2]. Another variable reported in the table is per capita expenditure (PCE). Per capita expenditure also improved in 1993-94. For the 10^{th} quantile of expenditure distribution, per capita expenditure was just Rs. 81 in 1987-88 but had improved to Rs. 152 by 1993-94. This wide variation observed in the nutrient consumption pattern suggests the nutrient demand pattern is not only determined by the 'measurable physiological needs' of the human body but also by diversity in agro-climatic conditions, food habits, life styles and spiritual/philosophical inclinations. Researchers have concentrated on both the determinants of health and nutrition and also the impact of health and nutrition in the process of economic development. In the presence of such heterogeneity, different nutritional policies have to be prescribed for different members of a society, making it essential to have proper estimates of nutrient consumption responses to prices and income for different sections of the society. Policy makers often overlook the case where there is

[1] More details on the data are presented in a later section.

[2] Economic reforms took place in India in 1991-92. Here 1987-88 is referred to pre-reform period and 1993-94 is referred to post reform period.

Table 1: Distribution of Calorie Consumption and Expenditure for Rural Households in India, 1987-88 and 1993-94.

	Percentile								
	10	25	50	75	90	Mean	Std Dev.	Skewness	Kurtosis
1987-88									
Calorie (Kcal/day)	1616.99	2007.89	2477.75	3051.85	3775.66	2652.40	1270.77	7.99	171.88
Expenditure (Rs./ month)	80.93	105.94	145.93	210.75	311.88	185.26	236.06	52.69	5103.88
1993-94									
Calorie (Kcal/day)	1411.61	2272.74	3139.98	4198.09	5527.341	3416.31	1969.09	3.69	46.92
Expenditure (Rs./month)	144.04	187.56	260.37	370.43	529.44	317.67	303.29	27.92	1599.27

All the variables are in per capita terms.

Note: The 2400 KCal/day daily requirement was attained at 46^{th} **percentile in 1987-88, the actual value was 2401.16 KCal/day**

Note: The 2400 KCal/day daily requirement was attained at 28.5^{th} **percentile in 1993-94, the actual value was 2403.43 KCal/day**

Source: National Sample Survey 43^{rd} Round and 50^{th} Round a risk of inadequate or excess intake. Such inadequacy prevails at the tails of the nutrient intake distribution i.e., situations where calorie consumption is either very low (the left tail) or very high (the right tail) than at the mean (or the average). Thus in issues involving the public health and nutrition perspective it is important to characterize the population at the tails of nutrient intake distribution. Given the wide variation in calorie consumption at various points of the distribution a single policy measure depending on the average calorie consumption would be unrealistic and unable to reach the expected goals. An individual's demand for nutrition of an individual will depend on his present level of nutrition. An overnourished person might demand a lesser amount of nutrient vis-a-vis a person who is undernourished. Thus in designing nutrition policy it is necessary to take into account the "level of healthiness" of the population. With various policy measures taken by the government, the individuals at different points of a nutrient intake distribution might respond differently so that focusing the implication just on the mean would give an incomplete picture of the response. Thus, empirically, it is important to look for such behaviour by studying the whole distribution. Therefore, in focusing only on the conditional mean, a parametric approach such as the OLS would give an incomplete picture of the various factors promoting healthier diet behaviour. The present paper models the entire distribution of calorie consumption and is organized as follows. Section 2, theoretically models farm household behaviour and derives the reduced form demand equations for various commodities, one of which is nutrient demand. Section 3 presents a literature survey of past research pertaining to nutrient demand. Section 4 gives a detailed overview of the quantile regression technique used in the analysis. Section 5 explains the data used in the analysis. On the basis of the reduced form equations obtained in Section 2, Section 6 empirically models the demand of nutrients - calories - at the various points of the calorie consumption distribution and analyzes the results. The interpretation of the results concentrates on where the risks of inadequacy is higher i.e., undernourished and overnourished households. Section 7 discusses the conclusions.

2 Theoretical Model

An individual's health and nutrition status and the demand thereof are dependent on the household he belongs to and therefore, it is important to model the behaviour of the household in relation to nutritional intake. There are two main approaches to modeling such household behaviour Behrman & Deolalikar (1988). One is the Becker (1965) approach of household production and the other the farm household model of Nakajima (1969). Grossman (1972) developed a household production model considering health as a form of human capital. Nutrition is an important determinant of the health and well being of an individual and hence has important consequences for household behaviour. To explain the relationship between market factors, health, production and consumption the model of a farm household is considered in the presence of health effects. The model is very similar to the one designed by Pitt & Rosenzweig (1986) and Behrman & Deolalikar (1988). The household maximizes its preference function subject to a set of constraints. For simplicity a single period model under certainty or certainty equivalence is considered.

The rural household under consideration is assumed to maximize the following utility function.

Household utility function :

$$U = U(\chi_a, \chi_m, \chi_l, \chi_H; \xi) \tag{1}$$

where,

χ_a : Agriculture output produced at level Q by the household,

χ_m : Market purchased commodity,

χ_l : Leisure,

χ_H : Level of health of the household,

ξ : Environmental factors out of control of the household.

1. Time Constraint: The constraints to maximize this utility function are as follows:

   $$\chi_l + F = T \simeq \Omega(\chi_H) \tag{2}$$

   where,

   T : total time,

F : labour input of family.

2. Production Technology:

$$Q = Q(L, A; \chi_H) \tag{3}$$

where,

Q : Household agriculture production,

A : Household fixed quantity of land,

L : Total Labour input,

Health affects the production in a way such that $\frac{\delta^2 Q}{\delta L \delta \chi_H} > 0$ but may not have any direct impact on the production.

3. Effective Labour: The level of health of the household might also influence the household's ability to utilize resources. The quality of labour input supplied by households may be directly affected by quantity of labour input supplied. Thus, effective labour (L_f) may be a function of both health and time worked:

$$L_f = \Theta(F, \chi_H) \tag{4}$$

such that $\Theta_1 > 0$ and $\Theta_2 > 0$.

Let the market wage rate per unit of time be W and let σ be the efficiency units of labour for each time units of physical labour. Thus, labour input L in terms of efficiency is $L_f + \sigma L_H$ where L_H is hired labour time. Thus, the price of an efficiency unit is $\omega = \frac{W}{\sigma}$ and labour cost of production on farm is ωL. This ω can be determined by either the efficiency wage models of Leibenstein (1957) or Stiglitz(1976) or may be a direct outcome of standard supply demand equilibrium. In this model hired labour and the household labour are perfect substitutes of farm production.

4. Health Production:

$$\chi_H = h(Q, \chi_m, Z, F) + \mu \tag{5}$$

where,

Z : is a health input (such as nutrition or medical services) which yields no direct utility.

μ : Environmental factors and household health endowment beyond the control of household.

$\frac{\delta\chi_H}{\delta Q} > 0$; $\frac{\delta\chi_H}{\delta\chi_m} > 0$; $\frac{\delta\chi_H}{\delta Z} > 0$; $\frac{\delta\chi_H}{\delta F} < 0$. This health production function elucidates how changes in work time, food consumption, health goods(such as nutrition and medical services) and environmental factors affect household health.

5. Budget Constraint:

$$p_z Z + p_m\chi_m = p_a(Q - \chi_a) - \omega(L - F) \tag{6}$$

$\rightarrow$

$$p_z Z + p_m\chi_m + p_a\chi_a = (p_a Q - \omega L) - \omega F) \tag{7}$$

Maximizing utility subject to the constraints gives the optimal quantities of consumption and household production inputs χ_a, χ_m, χ_l, Z and farm production input labour L gives the following first order conditions:

$$U_{\chi_a} + U_{\chi_H} h_{\chi_a} = \lambda[p_a - \omega h_{\chi_a}(\Theta, \Omega' + \Theta_2)] \tag{8}$$

$$U_{\chi_m} + U_{\chi_H} h_{\chi_m} = \lambda[p_m - \omega h_{\chi_m}(\Theta, \Omega' + \Theta_2)] \tag{9}$$

$$U_{\chi_H} h_Z = \lambda[p_Z - \omega h_Z(\Theta, \Omega' + \Theta_2)] \tag{10}$$

$$p_a Q_L = \omega \tag{11}$$

These equations can be empirically estimated to determine household demand and the effect of various factors. It can be seen that all the prices and predetermined variables appear in the demand of each of the endogenous variables. Further, government policies will affect households through prices, lump sum transfers and community endowments. However, one lacuna left in such theoretical models is that it is not possible to infer as to exactly where along the distribution of the dependent variable the predicted effect is likely to occur. This is crucial for nutritional policy measures. As mentioned in the theoretical model, the health of an individual affects the number of healthy days which he can use either in deriving leisure or increasing time at work. Although it can be easily assumed that more nutrition will result in improving health, there can be a risk of inadequate or excessive nutrient intake at extreme levels of calorie consumption i.e., the tails of the calorie consumption distribution[3]. In the empirical analysis, the reduced form nutrient demand equation (derived earlier) is modeled and estimated for calories at various points of the calorie consumption equation. Although extant literature possesses estimations of such reduced form equations, such as Bouis & Haddad (1992) and Behrman & Deolalikar (1987). The crucial difference lies in the methodology adopted. In the present analysis we estimate separate nutrient demand equations for different strata of the population, where the strata is determined by the level of nutrient intake of the households and hence their health status. The quantile regression methodology adopted for this analysis is discussed in section 4 of the present chapter.

3 Literature Survey

Most of the extant literature addressing nutrition consumption has concentrated on: (a) estimating the calorie income relationship, and (b) debating the calorie income elasticity estimate values. The importance of nutrient intake and its relationship with income (among other factors) has been widely justified in the extant literature. Bliss & Stern (1978) present a survey of the relationship between wages and nutrition. Pinsturp-Anderson (1985) presents a survey on the literature of food price subsidies in less developed countries. Bank (1981) emphasizes the crucial role of redistribution and income growth in improving nutrition. It has been suggested in the literature that intrahousehold nutrient allocation differs among individuals of different age and sex. Bouis (1994) provides a summary of the literature on calorie elasticity estimation. A range of studies including Reutlinger & Selowsky (1976) and Bouis & Haddad (1992) for the Philippines, and Ravallion (1990) for Indonesia, suggest the elasticity to be close to zero. However, other studies, including Behrman & Deolalikar (1987) for India, and Strauss (1984) for Sierra Leone, suggest the

[3]Recall the wide diversity in per capita calorie consumption for the different quantiles discussed in Table 1

elasticity is closer to 1. Papers studying farm productivity and calorie intake include Strauss (1986), who estimates a significant output calorie elasticity.

Gibson & Rozelle (2002) study the urban areas of Papua New Guinea and seek evidence of the elasticity of calorie demand with respect to household resources. The authors find the relationship between per capita calorie consumption and per capita expenditure is consistent with the assertion that income changes have a negligible effect on nutrient intake. The results are not seen to alter when parametric and semiparametric estimation is done to control for other influences on calorie consumption.

Tiffin & Dawson (2002) examine the long run relationship between per capita calorie intake, per capita income and food prices for Zimbabwe. The authors identify strong evidence of a long-run relationship between calorie and income and their feedback effects. Therefore, calorie intake is determined by income and simultaneously nutritional status constrains income. Impulse responses suggest a shock to calorie (income) increases income (calorie) permanently and these effects are complete in four years. Thus, income growth can act as a catalyst in alleviating inadequate calorie intake and income can increase with improvements in nutritional status - supporting the efficiency wage hypothesis.

Few studies on the nutrient demand in India have been done such as the ones by Behrman & Deolalikar (1989, 1990). Behrman & Deolalikar (1989) explore the quantifiable explanation of the assertion that calorie elasticity are substantially less than food expenditure elasticity. This implies people prefer food variety. As income increases households purchase a variety of food even though this might not result in altering calorie intake. The estimates suggest that as income and total expenditures on food increase consumers display a behaviour of increasingly preferring food variety. This suggests the income elasticity of calorie intakes is less than food expenditure elasticities with respect to income at lower levels of per capita income.

Behrman & Deolalikar (1987) investigate the relatively poor population of rural south India. The authors introduce the concept of 'direct' and 'indirect' calorie -income elasticity estimation. Direct elasticity estimation is the conversion of food group quantities into aggregate calories before estimation and indirect elasticity estimation is when food group's expenditure elasticities are calculated and a weighted average computed. The authors calculate calorie-income elasticities for the same households from two different data sources, viz., calorie intake as a function of predicted total expenditure (this is from a two hourly recall of 120 foods) and food group expenditure as a function of predicted total expenditure in a non system framework (for only 6 aggregate food groups). Their results thereby infer direct nutrient elasticities are not significantly different from zero whereas indirect nutrient elasticities are close to one. Similar results for developing countries are reported in: Knudsen & Scandizzo (1982) for Sri Lanka, India and Morocco, Ravallion (1988) for Indonesia, Greer & Thorbecke (1986) for Kenya, and Alderman (1986) for Sri Lanka, Thailand, Egypt, Sudan, Indonesia, Nigeria, Malaysia, Brazil, Bangladesh and Morocco. All these studies indicate that relatively poor individuals give importance to food attributes other than calorie content when making their marginal food choices in response to an income change.

Behrman et al. (1997) take a panel data of farm households in rural Pakistan and calculate the calorie response to different components of income. In particular the authors take into account the sequential nature of agricultural production, labour and capital market imperfections, heterogeneity and productive effects of calories. A theoretical model is considered taking into account the aforementioned conditions. The analysis suggests that to understand the impact of income on calorie consumption it is critical to distinguish between the stages of agricultural production. This is due to the differential cost of consumption in calorie's consumed in the planting stages. Thus the authors infer calorie-income elasticity is not only affected by the wealth class but also by the stages of production within class.

In his study of wages and nutrition in rural India Deolalikar (1988) was unable to trace any evidence of nutrition determining wages.

Dawson & Tiffin (1998) use annual data for India for 1961-1992 and examine the long run relationship between calories and income using a cointegration approach. The authors do not make any assumptions regarding the direction of causality ex ante. The results show calorie intake to be Granger caused by income and food prices were observed to be constant.

Bouis & Haddad (1992) discuss the calorie income elasticities estimated in the extant literature. The authors attempt to address the question: "what effect do increases in the income levels of the poor in developing countries have on their level of calorie consumption?" This question is crucial to nutrition policy analysis because sound nutrition policy must have an accurate calorie income elasticity measurement. The authors suggest that there is a wide variation in the calorie income elasticities calculated in the ex ante literature. This variation is due to the particular calorie and income variables used by economists in their econometric analysis. To see this, the paper compares elasticities across four estimation techniques and four calorie-income variable pairs for a sample of Philippine farm households. The four possible pairs of dependent and independent variables considered in the analysis are: calorie availability, calorie intake (this is an alternative dependent variable considered), total expenditure and current income (this is an alternative dependent variable). Considering the calorie availability and total expenditure pair the authors observe that both variables are affected by measurement errors - the random error in measuring food purchases is transferred both to calorie availability and total expenditure. Therefore, there is correlation between the measurement errors for these two variables. This results in the coefficient of total expenditure estimator to be biased upwards. The other observation is that the residual difference between family calorie intake and household calorie availability will often increase as a percentage of total food expenditure as income increases. With this, the underestimate of meals served to non-family members will be positively correlated with any income variable which in turn will result in an overestimate of the true elasticity. Analysing the past literature the authors note that larger elasticities are derived from calorie availability and total expenditure. They observe that on disaggregation by expenditure quantile, there is a clear pattern well below the family calorie intake for low-income households and for family calorie availability to be well above calorie intake for high income households. Finally, the authors conclude the calorie intake and total expenditure variable pair gives a reliable elasticity estimate and is important for the policy debate to take into account the absolute change in income as against the percentage change in income.

Majority of the extant literature has concentrated on an average household i.e., a representative household assuming that behaviour of all households in the society is homogenous because the analysis in these studies is mostly done at the mean. However, policy measures taken according to these results are not likely to be equally effective for all members of the society. Therefore, it is important to take account of the heterogeneity of the population. Various policy measures taken by the government affect the behaviour of the various strata of the population differently. Thus, policy has to be tailored differently for different sections of the society. When deciding on an adequate dietary intake and policies for its enhancement policymakers often overlook the case where there is a risk of inadequate or excess intake. Only one study by Variyam et al. (2002) has dealt with this issue. The next section will empirically analyse the issue of nutritional status taking into account the heterogeneity in nutrient consumption.

4 Methodology

Recent empirical research has provided evidence to show that for data having outliers, the traditional conditional mean estimates do not give an efficient outcome. Yu et al. (2003) mention the "sample median is more robust to outliers than a sample mean for estimating the average location of population" and hence quantile regression is more stable than mean regression for analysing data with outlying observation.

In the classical least square regression methodology it is only necessary to know the conditional mean function i.e., the function that describes how the mean of y changes with the vector of covariates x. Simply said, it is the true value around which y fluctuates due to an accidental error. The error is assumed to have exactly the same distribution irrespective of the values taken by the components of the vector x. This is known as a pure location shift model as it assumes the x vector affects only the location of the conditional distribution of y, neither its shape nor any other aspect of its distribution shape. With the additional assumption that the error terms are normally distributed, the least square methods give the maximum likelihood estimates of the conditional mean functions. It has been argued in the econometric literature that the covariates may influence the conditional distribution of the response variable in ways other than just the location. These factors are : induce multimodality, expand the dispersion of the response variable as in the models of heteroskedasticity, stretch one tail of the distribution and/or compress the other tail of the distribution. All these issues can be addressed by performing quantile regressions. Quantile regression models possess certain features that make this technique a better alternative than the ordinary least square model:

- Quantile regression models can be used to characterize the entire distribution of a dependent variable for a given set of regressors.

- A quantile regression model has a linear programming representation which makes estimation easy.

- The objective function for quantile regression is the weighted sum of absolute deviations. This gives a robust measure of location and thereby the estimated coefficient is not sensitive to outlier observations of the dependent variable.

- Quantile regression estimators are more efficient than least square estimators if the distribution of the error term is non-normal.

- Potential different solutions at distinct quantiles may be inferred as differences in the response of the dependent variable to changes in the regressors at various points in the distribution of the dependent variable.

- Quantile regression is more stable than mean regression for analysing contaminated data. [4] Yu & Jones (1998) established that the variance of a typical kernel smoother is greater than the variance of a smooth quantile regression curve.

In the present analysis nutrient demand equations will be estimated using the quantile regression methodology. The quantile regression estimates will also be compared with the OLS regression estimates and inferences drawn.

[4]If a pair (x_i, y_i) is bad with probability π and good with probability $(1-\pi)$ and (x_i, y_i) are distributed as

$$(X, Y) = \begin{cases} \sim N(0,0,1,1) & \text{if } (x_i, y_i) \text{ is good} \\ N(0,0,k,k) & (x_i, y_i) \text{ is bad} \end{cases}$$

where $N(\mu_1, \mu_2, r, {\sigma_1}^2, {\sigma_2}^2)$ is a bivariate normal distribution with correlation coefficient r, means μ_1, μ_2 and variances ${\sigma_1}^2$ and ${\sigma_2}^2$. Then (x_i, y_i) are independent realization from the underlying *contaminated density*

$$f(x, y) = (1-\pi) f_1(x, y) + \pi f_2(x, y) \tag{12}$$

where f_1 and f_2 are density functions for N(0,0,r,1,1) and N(0,0,r,k,k) respectively.

4.1 Quantile Regression

The Basic Model: Before formally defining quantile regression the elementary definition of a sample quantile is explained. The word quantile is a synonym for percentile or fractiles and refers to the general case of dividing the the reference population into four segments, a quintile divides the reference population into five parts and a decile divides the population into 10 segments. The median divides the population into two parts. In a sense, quantiles are related to the process of ordering and sorting. As a sample population mean is defined as a solution of minimizing the sum of squared residuals, the median is defined as the solution to minimizing a sum of absolute residuals. Suppose that the θ^{th} quantile of a population is m_θ where $0 < \theta < 1$ and F_N is the cumulative distribution function, in the population, of y then m_θ is defined as:

$$\theta = Pr[y \leq m_\theta] = F_N(m_\theta) \tag{13}$$

For a sample the analogous expression for defining $\widehat{m_\theta}$ is:

$$\widehat{m_\theta} = \inf[y : F_N(y) \geq \theta] \tag{14}$$

Thus, for example, these equations say that in a class of pupils, a pupil scores at the θ^{th} quantile of an exam if he or she performs better than the proportion θ of the reference group of students and worse than the proportion $(1-\theta)$ of the reference group of students. The median is the case when $\theta = 1/2$.

4.1.1 Quantile Regression Empirical Literature

A nice update on the quantile regression technique is provided in Yu et al. (2003).
There has been considerable use of the quantile regression technique in labour economics. Chamberlain (1994) on the basis of his quantile regression model infers that for manufacturing workers, the union wage premium, which is at 28 percent at first decile, declines continuously to 0.3 percent at the upper decile. The author suggests that the location shift model estimate(least square estimate) which is 15.8 percent, gives a misleading impression of the union effect. In fact, this mean union premium of 15.8 percent is captured primarily by the lower tail of the conditional distribution. The labour market issues addressed using

quantile regression include a number of studies by Buchinsky (for example, see Buchinsky (1994) and Buchinsky (2001)) among others.

Machado & Mata (2001) estimate the earning function for Portugal for the period 1982-1994. The objective of the analysis is to analyse the structure and evolution of the returns to education and their relationship with increased wage inequality. The authors use quantile regression technique to document the heterogeneity in the way wages respond to variations in the variables - gender, human capital, firm attributes and industry indicators. Unlike meas square regression these techniques allow the study of the effect of each of the covariates along the whole distribution and, consequently, the estimation of the effect of employers and workers heterogeneity upon wages. The authors observe that despite substantial improvement in the level of education of the working population, returns to secondary education increased at all quantiles, however the effect was more prominent at the top of the wage distribution. It was observed that the returns to education were higher at higher quantiles and the difference in returns at the top and the bottom of the wage distribution had widened over the time period.

Min & Kim (2004) compare the parametric and nonparametric quantile regression methods using Monte Carlo simulations. The authors suggest "... over a wide-class of non Gaussian error, with asymmetric and fat tail distribution, the simple mean regression cannot satisfactorily capture the stylized facts on the data. Also, dependent variables in the household survey data, under these circumstances, the conditional mean estimator and thus can be misleading." The authors conclude that the nonparametric quantile regression approach proves to be more appropriate when the underlying model is nonlinear or when the error term follows a non-normal distribution. Abrevaya (2001) investigates the impact of various demographic characteristics and maternal behaviour on the birth weight of the infants born in the U.S.

Eide & Showalter (1998) and Levin (2001) have addressed school quality issues. Levin (2001) studies a panel survey of the performance of Dutch school children. The author finds some evidence of positive peer effects in the lower tail of the achievement distribution. However, there seems to be little support for the claim that student outcomes are improved by reducing class size.

Nguyen et al. (2003) attempt to examine the source of inequality in rural and urban Vietnam. The urban rural gap has been an important feature of Vietnam and the authors attempt to address this gap by employing quantile regression. The paper uses the Machado & Mata (2000) quantile regression decomposition technique. The marginal effects of the covariates calculated at each quantile are considered to be the returns to household characteristics at that quantile. The authors use the Vietnam Living Standard Surveys of 1992-93 and 1997-98 which is a country wide stratified clustered household survey. The authors use real per capita household expenditure as a proxy for household welfare. Other authors using this as a proxy are Liu (2001) and de Walle & Gunewardena (2001). The choice of real per capita consumption expenditure instead of real income rests on two principal grounds. Firstly, the expenditure data are less likely to be subject to measurement error vis-a-vis the income data. Questions regarding expenditure are easier, less invasive to respondents as compared to questions regarding income and more straightforward. Other than this, in developing countries agriculture is important and self employment and home production are common sources of income, income sources may be missed and hence social welfare may be estimated. Second, consumption can be smoothed and this is a better measure of welfare than current income. The urban-rural log per capita consumption expenditure gap is decomposed into two components i.e., gap due to differences in household characteristics and gap due to differences in returns to those characteristics. These two effects are named the covariate effect and the return effect respectively. The authors thereby infer that the covariates effect dominates at the bottom of the distributions and the returns effects dominate the top of the distribution. Alternatively, for the poor section of the people urban households are better off than their rural counterparts. This is due to the difference between rural and urban household characteristics. For the high welfare households, on the other hand, the difference is due to urban and rural rewards for their characteristics. Secondly, the authors suggest that of all the covariates education appears to be particularly important and its effect is significantly positive. The effect of education on the urban-rural gap is more significant in the south than in the north. Also, the marginal effect of agriculture is large and increased in the second survey - both in the north and the south.

In an attempt to study the wage structure in West Germany Fitzenberger et al. (2001) investigate the uniformity of wage trends for male full time workers. The authors employ quantile regression technique for their study. The data are grouped into cells defined by education, age, and year of observations and then the empirical cell medians and quantile differences are explained by weighted least squares regressions - polynomials in year, age and cohort taking into account the identification issue. This kind of analysis is done for all the quantiles except the highest education group. For the highest education group a censored quantile regression model is estimated. the paper puts forth a new framework to describe trends in the entire wage distribution across age groups and education. It is observed that each education group wage are uniform across cohorts and wage inequality within age education group stayed constant. The authors also observed that although the wage distribution in West Germany was fairly constant, the wage of workers with intermediate education level (especially for young workers) deteriorated slightly.

Buchinsky (1998) attempts to clarify ambiguous literature and clarify important ideas and fill certain gaps in the quantile regression literature. The paper provides some guidelines for the practical use of semi parametric quantile regression giving special attention to applications to cross sectional data. The author provides an empirical example for the estimation of a logarithmic wage regression at five quantiles. The derivatives of the conditional quantiles with respect to education at various points of logarithmic wage distribution are investigated. Thereby defining the basic model of quantile regression the author explains the interpretation, efficient estimation and equivariance properties of quantile regression. Therefore, Buchinsky addresses the alternative estimators for the covariance matrix of the quantile regression estimates. These estimators hold under different assumptions about the nature of dependence between the error term and the regressors. Other than this the paper also discusses the various procedures for testing homoskedasticity and symmetry of the error distribution using the minimum distance framework. Finally, an extension of the censored quantile regression model is discussed. This paper is an important contribution in the quantile regression literature.

Nahm (2001) investigates the innovative firm size relationships for Korean firms. A data set taken form Financial Statement Analysis files of the Bank of Korea comprises of 1400 manufacturing firms for the period of 1987-1988. A statistical analysis of the data on R & D of the firms it is observed that the underlying distribution is asymmetric and hence the mean regression would be unable to capture the stylized facts of R & D behaviour and give an underestimate of sales elasticity. Comparing the parametric and nonparametric estimates suggest that there is evidence of a nonlinear relationship between R & D expenditure and sales. The author divides the data into three groups according to the sales volume and observe that doing this division was fruitful. It is observed that in the subsample of scientific firms the sales elasticity is the biggest for medium sized firms. In other words, R & D expenditure increases faster than firm size up to a point and thereby moves at a lower rate among larger firms. For non scientific firms, the R & D expenditure increases steadily, suggesting increasing returns to scale in innovative activity in large firms.

Viscusi & Born (1995) consider liability reform effects on medical malpractice. Viscusi & Hamilton (1999) consider public decision making on hazardous waste cleanup. Manning et al. (1995) study the demand for alcohol using survey data from National Health Interview Study. They report considerable heterogeneity in the price and income elasticity over the entire range of conditional distribution. Quantile regression are frequently applied to earnings inequality and mobility. Conley & Galenson (1998) investigate wealth accumulation in U.S cities during mid 19^{th} century. In the empirical finance literature Taylor (1999) and others address the issue of value -at - risk using quantile regression methods.

4.2 The Model

The concept of quantile regression was introduced by Koenker & Bassett (1978). Quantile regression is the generalization of the concept of ordinary quantiles in a location model. Consider a sample (y_i, x_i), $i = 1...n$ from a population where x_i is an K X 1 vector of regressors. Then it is assumed that:

$$y_i = x_i' \beta_\theta + u_{\theta_i} \tag{15}$$

where u_{θ_i} is the error term such that $Quant_\theta(u_{\theta_i}|x_i) = 0$. Thus,

$$Quant_\theta[y_i|x_i] = x_i^{'} \beta_\theta \tag{16}$$

Where $Quant_\theta(y_i|x_i)$ represents the conditional quantile of y_i conditional upon the set of independent variables vector x_i. The assumption that $Quant_\theta(u_{\theta_i}|x_i) = 0$ implies that only the distribution term u_{θ_i} satisfies the assumption that the θ^{th} quantile of u_{θ_i} i.e., $y_i - x_i'\beta_\theta$ conditional upon the vector of regressors is equal to zero. This can be expressed in terms of statistical probability theory for a given scalar τ as:

$$Pr[y_i \leq \tau|x_i] = Pr[x_i^{'}\beta \leq \tau + u_{\theta_i}|x_i] = Pr[u_{\theta_i} \leq \tau - x_i^{'}\beta_\theta|x_i] = F_{u_\theta}[\tau - x_i^{'}\beta_\theta|x_i] \quad (17)$$

No assumption is made regarding the distribution of the error term u_{θ_i}. The only assumption made in this model is that the θth quantile of $y_i - x_i^{'}\beta_\theta$ conditional upon the regressor vector x_i equals zero. This assumption is made simply to identify the intercept term in β_θ. The θ^{th} quantile regression result is the solution to the following minimization problem:

$$\min_\beta \frac{1}{n}[\sum_{i:y_i \geq x_i^{'}\beta} \theta|y_i - x_i^{'}\beta| + \sum_{i:y_i < x_i^{'}\beta} (1-\theta)|y_i - x_i^{'}\beta|] \quad (18)$$

The parameter space for β is B_θ and $B_\theta \subseteq \Re^k$. The above minimization problem can be written alternatively as:

$$\frac{1}{n}\min_\beta[\sum_{i=1}^{n}(\theta - 1/2 + 1/2sgn(y_i - x_i^{'}\beta))(y_i - x_i^{'}\beta)] \quad (19)$$

where, $sgn(u) = I(u \geq 0) - I(u \leq 0)$. The first order condition corresponding to the above minimization problem is:

$$\frac{1}{n}\sum_{i=1}^{n}(\theta - 1/2 + 1/2sgn(y_i - x_i^{'}\widehat{\beta}_\theta))x_i = 0 \quad (20)$$

This minimization problem suggests the presence of a moment function $g(x_i, y_i; \beta) = (\theta - 1/2 + 1/2sgn(y_i - x_i^{'}\widehat{\beta}_\theta))x_i$

Koenker & Bassett (1978) have proved that the following asymptotic properties are proved to hold :

1. Dropping the i subscript it can be shown that:

$$E[g(x, y; \beta)] = 0 \quad (21)$$

This equation suggests that g(.) is a moment function.

2. Define the asymptotic covariance matrix as:

$$\Lambda_\theta = \theta(1-\theta)(E[f_{u_\theta}(0|x_i)x_i^{'}])^{-1}E(x_ix_i^{'})(E[f_{u_\theta}(0|x_i)x_i^{'}])^{-1} \tag{22}$$

If $f_{u_\theta}(0|x) = f_{u_\theta}(0)$ for all x with probability 1 i.e. the density of the error term u_θ evaluated at 0 is independent of x then:

$$\Lambda_\theta = \frac{\theta(1-\theta)E(x_ix_i^{'})}{f_{u_\theta}^2(0)} \tag{23}$$

which implies $\sqrt{n}(\hat{\beta}_\theta - \beta_\theta) \rightarrow N(0, \Lambda_\theta)$

This result implies that for any error distribution for which the median is a more efficient estimator of location than the mean, the quantile regression estimator at the median i.e., the Least Absolute Deviation (LAD) estimator is more efficient than the least square (OLS) estimator in the linear model.

The quantile regression problem can be represented in a linear programming framework and can be solved by applying the simplex algorithm. The linear programming representation is very important as it has some implicit implications (Buchinsky 1998). Firstly, the quantile regression estimator will be achieved in a finite number of simplex iterations. Secondly, due to the duality theorem a feasible solution is guaranteed. Thirdly, unlike the ordinary least square estimator the parameter estimate is robust to outliers. That is, if $y_i - x_i^{'}\hat{\beta}_\theta > 0$ then y is increased towards ∞ ; however if $y_i - x_i^{'}\hat{\beta}_\theta < 0$ then y is decreased towards $-\infty$ and thus the solution $\hat{\beta}_\theta$ remains unaltered.

4.2.1 Asymptotic Covariance Matrix

The asymptotic covariance matrix ((22) and (23)) of the quantile regression estimate can be calculated using various methods as suggested by Buchinsky (1998). However, on the basis of his Monte Carlo study Buchinsky (1995) suggests that the design matrix bootstrap estimator provides a consistent estimator for the covariance matrix of a quantile regression estimate. The present analysis uses the design matrix bootstrap method for calculating the standard errors.

Design Matrix Bootstrap: The bootstrap method was proposed by Efron (1979) and offers several options for computing confidence intervals and standard errors. The method is also known as the (x, y) - pair bootstrap. Under an independent but identical distributed setup, this method starts by randomly drawing a sample (y_i^*, x_i^*), $i = 1...n$ from the empirical distribution F_{nxy}. For the quantile regression model, equation (11) - (12), this translates into saying that $y^* = x^*\beta_\theta + u_{\theta_i^*}$ where $y^* = (y^* = y_1^*....y_n^*)'$ and $x^* = (x_1^*....x_n^*)'$. On applying the simplex algorithm to this model we get the bootstrap estimate as β_θ^*. The process is repeated B times to get the bootstrap estimates $\hat{\beta}_{\theta 1}^*, ...\hat{\beta}_{\theta B}^*$. The bootstrap estimate of the asymptotic variance covariance matrix (Λ_θ) is thus calculated by:

$$\hat{\Lambda}_\theta^B = \frac{n}{B}\sum_{j=1}^{B}(\hat{\beta}_{\theta j}^* - \bar{\beta}_\theta^*)(\hat{\beta}_{\theta j}^* - \bar{\beta}_\theta^*)' \tag{24}$$

where $\hat{\Lambda}_\theta^B$ is the bootstrap estimate of the variance covariance matrix; $\bar{\beta}_\theta^* = \frac{1}{B}\sum_{j=1}^{B}\hat{\beta}_{\theta j}^*$ is the pivotal value, an alternative pivotal value can be $\hat{\beta}_\theta$. This estimate of the asymptotic covariance matrix of $\hat{\beta}_\theta$ is consistent as the conditional distribution of $\sqrt{n}(\hat{\beta}_\theta^* - \hat{\beta}_\theta)$ weakly converges to the unconditional distribution of $\sqrt{n}(\hat{\beta}_\theta - \beta_\theta)$.

4.2.2 Hypothesis Testing

According to Buchinsky (1998) the equality of slope coefficients of a given dependent variable can be tested using the minimum distance (MD) method. This method has been used to test for the equality of coefficients.

In the minimum distance distance framework, first the slope coefficients are estimated from quantile regression at P quantiles. The unrestricted parameter vector estimates thereby obtained is a KP X 1 vector:

$$\hat{\beta}_\theta = (\hat{\beta}_{\theta_1}'....\hat{\beta}_{\theta_p}')_{KPX1} \tag{25}$$

If $\beta_\theta^R = (\beta_{\theta_1 1}....\beta_{\theta_p 1}, \beta_2....\beta_k)'$ is a $(K + P - 1)X1$ vector comprising P unrestricted intercepts and $(K - 1)$ restricted slope quantile regression at P quantiles. Then the restricted coefficients vector minimizes,

$$\min_{\beta^R} Q(\beta^R) = (\hat{\beta}_\theta - R\beta^R)'A^{-1}(\hat{\beta}_\theta - R\beta^R) \tag{26}$$

where A is a positive definite weight matrix and the restriction matrix R is given by:

$$R' = (R_1...R_p) \tag{27}$$

and

$$\mathbf{R_j} = \begin{bmatrix} e_j & 0_n \\ 0_V & I_{K-1} \end{bmatrix};$$

where e_j is a $pX1$ vector of zeros except for 1 in the j^{th} place, 0_V is a $(K-1)X1$ vector of zeros, 0_m is a $pX(K-1)$ vector of zeros and $I_{(K-1)}$ is the identity matrix of order $(K-1)$. The optimal minimum distance estimator $\hat{\beta}_\theta^R$ has the asymptotic distribution given by $\sqrt{n}(\hat{\beta}_\theta^R - \beta_\theta^R) \rightarrow N(0, \Lambda_\theta^R)$ where $\Lambda_\theta^R = (R'\Lambda_\theta R)^{-1}$. The test statistic from the minimum distance fraomework under the null hypothesis of equality of slope coefficient is :

$$n(\hat{\beta}_\theta - R\hat{\beta}_\theta^R)'A^{-1}(\hat{\beta}_\theta - R\hat{\beta}_\theta^R) \rightarrow \chi^2(pK - p - K + 1) \quad (28)$$

In the present analysis we get the quantile regression parameter estimates by estimating a separate equation for various quantiles of calorie consumption. The variance covariance matrix for θ quantiles is obtained by design matrix bootstrap. $\hat{\Lambda}_\theta$ was calculated to obtain the standard error of coefficient estimates and thereby the equality tests are conducted.

5 Data

Data for the present study is drawn from the National Sample Survey (NSS) for rural households in India. The National Sample Survey Organization of India (NSSO) has had a program of quinquennial survey on Consumer Expenditure and Employment since 1972-73. The present data is taken from the 43^{rd} and 50^{th} rounds of this survey conducted in June 1987 to July 1988 and June 1993 to July 1994, respectively. The survey covered the total population of the rural and urban areas of India and has detailed information about the expenditure incurred by the sample household for the purpose of domestic consumption.

The present paper concentrates on the rural areas of India.

5.1 Data Extraction

One long and tedious process of the present paper has been the data extraction. The NSS data is available in the form of strings of 105 numbers and each number of a row represents some variable such as the sample number, sub-sample number, etc. On the basis of the information provided in the NSS documentation a 16 digit household ID is constructed.

Table 2: Summary Statistics of variables

	1987-88			1993-94			
Variable	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Units
Calorie Cons.	25442	2652.41	1270.78	26517	3416.31	1969.09	K Cal/day
PCE	25442	0.28	0.37	26517	0.26	0.25	Rs./month
HHSize	25442	5.63	2.89	26517	5.55	2.86	Integer
Head Age	25442	44.90	14.15	26517	44.68	13.91	Years
Wheat Price	25442	0.35	0.07	26517	0.33	0.05	Rs./ Quintal
Rice Price	25442	0.36	0.14	26517	0.35	0.12	Rs./ Quintal
Bajra Price	25442	0.29	0.06	26517	0.26	0.04	Rs./ Quintal
Gram Price	25442	0.69	0.10	26517	0.80	0.10	Rs./ Quintal

Once the household ID's are constructed on the basis of the item codes and the state codes (provided in the NSS documentation), the relevant data for the analysis is extracted. The present analysis uses the data for per capita calorie consumption which is not provided by the NSS survey. The method of constructing this variable is as follows: First, the data of food consumption by food item was extracted for each household. Then this item wise food consumption data was converted to nutrient equivalents using the Gopalan (1992) norms. These nutrients include calorie, protein, fats, carbohydrates, vitamins and minerals. Though data for all the nutrients was computed in the present paper we concentrate on only one nutrient, calorie because of its importance in the functioning of human body. [5] Table 2 gives the summary statistics of the variables considered in the analysis. The number of households are 25442 for the year 1987-1988 and 26517 for 1993-94. The effect of income is captured by including the per capita expenditure of the household, PCE. Bouis & Haddad (1992) have made the following suggestions to avoid biased nutrient income elasticity estimates:

1. *Calorie Conversions:* Calorie income elasticity calculated "indirectly" tends to be higher than the calorie-income elasticity calculated "directly". Indirect elasticity estimates are the estimates where first the elasticities of demand for a series of food groups are calculated and these elasticities are then converted to calorie elasticities using standard food composition tables. Direct estimates are those where firstly in-

[5] Energy (calorie) is vital for activity, growth and rest in a human body.

formation on the quantities of each food consumed is gathered and calorie conversions are done and the relationship with income calculated.

In the present paper the "direct" method is adopted. The calorie conversions for the food consumed is done using the Gopalan (1992) conversion equivalent tables.

2. *Measuring Income:* Measuring income is crucial and, in some household surveys this is not reported clearly. In such cases a common equivalent of income is the expenditure. However it has been shown that calorie-income elasticities calculated using current income are lower than calorie-income elasticities based on expenditure.

   Some studies have assumed that income is endogenous. If increased nutrient intake results in increased productivity and/or labour supply, especially in low income households, estimated calorie income elasticities will be biased upwards and this bias might be greater for lower income households. In addition, the unobserved tastes for work might be correlated with taste for nutrients. Expenditure, which is a function of income, might be considered to be jointly determined with income (Strauss & Thomas 1995). In the present chapter, per capita expenditure is taken as a proxy for household income, and income is not assumed to be endogenous.

3. *Measurement Error:* There might be a measurement error problem which results in a biased calorie-income elasticity. The nutrient consumption data collection method might result in measurement error. There are two methods of nutrient data collection. One is to infer households nutrient 'availability' from the information on food purchases and imputed values based on the consumption of part of own production or wages received in kind. A second method is the information on nutrient 'intake' where actual meals consumed is used. Elasticities based on availability tend to be higher than those based on intakes.

   In the NSS surveys the nutrient consumption 'availability' data is collected, hence the elasticities estimates here might be biased upwards.

Given all these reasons for biased estimates and the limitations of data the calorie-income elasticities estimates in the present analysis might be biased upwards. However it has been suggested by Strauss & Thomas (1995) that the bias with these limitations is not very large.

Along with per capita expenditure of the household the farm harvest prices for various food items is included as the data is for rural agricultural households in India and households are likely to be affected by the farm harvest price. In order to take into account the effect of various food prices the prices of wheat and rice have been considered as superior goods.

Apart from this, the price of bajra is considered to take into account the effect of the price of an inferior good and the price of gram is taken to take into account the effect of the price of a normal good. In addition to these variables certain variables accounting for household characteristics and environmental factors are also included. These variables are household size, age of household head, sex of household head, literacy of household head, whether the household owns land or not, occupation of the household, social background of the household, type of employment, religion of the household and various interaction terms. A brief summary of all these variables is presented in Table 3.

Household size, $HHSize$ is included to take account of economies of scale and congestion effects. Next, these dummy variables are defined. As the financial status of the household is of importance in determining the quality of food consumed the variable *LandOwned* is considered. This variable is defined as: Land owned by the household and can give some indication about household's financial situation. A household possessing land is obviously better off than a household not possessing land. Therefore, the variable captures whether there is some effect of owning land on the calorie consumption of household members. Base case is that the household owns land.

The sex and literacy of the household head is represented by the variables, $FemaleHead$ and *HeadLit*. $FemaleHead$ aims to capture the effect of the sex of the household head on per capita calorie consumption of the household. *HeadLit*, captures the effect of a household head who is literate beyond primary level education rather than being illiterate or educated below primary standard. The base case is that the household head is either not educated or educated below primary level.

The occupation of the household is also considered, as the type of occupation can have an effect on calorie consumption. The dummy variable considers four types of occupations: Self employed in non agricultural activities ($SEmpNon - Ag.$), Agricultural Labour (*Ag.Lab*), Other Labour (*OthLab*) and Self Employed in Agriculture ($SelfEmpAg$). The base case is being Self Employed in Agriculture ($SelfEmpAg$).

Another dummy variable taken into account is the social group affiliation of the household. If the household belongs to a backward social group i.e., Scheduled Castes, Scheduled tribe or other backward castes (OBC) then the variable takes the value one i.e., The base case is that $SC/ST = 1$ thus implying that the effect of a household 'not' belonging to SC/ST vis-a-vis a group belonging to SC/ST.

The religion of the household is also taken into account as an indicator of the household's ethnic background. The religion categories considered are, Hinduism, Islam, Christianity, Sikhism and Other religion ($OtherRel$) such as Jainism, Buddhism, Zoroastrianism etc. The base case is Hinduism.

The analysis takes into account the state dummies for 15 states to get rid of the state effects. These states are Assam, Bihar, Gujarat, Karnataka, Kerela, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, West Bengal and Uttar Pradesh. The base state is Punjab. For any state S_i, the dummy variable takes the value 1 and zero otherwise. Having explained the variables and their meaning, next we present the results of the analysis.

6 Estimation and Results

As mentioned earlier, the analysis is done for two rounds of NSS data i.e., the 43^{rd} and 50^{th} Round corresponding to the years 1987-88 and 1993-94 respectively. Table 4 and 5 display the results of the analysis. In addition, the quantile regression plots are shown in Figures 1, 2, 3 and 4. These plots compare the coefficients of the quantile and OLS regressions for a particular variable. The results are discussed by considering the effect of one independent variable at various levels of calorie consumption at a time.

Responsiveness to Income: From Table 1, showing the distribution of the calorie consumption of rural households in India, it is observed that people at the 10^{th}-30^{th} quantile of the calorie consumption distribution have less than 2400KCal/day per capita consumption, so that a larger proportion of people are undernourished. The quantile regression results for the 43^{rd} Round show that the effect of an increase in income on the per capita calorie consumption is low at the lower quantiles and high at the higher quantiles. For the highly undernourished people at the 10^{th} and 25^{th} percentiles, a one percent increase in the income of the household increases per capita calorie consumption by 0.29 percent and 0.32 percent, respectively. However, beyond the median quantile the effect is greater, suggesting that well nourished households i.e., those with a per capita calorie consumption of greater than 2400 KCal/day, spend a higher proportion of additional income on calorie consumption. For the year 1993-94, the robust OLS regression suggests that a one percent increase in the income of households increases calorie consumption by around 0.57 percent. The quantile regression results show that for households with very low levels of nutritional status i.e., between the 10^{th} and 25^{th} percentiles, a one percent increase in income increases per capita calorie consumption by 0.51 percent. These people are the undernourished strata of the sample with a per capita calorie intake of 1723.469 KCal/day (Table 1). The effect of income on the per capita calorie consumption is progressive and rising over the quantiles. For people with larger quantities of per capita calorie consumption an increase in per capita income increases per capita calorie consumption by a larger proportion. At the 90^{th} quantile a one percent increase in income means a 0.59 percent increase in calorie consumption. These results are different and statistically significant (Table 5 - 6).

The debate on the responsiveness of household nutrient intake to income is large, some surveys are presented in Behrman & Deolalikar (1990) and Bouis & Haddad (1992). Researchers have argued households have a special preference for tastes and thereby, for even the poorest of households an increase in income results in an increase in the purchase of tasty foods which might not be rich in nutrients. *This analysis sheds further light on this view and it is observed that the effect of an income increase is not uniform for all households and responsiveness also depends on the existing nutritional status of the household. A undernourished household will respond differently to an income increase compared with an adequately nourished or over nourished household.* Thus, it will be an incomplete statement to suggest that an income increase results in people diverting consumption towards tasty food (Behrman & Deolalikar 1987). It is necessary to take into consideration the fact that the responsiveness of calorie consumption to income is contingent upon the nutritional status of the households.

However, the results in this analysis are not indicative of the actual magnitude of the calorie-income elasticity. Our analysis emphasizes that the elasticity varies across the quantiles. The Extant literature has examined the calorie income elasticity and pointed out certain reasons for biased calorie-income elasticity estimates. **Responsiveness to Household Size:** The effect of household size on calorie consumption indicates scale and congestion effects. The results in the present chapter show that an additional household member has a positive and significant effect on per capita calorie consumption. The OLS result for 1987-88 suggests an additional member in the household will increase the per capita calorie consumption by 0.02 percent. On the other hand the quantile regression result paints a different picture. At the lower quantiles i.e.,between the 10^{th} and 25^{th} percentiles, an additional household member will increase per capita calorie consumption by 0.02 and 0.03 percent respectively. This effect is negative for higher quantiles. At the median quantile, where the unconditional per capita calorie consumption as shown in Table 1 is around 2438.60 KCal/day, an additional household member decreases per capita calorie consumption by just 0.008 percent. However, this result is to be viewed with caution as the coefficient is not statistically significant at 5 percent level of significance. The over nourished households (at the 75^{th} and 90^{th} quantiles) reduce per capita calorie consumption for an additional household member. A similar pattern is observed in the post reform period, i.e., 1993-94. The effect of an additional household member is descending across the quantiles. It becomes statistically insignificant at the 75^{th} quantile and negative and significant at the 90^{th} quantile. This result suggests that in poorly nourished households an additional member results in an increase in calorie consumption because this member is a potential income earner and it is beneficial to increase the calorie consumption of the household. For the higher quantiles, the households are overnourished so an additional member does not require an increase in calorie consumption as an intra household reallocation of calories is done without severely affecting the nutritional status of existing household members.

Responsiveness to Household Head Age: In Indian rural households, the household head is a dominant decision maker and hence has an effect on the nutritional status of the household members. The age of the household head could also influence his or her decisions. Extant literature, such as the seminal work of Grossman (1972), suggests that an older individual demands more health inputs- such as medical care and nutrition. The OLS results show responsiveness of per capita calorie consumption to the age of the household decision maker was positive (0.01) in 1987-88 and negative (-0.02) in 1993-94. This effect was very small but statistically significant at 5 percent level of significance. The quantile regression results estimates suggest that the responsiveness of per capita calorie consumption of the household to the age of the household head in 1987-88 was around 0.02 percent for undernourished households (i.e., 10^{th} to 50^{th} quantiles) and even smaller for higher quantiles (75^{th} to 90^{th} quantiles). In contrast, in the post reform period (i.e., 1993-94), the percapita calorie consumption reduced with higher age of the household head for all the quantiles. However, these results are statistically insignificant for undernourished households.

Responsiveness to Food Prices: As per the theoretical model framework the effect of prices should be such that own price effects are negative and cross price effects positive. Since there is no clear price of calories to account for the price effect we have taken the price of four food items. The effect of prices of various food items is of crucial importance as calorie consumption might be directly affected by the prices. The effect of prices is mixed in both the OLS and quantile regression results, for both the pre-reform and the post reform period. The OLS results for the 43^{rd} Round show that the price of wheat had a positive and significant effect while that of bajra and gram had a negative effect. The quantile regression results show the effect of the price of different types of food commodities has a varied effect across quantiles. In the pre-reform period an increase in the price of wheat by one percent increases per capita calorie consumption at all quantiles. However, this effect varies algebraically across quantiles. The effect of the price of rice, gram and bajra is negative and varies across quantiles. The price effect on the undernourished population is the most negative or less positive than for adequately nourished or over nourished households. Thus, our results show there was asymmetric behaviour of undernourished households to price change such that when food prices change the nutrient consumption of undernourished households is reduced more than for overnourished households. For undernourished households (at the 10^{th} and 25^{th} percentile) in 1987-88 the per capita calorie consumption increases as the price of wheat increases. The effect of the prices of gram and rice is statistically significant for the 25^{th} quantile. In the post reform period i.e., in 1993-94, OLS results suggest the effect of the price of wheat and bajra was negative and that of the price of rice and gram positive. According to the quantile regression results the price effect of wheat is negative at all the quantiles, however this effect is least negative for the undernourished households. Suggesting that as the price of wheat increases the calorie consumption for undernourished households reduces by a lesser amount than of an overnourished household.

The positive price effect implies there is strong substitution among various foods with changing prices. This result is similar to that of Behrman & Deolalikar (1989). The results obtained in the analysis suggest that subsidies on certain foods such as gram, rice can affect the individual nutrient intakes for undernourished households by a larger amount vis-a-vis an overnourished household. Hence, a revenue neutral method of improving calorie intake for undernourished households should be designed.

Literate Household Head Effect: The effect of education on the demand for nutrition and thereby health has been well documented in the extant literature. Education has both demand side and supply side effects on household behaviour. There is a positive association between education and labour market returns. Education can improve the efficiency of an individual both in terms of producing investment in health and labour market productivity. There is very high correlation between the demand for health and nutrition and education. From the demand side, educated people recognize the benefits of improved health and would have a better taste for health and nutrition.

In the 43^{rd} round (the pre reform period), the literacy of household head had a negative effect on the per capita calorie consumption of the household on the lower quantiles. In the post reform period, the OLS results suggest a literate household head will have a positive effect on the per capita calorie consumption. *The quantile regression results show that in the pre-reform period a literate household head does not influence the percapita calorie consumption at median quantiles. Similarly, in the post reform period for the overnourished households at the* 90^{th} *percentile the per capita calorie consumption is not significantly affected by literacy of household head.*

Responsiveness of Land Owned by Household: If the household owns land there are possibilities for home production that can be indicative of the asset status of the household. Both, the OLS and quantile regression results indicate that owning land had a positive but statistically insignificant effect on per capita calorie consumption. *The per capita calorie consumption of the household is not affected by the land ownership of the households.*

Responsiveness to Literate Household Head and Land Ownership: If the household head is literate and the household owns land then the OLS results suggest per capita calorie consumption is not affected significantly. The quantile regression results show a similar result except for the 90^{th} percentile in the pre reform period. *The result indicates that if the household head is literate and the household owns land per capita calorie consumption of households corresponding* 90^{th} *percentile will decrease by 0.36 percent. This result suggests that if the household has assets and the household head is also literate then they indulge in consuming tasty foods and might be less concerned about the nutritional content of their diet.*

Responsiveness to Social Group: This variable captures the effect of the household's social background on preferences for nutritious food. The background variable include a Non-Schedule Caste/ Schedule Tribe household i.e., belonging to a upper caste. The regression results at the mean, i.e., robust OLS regression, show that if the household belonged to a non-SC/ST social group rather than to a backward social group, per capita calorie consumption increased in the pre-reform period and decreased in the post reform period. On the other hand the quantile regression results suggest that belonging to an upper caste reduced the demand for calorie consumption in 1987-88. At the lowest quantile the calorie consumption was not significantly affected by the social group affiliation of households. However, for the 25^{th} - 90^{th} quantiles, belonging to a non-SC/ST increased per capita calorie consumption by 0.02 units at the 25^{th} percentile and by 0.04 at the 90^{th} quantile. In the post reform period, belonging to an upper caste decreased calorie consumption of undernourished people by a larger amount than for the households at the 50^{th} percentile. For overnourished households at 90^{th} percentile, the social group did not affect calorie demand significantly. *Thus, belonging to an upper caste affects calorie consumption differently in pre-reform period and the post reform period. The calorie consumption was seen to improve in 1987-88 if the household belonged to non SC-ST social group. however in the 1993-94 the calorie consumption was seen to fall if the household belonged to a non SC-ST social group, suggesting that the backward household's calorie consumption improved in the post reform period.*

Responsiveness to Occupation of the Household: The occupation type of the household can also affect calorie demand. The OLS result for 1987-88 shows that a household belonging to Agricultural labourers or Self Employed in non agriculture occupation, rather than belonging to Self Employed Agriculture had a negative effect on the calorie consumption of the household. In 1993-94, belonging to any of the occupations type decreased the per capita calorie demand of the households. The effect however was smaller for the pre reform period. the quantile regression results show that in the pre-reform period the occupation of the household had a negative influence on the calorie consumption of the households. In the post reform period the effect of occupation was mixed. Belonging to aggriculturer labourer and other labour occupation categories rather than being self employed in agriculture had a negative and statistically significant influence on the calorie consumption. This result was positive but not statistically significant for households self employed in non agriculture category.

Responsiveness to Literate Household Head and Occupation Type: For almost all the occupation types the category literate household head as against an illiterate household head belonging to the occupation of 'agriculture labourer' does not significantly affect the calorie consumption of the household, at any quantile other than the 10^{th} percentile in 1987-88. The effect is negative and declining over the quantiles for a household self employed in non-agriculture with a literate household head. At the 90^{th} quantile the effect is insignificant. In the post reform period none of these variables had a statistically significant effect.

Responsiveness to Female Household Head: If the household head is a female per capita calorie consumption is higher than for a household where the head is a male. The OLS results suggest calorie consumption is positively affected by a female household head and the effect is algebraically consistent for 1987-88 and 1993-94. *In 1987-88 the effect was increasing across all the quantiles whereas in 1993-94 it was declining across the quantiles. This effect was higher in absolute terms for 1993-94.*

Responsiveness to Occupation and Land Owned: For all occupation types the OLS results suggest that if the household also owned land per capita calorie consumption decreased significantly in the pre reform period and in the post reform period this was significant only for households belonging to other than agricultural labour category. *The quantile regression results throw further light on the impact of this interaction variable and suggest that the effect was generally negative and numerically different for all the quantiles in 1987-88. In 1993-94 per capita calorie consumption increased only for households owning land and belonging to the occupation category 'other labourer'. This effect was largest* *at the* 10^{th} *quantile and smallest for the* 50^{th} *quantile.*

Responsiveness to Religion Effect: According to the OLS and quantile regression results for 1987-88, the percapita calorie consumption is affected significantly if the household is a Muslim rather than being a Hindu. In the post reform period, the result suggest that if the household is a Muslim or a Sikh rather than being a Hindu, then the per capita calorie consumption will be higher by 0.03 percent. Quantile regression result show that belonging to any religion does not effect the per capita calorie consumption for the undernourished households at the 25^{th} and 50^{th} quantiles, however the effect is positive and significant for Muslims and negative for Christians. The calorie consumption of overnourished households at the 90^{th} percentile is again not affected by the religion of the households. *Hence we can conclude that the severely undernourished and over nourished people do not show any sign of religion effect on the household's calorie consumption.*

6.1 Hypothesis Tests Results

Table 7 and 8 show the results for hypothesis testing. Wald test is applied to test the equality of slope coefficients across the quantiles for the independent variables [6]. The diagonal matrix consists of the F-statistic with $(1, N-K)$ degrees of freedom. The associated p-values are reported in parentheses. Since the sample size is large F is distributed as χ^2_q/q. The large sample critical values of χ^2_q/q for $q=1$ is 3.84. Hence the decision rule is that an F value greater than 3.84 rejects H_o. Alternatively if the p-value is very small then we reject the hypothesis of equality of slope coefficients. These test results show that the slope coefficients indeed vary across the quantiles. In 1987-88 the slopes were significantly different from each other between the 10^{th} and 90^{th} quantiles for per capita expenditure and household size and between 25^{th} and 75^{th} percentile for per capita expenditure, household size, bajra price and gram price. These test results confirm the argument that the income and the size of the households along with the food prices affect the calorie consumption differently across the quantiles. It is also suggested that the prices of normal goods and inferior goods affect the calorie consumption differently for undernourished and over nour-

[6] The results for the categorical variables are not included

ished population.
Although the null hypothesis of equality of slope coefficients can not be rejected for the age of the household head and the prices of wheat and rice in 1987 -88. In 1993-94 the null is seen to be rejected for all of these variables too. Suggesting that the responsiveness of calorie consumption to the prices and the household characteristics has become more varied in the post reform period.

Table 3: OLS and Quantile Regression Results : 43^{rd} NSS Round (1987-88)

Variables	OLS	10th per	25th per	50th per	75th per	90th per
Ln(PCE)	0.391^*	0.299^*	0.322^*	0.350^*	0.396^*	0.443^*
	(0.007)	(0.009)	(0.007)	(0.006)	(0.006)	(0.009)
Ln(HHSize)	0.017^*	0.033^*	0.003	-0.008	-0.022^*	-0.032^*
	(0.006)	(0.010)	(0.006)	(0.005)	(0.005)	(0.008)
Ln(Head Age)	0.012	0.019	0.023^*	0.022^*	0.020^*	0.011
	(0.008)	(0.012)	(0.009)	(0.007)	(0.008)	(0.010)
Ln(Wheat Pr.)	0.524^*	0.367^*	0.501^*	0.577^*	0.562^*	0.476^*
	(0.051)	(0.104)	(0.063)	(0.055)	(0.057)	(0.070)
Ln(Rice Pr.)	0.005	-0.070^*	-0.078^*	-0.039^*	-0.046^*	-0.028
	(0.024)	(0.036)	(0.026)	(0.020)	(0.021)	(0.043)
Ln(Bajra Pr.)	-0.182^*	-0.140^*	-0.093^*	-0.137^*	-0.177^*	-0.123^*
	(0.033)	(0.065)	(0.038)	(0.038)	(0.032)	(0.046)
Ln(Gram Pr.)	-0.152^*	-0.149	-0.178^*	-0.171^*	-0.025	-0.043
	(0.052)	(0.091)	(0.059)	(0.057)	(0.054)	(0.069)
Land Owned	0.064	0.039	-0.018	0.057	0.047	0.081
	(0.037)	(0.047)	(0.051)	(0.049)	(0.059)	(0.048)
Head Lit	-0.080^*	-0.130^*	-0.103^*	-0.058	-0.051^*	-0.094^*
	(0.025)	(0.033)	(0.033)	(0.031)	(0.022)	(0.043)
Lit.HeadXLandOwn	-0.186	-0.250	-0.181	-0.072	-0.111	-0.363^*
	(0.118)	(0.339)	(0.235)	(0.144)	(0.146)	(0.140)
Non-SC/ST	0.019^*	-0.00010	0.023^*	0.031^*	0.034^*	0.041^*
	(0.006)	(0.012)	(0.006)	(0.005)	(0.005)	(0.007)
Gujarat	-0.265^*	-0.190^*	-0.258^*	-0.282^*	-0.255^*	-0.220^*
	(0.032)	(0.057)	(0.035)	(0.030)	(0.032)	(0.051)
Jammu n Kashmir	0.183^*	0.147^*	0.150^*	0.160^*	0.233^*	0.242^*
	(0.026)	(0.041)	(0.028)	(0.024)	(0.026)	(0.042)
Karnataka	-0.214^*	-0.273^*	-0.268^*	-0.242^*	-0.143^*	-0.036
	(0.038)	(0.068)	(0.045)	(0.037)	(0.039)	(0.056)
Madhya Pradesh	0.024	0.062	0.024	-0.001	0.072^*	0.116^*
	(0.030)	(0.048)	(0.034)	(0.028)	(0.029)	(0.049)
Maharashtra	-0.128^*	-0.110^*	-0.161^*	-0.161^*	-0.068^*	-0.011
	(0.033)	(0.054)	(0.036)	(0.031)	(0.033)	(0.051)
Rajasthan	0.017	0.085	0.048	0.028	0.105^*	0.119^*
	(0.033)	(0.050)	(0.035)	(0.028)	(0.030)	(0.053)
Tamil Nadu	-0.195^*	-0.295^*	-0.219^*	-0.192^*	-0.138^*	-0.107^*
	(0.031)	(0.057)	(0.035)	(0.029)	(0.030)	(0.050)
Uttar Pradesh	0.135^*	0.053	0.065^*	0.100^*	0.190^*	0.231^*

Continued . . .

Table 3: (continued)

Variables	OLS	10th per	25th per	50th per	75th per	90th per
	(0.025)	(0.037)	(0.026)	(0.023)	(0.024)	(0.040)
Self Emp Non-Ag(SEmp Non-Ag)	-0.058^*	-0.062^*	-0.068^*	-0.069^*	-0.063^*	-0.074^*
	(0.008)	(0.014)	(0.009)	(0.009)	(0.008)	(0.010)
Agri. Lab (AgLab)	-0.019^*	-0.039^*	-0.032^*	-0.030^*	-0.025^*	-0.016^*
	(0.007)	(0.014)	(0.008)	(0.006)	(0.007)	(0.008)
Other Lab (OthLab)	-0.008	-0.029	-0.040^*	-0.020	-0.024^*	-0.012
	(0.010)	(0.016)	(0.011)	(0.010)	(0.009)	(0.013)
SEmpNon-AgX Head Lit	-0.171^*	-0.053	-0.180^*	-0.244^*	-0.275^*	-0.059
	(0.065)	(0.091)	(0.058)	(0.061)	(0.102)	(0.107)
AgLab X Head Lit	0.212^*	0.320^*	0.154	0.196	0.067	0.189
	(0.090)	(0.122)	(0.110)	(0.123)	0.142)	(0.163)
OthLab X Head Lit	0.192	0.291	0.340^*	0.152	0.034	0.345
	(0.139)	(0.165)	(0.162)	(0.158)	0.230)	(0.244)
SEmpNon-Agg X Land Own	-0.125^*	-0.118	-0.024	-0.085	-0.089	-0.095
	(0.042)	(0.069)	(0.055)	(0.053)	0.062)	(0.055)
AgLab X Land Own	-0.101^*	-0.069	0.003	-0.061	-0.052	-0.097
	(0.040)	(0.056)	(0.053)	(0.050)	0.061)	(0.050)
OthLab X Land Own	-0.118^*	-0.088	-0.020	-0.115^*	-0.113	-0.170^*
	(0.042)	(0.063)	(0.057)	(0.053)	0.064)	(0.055)
Islam	0.058^*	0.045^*	0.049^*	0.048^*	0.059^*	0.056^*
	(0.008)	(0.015)	(0.010)	(0.010)	(0.009)	(0.011)
Christian	0.008	0.031	-0.001	-0.055	0.019	-0.015
	(0.052)	(0.112)	(0.047)	(0.050)	0.073)	(0.103)
Sikhism	0.005	-0.017	-0.017	-0.008	0.002	0.023
	(0.020)	(0.027)	(0.021)	(0.018)	0.019)	(0.032)
Other Rel.	0.021	0.032	0.026	0.033	0.021	0.011
	(0.021)	(0.043)	(0.016)	(0.022)	0.019)	(0.021)
Female Head	0.063^*	0.037	0.046^*	0.054^*	0.059^*	0.069^*
	(0.011)	(0.020)	(0.013)	(0.011)	(0.010)	(0.013)
Const.	8.592^*	7.896^*	8.340^*	8.637^*	8.804^*	9.027^*
	(0.066)	(0.110)	(0.075)	(0.063)	(0.075)	(0.101)
R^2 and Adj.R^2	0.272	0.117	0.137	0.161	0.199	0.248

$*$: statistically significant at 5% level of significance.

Design Matrix Bootstrap Standard Errors are in parentheses.

R^2 for the quantile regression is calculated using the method suggested in Buchinsky (1998).

Table 4: OLS and Quantile Regression Results : 50^{th} NSS Round (1993-94)

Variables	OLS	10th per	25th per	50th per	75th per	90th per
Ln(PCE)	0.575*	0.519*	0.534*	0.549*	0.575*	0.599*
	(0.009)	(0.013)	(0.010)	(0.008)	(0.009)	(0.010)
Ln(HHSize)	0.010	0.052*	0.040*	0.025*	-0.013	−0.055*
	(0.007)	(0.011)	(0.008)	(0.007)	(0.008)	(0.009)
Ln(Head Age)	−0.023*	-0.008	-0.007	−0.029*	−0.045*	−0.047*
	(0.010)	(0.015)	(0.012)	(0.008)	(0.010)	(0.012)
Ln(Wheat Pr.)	−0.771*	−0.668*	−0.449*	−0.586*	−0.817*	−1.225*
	(0.093)	(0.177)	(0.146)	(0.105)	(0.106)	(0.126)
Ln(Rice Pr.)	0.593*	0.727*	0.550*	0.246*	0.144*	0.106
	(0.063)	(0.119)	(0.095)	(0.066)	(0.057)	(0.066)
Ln(Bajra Pr.)	−0.237*	−0.356*	−0.300*	-0.031	0.083	0.216*
	(0.053)	(0.092)	(0.075)	(0.053)	(0.050)	(0.061)
Ln(Gram Pr.)	0.880*	0.332	1.116*	1.135*	1.237*	1.011*
	(0.116)	(0.213)	(0.157)	(0.117)	(0.119)	(0.155)
Land Owned	0.0002	-0.024	0.007	0.021	-0.042	-0.026
	(0.025)	(0.038)	(0.047)	(0.023)	(0.025)	(0.038)
Head Litracy	0.039*	0.035*	0.034*	0.034*	0.032*	0.015
	(0.008)	(0.015)	(0.011)	(0.008)	(0.009)	(0.011)
Lit. Head X Land Own	-0.033	-0.050	-0.016	-0.043	0.007	0.001
	(0.019)	(0.030)	(0.026)	(0.023)	(0.019)	(0.025)
Non- SC/ST	−0.047*	−0.075*	−0.055*	−0.029*	−0.014*	-0.016
	(0.007)	(0.013)	(0.009)	(0.007)	(0.007)	(0.008)
Bihar	0.518*	0.471*	0.457*	0.418*	0.486*	0.550*
	(0.025)	(0.046)	(0.034)	(0.024)	(0.026)	(0.034)
Gujarat	−0.237*	−0.307*	−0.504*	−0.281*	-0.101	0.193*
	(0.067)	(0.136)	(0.100)	(0.071)	(0.078)	(0.097)
Jammu n Kashmir	−0.547*	−0.703*	−0.582*	−0.275*	−0.142*	-0.044
	(0.061)	(0.110)	(0.088)	(0.066)	(0.061)	(0.069)
Karnataka	−0.210*	−0.551*	−0.576*	−0.219*	0.094	0.415*
	(0.055)	(0.112)	(0.082)	(0.058)	(0.064)	(0.078)
Madhya Pradesh	-0.082	−0.502*	−0.184*	0.147*	0.325*	0.425*
	(0.049)	(0.090)	(0.069)	(0.049)	(0.051)	(0.060)
Maharashtra	-0.030	−0.562*	−0.280*	0.078	0.398*	0.576*
	(0.052)	(0.088)	(0.061)	(0.054)	(0.058)	(0.070)
Rajasthan	−0.384*	−1.009*	−0.652*	−0.099*	0.140*	0.313*
	(0.049)	(0.083)	(0.067)	(0.050)	(0.050)	(0.060)
Tamil Nadu	0.455*	0.312*	0.436*	0.482*	0.558*	0.569*

Continued ...

Table 4: (continued)

Variables	OLS	10th per	25th per	50th per	75th per	90th per
	(0.029)	(0.052)	(0.038)	(0.028)	(0.029)	(0.038)
SelfEmp Non-Ag.(SEmpNon-Ag)	0.022	0.035	0.012	-0.001	0.020	0.034*
	(0.014)	(0.021)	(0.016)	(0.016)	(0.015)	(0.016)
Agg. Lab (AgLab)	−0.037*	-0.022	−0.036*	−0.039*	−0.044*	−0.042*
	(0.010)	(0.020)	(0.012)	(0.010)	(0.011)	(0.013)
Other Lab (OthLab)	−0.114*	−0.193*	−0.150*	−0.053*	-0.035	−0.042*
	(0.023)	(0.043)	(0.035)	(0.022)	(0.018)	(0.019)
SEmpX Head Lit	0.022	0.013	0.012	0.034	0.004	-0.027
	(0.020)	(0.033)	(0.023)	(0.023)	(0.021)	(0.027)
AgLab X Head Lit	-0.003	0.031	-0.005	0.015	0.012	0.012
	(0.020)	(0.031)	(0.026)	(0.023)	(0.019)	(0.027)
OthLab X Head Lit	-0.004	-0.020	-0.0005	-0.010	-0.054	-0.053
	(0.030)	(0.054)	(0.047)	(0.035)	(0.030)	(0.041)
SEmp X Land Own	-0.016	0.010	-0.016	-0.034	0.010	-0.028
	(0.029)	(0.045)	(0.049)	(0.028)	(0.027)	(0.041)
AgLab X Land Own	-0.026	-0.003	-0.029	-0.048	-0.006	-0.026
	(0.027)	(0.043)	(0.048)	(0.024)	(0.026)	(0.040)
OthLab X Land Own	0.116*	0.225*	0.134*	0.036	0.067*	0.054
	(0.035)	(0.061)	(0.060)	(0.036)	(0.033)	(0.050)
Islam	0.035*	0.031	0.021*	0.043*	0.044*	0.023
	(0.009)	(0.017)	(0.010)	(0.009)	(0.010)	(0.014)
Christian	-0.053	-0.056	−0.089*	−0.069*	-0.036	0.007
	(0.035)	(0.056)	(0.035)	(0.021)	(0.052)	(0.082)
Sikhism	0.035*	0.028	0.030	0.006	0.011	-0.027
	(0.017)	(0.032)	(0.024)	(0.016)	(0.016)	(0.022)
Other Rel.	-0.026	-0.001	0.048	-0.016	-0.070	-0.016
	(0.036)	(0.062)	(0.059)	(0.030)	(0.038)	(0.031)
Female Head	0.110*	0.118*	0.100*	0.110*	0.099*	0.087*
	(0.013)	(0.023)	(0.018)	(0.014)	(0.014)	(0.017)
Const.	8.473*	7.979*	8.465*	8.560*	8.615*	8.463*
	(0.147)	(0.264)	(0.226)	(0.172)	(0.166)	(0.197)
R^2 and Adj.R^2	0.429	0.336	0.273	0.239	0.239	0.257

∗: statistically significant at 5% level of significance.

Design Matrix Bootstrap Standard Errors are in parentheses.

R^2 for the quantile regression is calculated using the method suggested in Buchinsky (1998).

Table 5: Sign and Significance of the variables in 1987-88.

	OLS		Quantile Regression 10^{th}		25^{th}		50^{th}		75^{th}		90^{th}	
	Sign	Signif.	Sign	Signif.	Sign	Signif.	Sign	Signif.	Sign	Signif.	Sign	Signif.
Ln(PCE)	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.
Ln(HHSize)	+	Insig.	+	Sig.	+	Sig.	+	Sig.	-	Insig.	-	Sig.
Ln(Head Age)	-	Sig.	-	Insig.	-	Insig.	-	Sig.	-	Sig.	-	Sig.
Ln(Wheat Pr.)	-	Sig.	-	Sig.	-	Insig.	-	Sig.	-	Sig.	-	Sig.
Ln(Rice Pr.)	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Insig.
Ln(Bajra Pr.)	-	Sig.	-	Sig.	-	Sig.	-	Insig.	+	Insig.	+	Sig.
Ln(Gram Pr.)	+	Sig.	+	Insig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.
Land Owned	+	Insig.	-	Insig.	+	Insig.	+	Insig.	-	Insig.	-	Insig.
Head Litracy	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Insig.
Lit. Head X Land Own	-	Insig.	-	Insig.	-	Insig.	-	Insig.	+	Insig.	+	Insig.
Non- SC/ST	-	Sig.	-	Sig.	-	Sig.	-	Sig.	-	Sig.	-	Insig.
Bihar	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.
Gujarat	-	Sig.	-	Sig.	-	Sig.	-	Sig.	-	Insig.	+	Sig.
Jammu n Kashmir	-	Sig.	-	Sig.	-	Sig.	-	Sig.	-	Sig.	-	Insig.
Karnataka	-	Sig.	-	Sig.	-	Sig.	-	Sig.	+	Insig.	+	Sig.
Madhya Pradesh	-	Insig.	-	Sig.	-	Sig.	+	Sig.	+	Sig.	+	Sig.
Maharashtra	-	Insig.	-	Sig.	-	Sig.	+	Insig.	+	Sig.	+	Sig.
Rajasthan	-	Sig.	-	Sig.	-	Sig.	-	Sig.	+	Sig.	+	Sig.
Uttar Pradesh	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.
Self Emp Non-Agg.	+	Insig.	+	Insig.	+	Insig.	-	Insig.	+	Insig.	+	Sig.
Agg. Lab (AgLab)	-	Sig.	-	Insig.	-	Sig.	-	Sig.	-	Sig.	-	Sig.
Other Lab (OthLab)	-	Sig.	-	Sig.	-	Sig.	-	Sig.	-	Insig.	-	Sig.
SEmpX Head Lit	+	Insig.	+	Insig.	+	Insig.	+	Insig.	+	Insig.	-	Insig.
AgLab X Head Lit	-	Insig.	+	Insig.	-	Insig.	+	Insig.	+	Insig.	+	Insig.
OthLab X Head Lit	-	Insig.	-	Insig.	-	Insig.	-	Insig.	-	Insig.	-	Insig.
SEmpNon-AggXLandOwn	-	Insig.	+	Insig.	-	Insig.	-	Insig.	+	Insig.	-	Insig.
AgLab X Land Own	-	Insig.	-	Insig.	-	Insig.	-	Insig.	-	Insig.	-	Insig.
OthLab X Land Own	+	Sig.	+	Sig.	+	Sig.	+	Insig.	+	Sig.	+	Insig.
Islam	+	Sig.	+	Insig.	+	Sig.	+	Sig.	+	Sig.	+	Insig.
Christian	-	Insig.	-	Insig.	-	sig.	-	Sig.	-	Insig.	+	Insig.
Sikhism	+	Sig.	+	Insig.	+	Insig.	+	Insig.	+	Insig.	-	Insig.
Other Rel.	-	Insig.	-	Insig.	+	Insig.	-	Insig.	-	Insig.	-	Insig.
Female Head	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.
Const.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.

Table 6: Sign and Significance of the variables in 1993-94.

	OLS		Quantile Regression 10^{th}		25^{th}		50^{th}		75^{th}		90^{th}	
	Sign	Signif.	Sign	Signif.	Sign	Signif.	Sign	Signif.	Sign	Signif.	Sign	Signif.
Ln(PCE)	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.
Ln(HHSize)	+	Insig.	+	Sig.	+	Sig.	+	Sig.	-	Insig.	-	Sig.
Ln(Head Age)	-	Sig.	-	Insig.	-	Insig.	-	Sig.	-	Sig.	-	Sig.
Ln(Wheat Pr.)	-	Sig.	-	Sig.	-	Insig.	-	Sig.	-	Sig.	-	Sig.
Ln(Rice Pr.)	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Insig.
Ln(Bajra Pr.)	-	Sig.	-	Sig.	-	Sig.	-	Insig.	+	Insig.	+	Sig.
Ln(Gram Pr.)	+	Sig.	+	Insig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.
Land Owned	+	Insig.	-	Insig.	+	Insig.	+	Insig.	-	Insig.	-	Insig.
Head Litracy	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Insig.
Lit.HeadXLand Own	-	Insig.	-	Insig.	-	Insig.	-	Insig.	+	Insig.	+	Insig.
Non- SC/ST	-	Sig.	-	Sig.	-	Sig.	-	Sig.	-	Sig.	-	Insig.
Bihar	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.
Gujarat	-	Sig.	-	Sig.	-	Sig.	-	Sig.	-	Insig.	+	Sig.
Jammu n Kashmir	-	Sig.	-	Sig.	-	Sig.	-	Sig.	-	Sig.	-	Insig.
Karnataka	-	Sig.	-	Sig.	-	Sig.	-	Sig.	+	Insig.	+	Sig.
Madhya Pradesh	-	Insig.	-	Sig.	-	Sig.	+	Sig.	+	Sig.	+	Sig.
Maharashtra	-	Insig.	-	Sig.	-	Sig.	+	Insig.	+	Sig.	+	Sig.
Rajasthan	-	Sig.	-	Sig.	-	Sig.	-	Sig.	+	Sig.	+	Sig.
Uttar Pradesh	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.
Self Emp(SEmp)	+	Insig.	+	Insig.	+	Insig.	-	Insig.	+	Insig.	+	Sig.
Agg. Lab(AgLab)	-	Sig.	-	Insig.	-	Sig.	-	Sig.	-	Sig.	-	Sig.
Other Lab(OthLab)	-	Sig.	-	Sig.	-	Sig.	-	Sig.	-	Insig.	-	Sig.
SEmpXHeadLit	+	Insig.	+	Insig.	+	Insig.	+	Insig.	+	Insig.	-	Insig.
AgLabXHeadLit	-	Insig.	+	Insig.	-	Insig.	+	Insig.	+	Insig.	+	Insig.
OthLabXHeadLit	-	Insig.	-	Insig.	-	Insig.	-	Insig.	-	Insig.	-	Insig.
SEmpXLandOwn	-	Insig.	+	Insig.	-	Insig.	-	Insig.	+	Insig.	-	Insig.
AgLabXLandOwn	-	Insig.	-	Insig.	-	Insig.	-	Insig.	-	Insig.	-	Insig.
OthLabXLandOwn	+	Sig.	+	Sig.	+	Sig.	+	Insig.	+	Sig.	+	Insig.
Islam	+	Sig.	+	Insig.	+	Sig.	+	Sig.	+	Sig.	+	Insig.
Christian	-	Insig.	-	Insig.	-	sig.	-	Sig.	-	Insig.	+	Insig.
Sikhism	+	Sig.	+	Insig.	+	Insig.	+	Insig.	+	Insig.	-	Insig.
Other Rel.	-	Insig.	-	Insig.	+	Insig.	-	Insig.	-	Insig.	-	Insig.
Female Head	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.
Const.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.	+	Sig.

Table 7: Wald Test for equality of slope coefficients of independent variables, 1987-88.

	$H_o: \beta_{i10} = \beta_{i90}$; $H_1: \beta_{i10} \neq \beta_{i90}$						
90^{th} Percentile → ↓ 10^{th} Percentile	Ln(PCE)	Ln(HHSize)	Ln(Head Age)	Ln(Wheat Pr.)	Ln(Rice Pr.)	Ln(Bajra Pr.)	Ln(Gram Pr.)
Ln(PCE)	147.72** (0.0000)						
Ln(HHSize)		29.6** (0.0000)					
Ln(Head Age)			0.33 (0.5628)				
Ln(Wheat Pr.)				0.8 (0.3697)			
Ln(Rice Pr.)					0.62 (0.4313)		
Ln(Bajra Pr.)						0.04 (0.8323)	
Ln(Gram Pr.)							0.92 (0.3371)

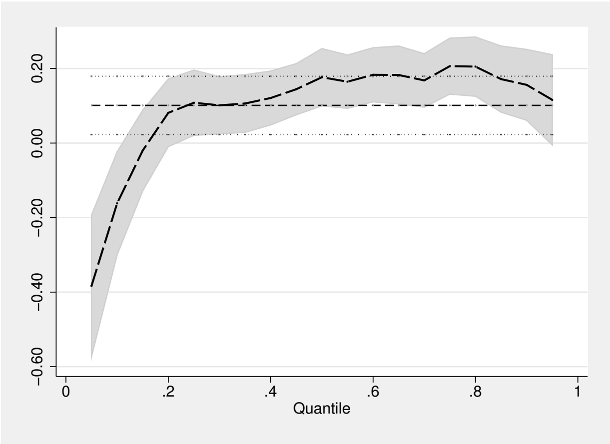
	$H_o: \beta_{i25} = \beta_{i75}$; $H_1: \beta_{i25} \neq \beta_{i75}$						
75^{th} Percentile → ↓ 25^{th} Percentile	Ln(PCE)	Ln(HHSize)	Ln(Head Age)	Ln(Wheat Pr.)	Ln(Rice Pr.)	Ln(Bajra Pr.)	Ln(Gram Pr.)
Ln(PCE)	100.89** (0.0000)						
Ln(HHSize)		14.63** (0.0001)					
Ln(Head Age)			0.05 (0.8229)				
Ln(Wheat Pr.)				0.77 (0.3791)			
Ln(Rice Pr.)					1.35 (0.2459)		
Ln(Bajra Pr.)						4.31** (0.0379)	
Ln(Gram Pr.)							5.34** (0.0208)

Note: The numbers are the F-statistic with $(1, N-K)$ degrees of freedom. The associated p-values are reported in parentheses.

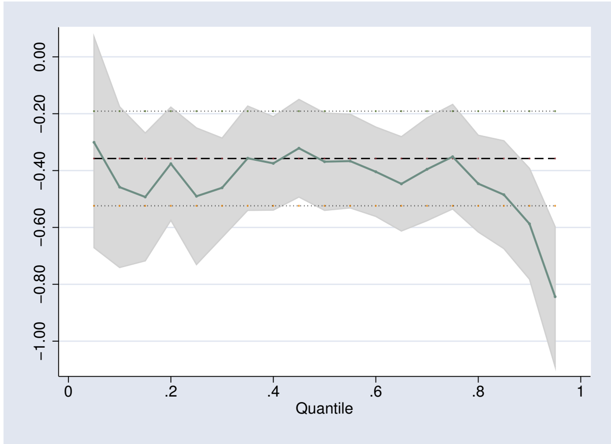
Table 8: Wald Test for equality of slope coefficients for the independent variables, 1993-94.

	$H_o : \beta_{i10} = \beta_{i90}$; $H_1 : \beta_{i10} \neq \beta_{i90}$						
90^{th} Percentile $\rightarrow$ $\downarrow$ 10^{th} Percentile	Ln(PCE)	Ln(HHSize)	Ln(Head Age)	Ln(Wheat Pr.)	Ln(Rice Pr.)	Ln(Bajra Pr.)	Ln(Gram Pr.)
Ln(PCE)	30.00** (0.0000)						
Ln(HHSize)		64.41** (0.0000)					
Ln(Head Age)			4.60** (0.0319)				
Ln(Wheat Pr.)				7.37** (0.0066)			
Ln(Rice Pr.)					22.36** (0.0000)		
Ln(Bajra Pr.)						31.07** (0.0000)	
Ln(Gram Pr.)							6.92** (0.0086)
	$H_o : \beta_{i25} = \beta_{i75}$; $H_1 : \beta_{i25} \neq \beta_{i75}$						
75^{th} Percentile $\rightarrow$ $\downarrow$ 25^{th} Percentile	Ln(PCE)	Ln(HHSize)	Ln(Head Age)	Ln(Wheat Pr.)	Ln(Rice Pr.)	Ln(Bajra Pr.)	Ln(Gram Pr.)
Ln(PCE)	16.64** (0.0000)						
Ln(HHSize)		33.55** (0.0000)					
Ln(Head Age)			8.39** (0.0038)				
Ln(Wheat Pr.)				6.19** (0.0128)			
Ln(Rice Pr.)					19.45** (0.0000)		
Ln(Bajra Pr.)						24.91** (0.0000)	
Ln(Gram Pr.)							0.54 (0.4645)

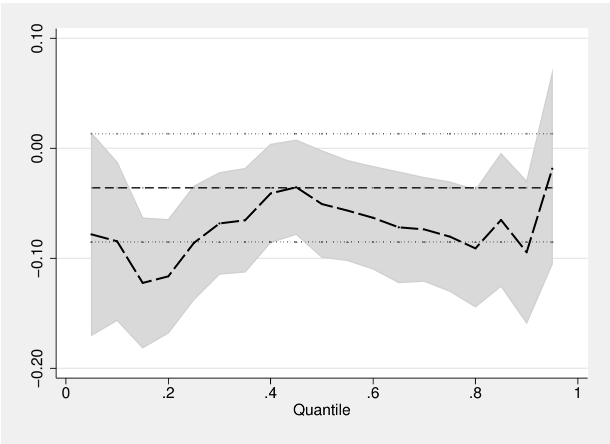
Note: The numbers are the F-statistic with $(1, N-K)$ degrees of freedom. The associated p-values are reported in parentheses.



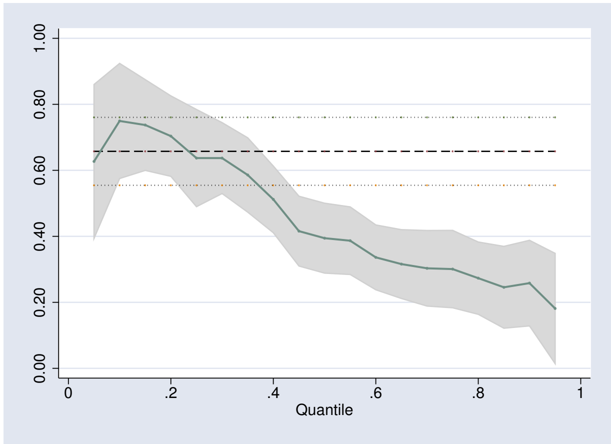
1987: Price of Wheat



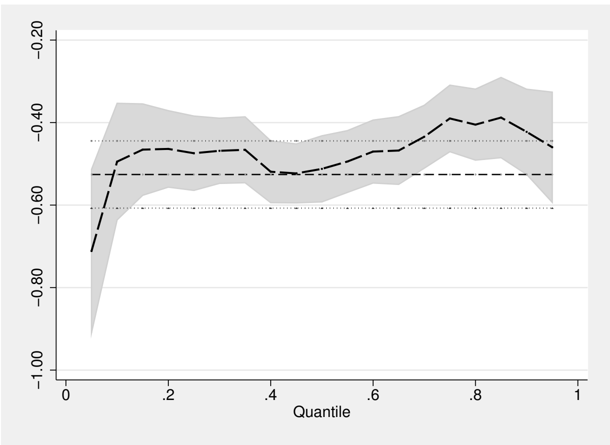
1993: Price of Wheat



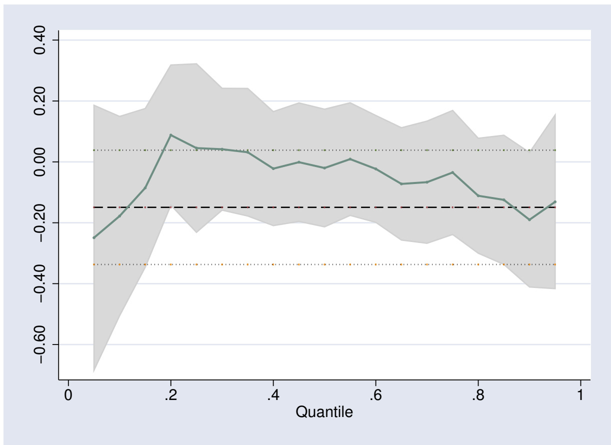
1987: Price of Rice



1993: Price of Rice

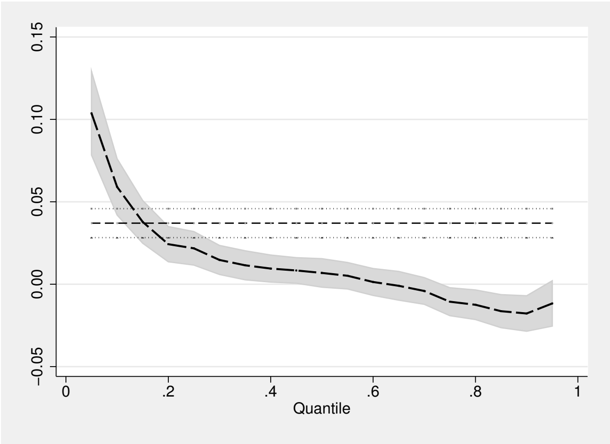


1987: Price of Gram

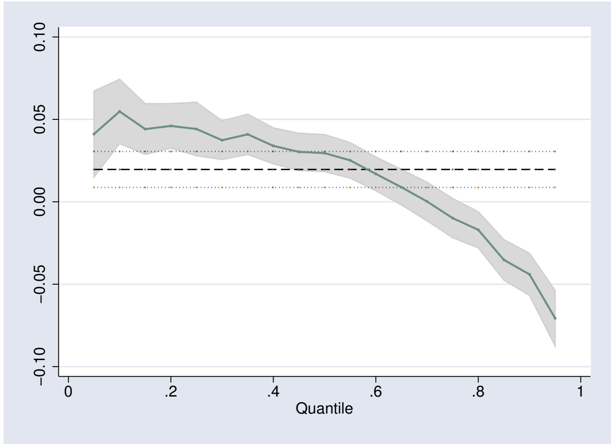


1993: Price of Gram

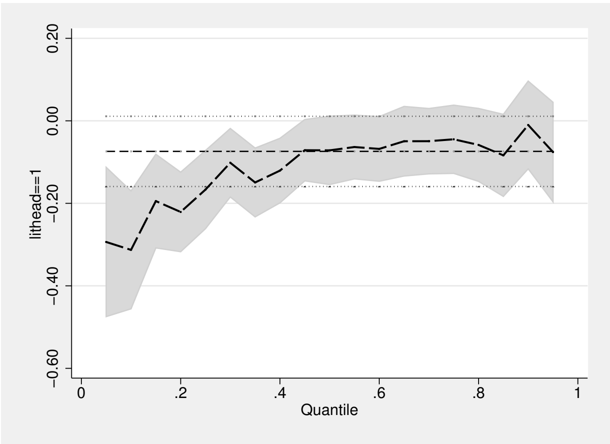
Figure 1: Quantile and OLS Plots: Response of Food Prices on Calorie Consumption



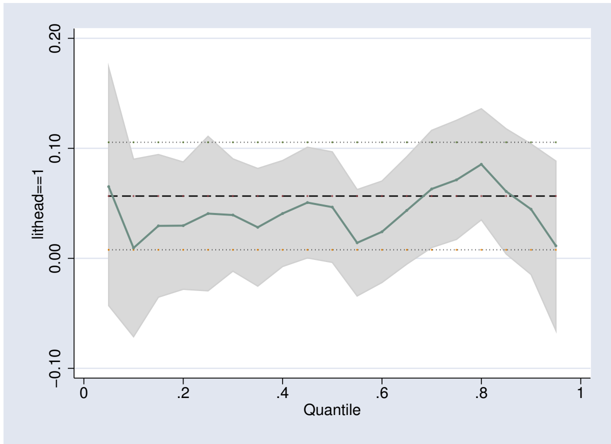
1987: HH Size



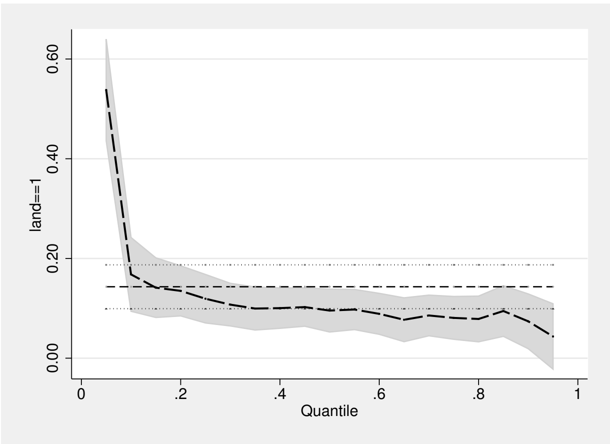
1993: HH Size



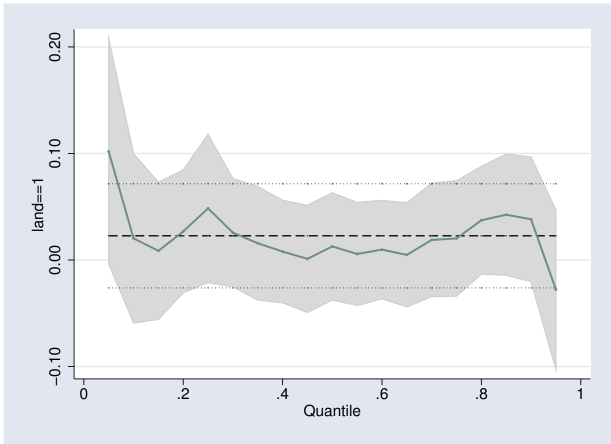
1987: HH Head Literacy



1993: HH Head Literacy

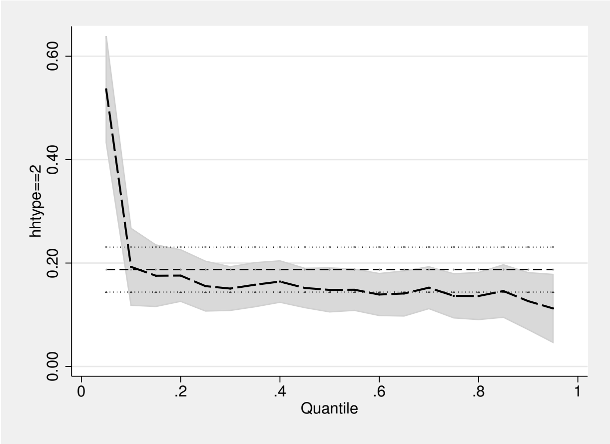


1987: HH owns Land

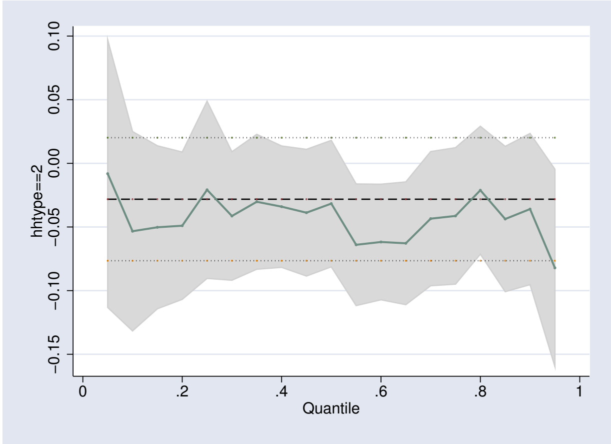


1993: HH owns Land

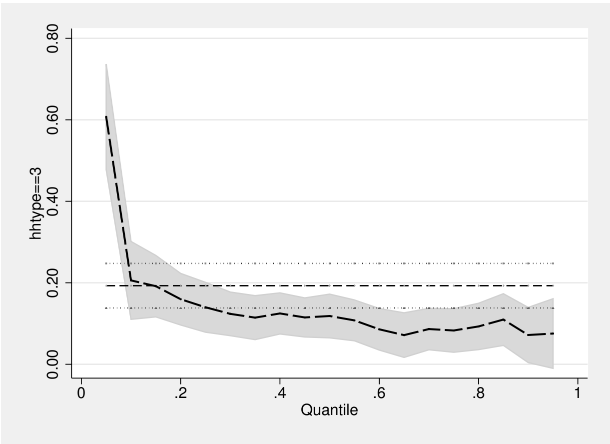
Figure 2: Quantile and OLS Plots: Response of HH characteristics on Calorie Consumption



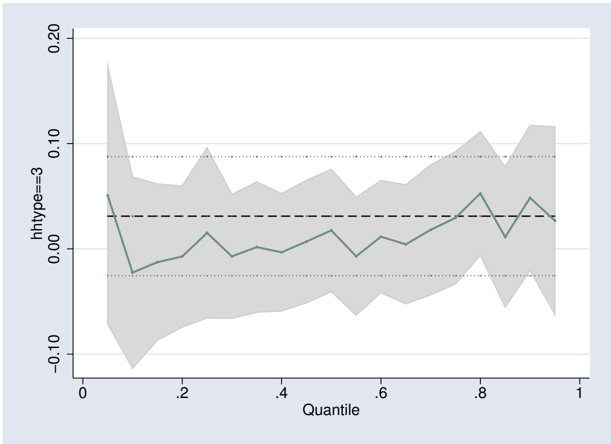
1987: Agr. Labour



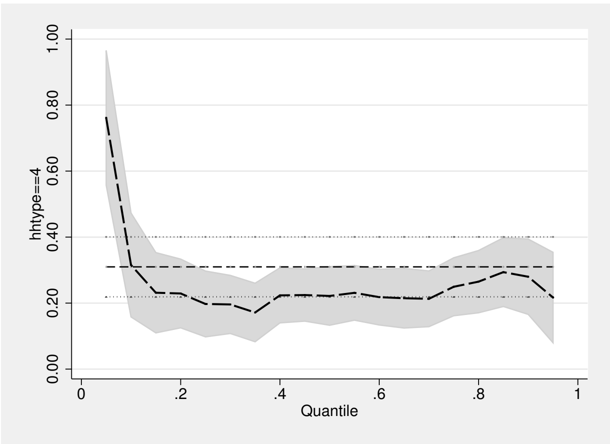
1993: Agr. Labour



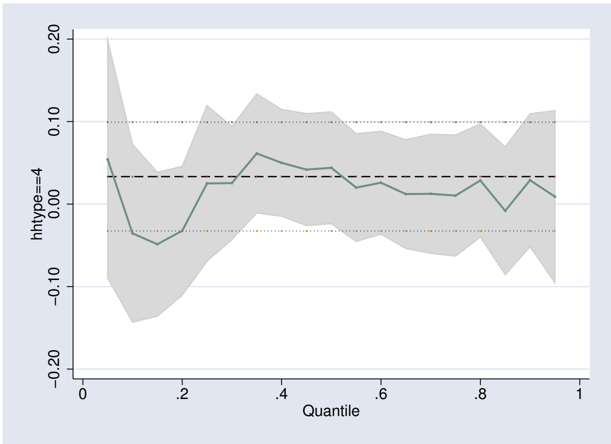
1987: Other Labour



1993: Other Labour

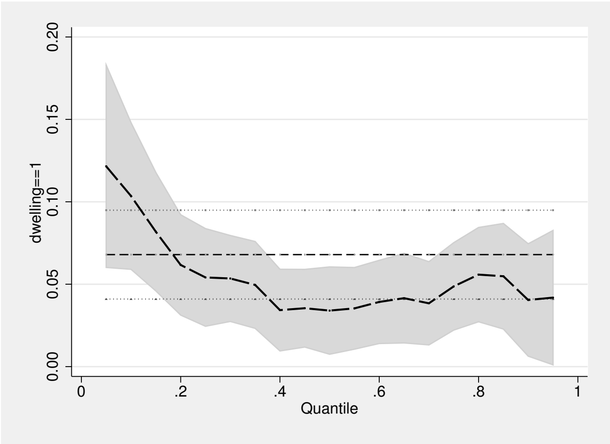


1987: Self Employed Agr. Labour

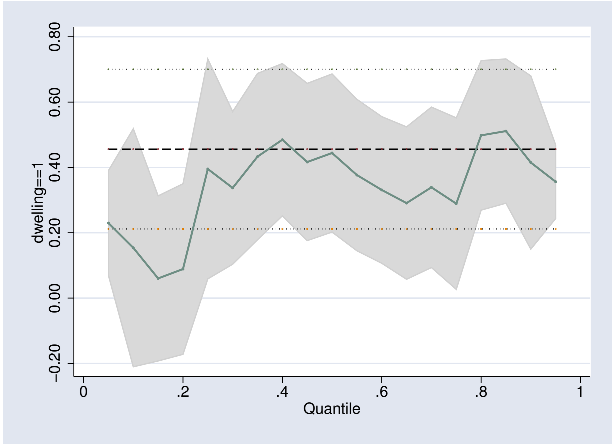


1993: Self Employed Agr. Labour

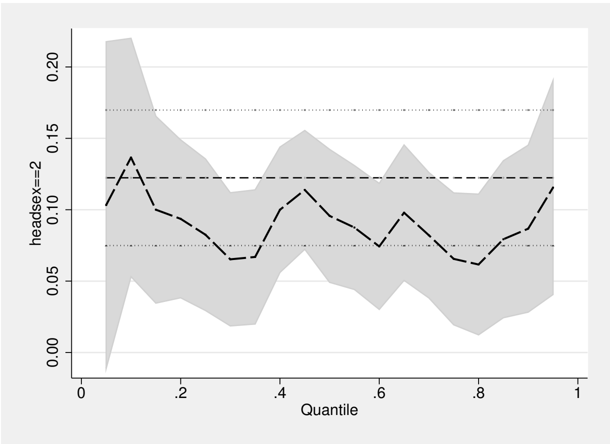
Figure 3: Quantile and OLS Plots: Response of HH Occupation on Calorie Consumption



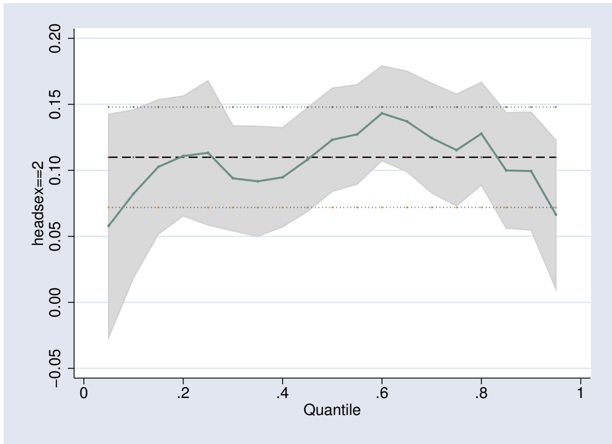
1987: Homeless



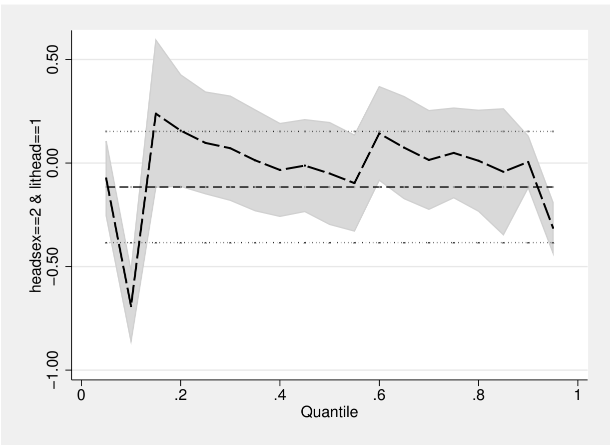
1993: Homeless



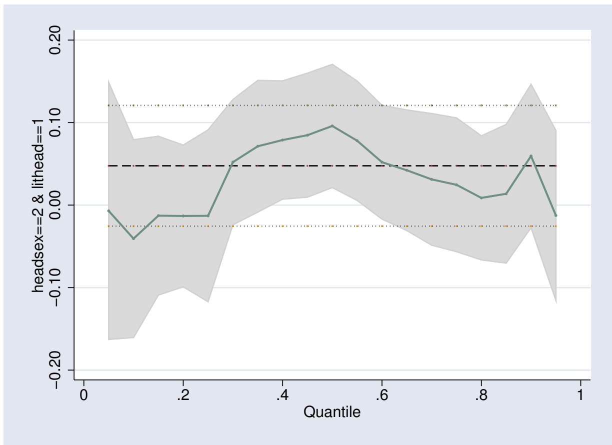
1987: HH Head Female



1993: HH Head Female



1987: HH Head Female and Literate



1993: HH Head Female and Literate

Figure 4: Quantile and OLS Plots: Response of HH characteristics on Calorie Consumption

7 Conclusion

This paper has been an attempt to model the effect of income and certain household characteristics affect the per capita calorie consumption in rural India. The main conclusions are:

There is much heterogeneity in the marginal effect of income and household characteristics on calorie consumption. The distribution for calorie consumption is affected differently at different levels depending on the household characteristics and the nutritional status of the household. The effect of income is not uniform across the conditional calorie consumption distribution. It is higher for individuals at higher positions in the calorie consumption distribution. Thus, OLS analysis does not give a complete picture of the effect of income and other household characteristics on the calorie consumption of the household's behaviour. The distribution of calorie consumption differs across households. The implications of price and income effects for a particular level of calorie consumption differs substantially from the effects at the mean. The price elasticities for nutrient consumption are substantially different for undernourished than for overnourished households. The behaviour at the average, as suggested by the OLS results, thus misrepresents the substantial nutritional status differences in adjustment to price changes of different commodities. The positive price elasticities for different quantiles has been justified by Behrman & Deolalikar (1988) in saying that there is strong substitution among various foods for price changes. The positive effect of prices is suggestive of the fact that the households do not always consume the diet which the can afford in minimum cost. In deciding upon the food choice the households also take into account other attributes of foods which might be non-nutritive in nature such as aroma, tastes, quality etc. The price elasticity results have important policy implications. The results suggests that while providing food subsidy, the nature of the food subsidized is also important. A subsidy on certain commodities might actually reduce the nutritional level of the households. Not only this, in designing the subsidy the policy maker has to take into account the actual "healthiness of the households". A subsidy on a less nutritious food might not be effective in improving the nutrition of the under nourished households whereas it might provide over nutrition for the over nourished households!

The analysis in this paper suggest that the ordinary least square method gives an incomplete picture of the responsiveness of the calorie consumption for various households. This is very important for policy design attempting to improve nutrition of the people in the economy.

8 Appendix

The dummy variables are defined as:

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Table 9: Sign and Significance of the variables in 1987-88.

Ln(PCE)	Log real per capita calorie consumption
Ln(HeadAge)	Log of the age of the household head
Ln(Wheat Pr)	Log real price of Wheat
Ln(Rice Pr)	Log real price of Rice
Ln(Bajra Pr)	Log real price of Bajra
Ln(Gram Pr)	Log real price of Gram
Land Owned	Dummy for land ownership; 1 if household owns land otherwise 0 Base Case : household doesnot own land
Head Lit.	Dummy for household head literacy. 1 if the household head is literate beyond primary education; 0 if the head is wither illiterate of literate belowprimary level. Base Case: If household head is not literate or literate below primary
SEmpNonAg.	Occupation dummy. 1 if self employed in non agriculture. Base Case: Self Employed in agriculture.
AgLab	Occupation dummy. 1 if household is agricultural labourer, 0 otherwise Base Case: Self Employed in agriculture.
OthLab	Occupation Dummy. 1 if household occupation is other than agricultural labourer, 0 otherwise Base Case: Self Employed in agriculture.
Non SC/ST	Social Group dummy. 1 if household belongs to non SC/ST group. Base Case: Household belongs to Sc/ST
$State_i$	State dummy for i^{th} state. 1 if household belongs to state i 0 otherwise. i = Andhra Pradesh, Assam, Bihar, gujarat, Punjab, Jammu and Kashmir, Karnataka. Kerala, MP, Maharashtra, Orissa, Rajasthan, Tamil Nadu, UP, West Bengal. Base Case: Punjab
$Religion_j$	Religion Dummy: 1 if household follows religion j, 0 otherwise j = Hindu, Islam, Sikh, Christian, Other rel (Other Religion such as Zorastrianism, buddhism etc.) Base Case: Hindu
Female Head	Sex of the Household Head; 1 if female and 0 is male Base Case: Male household head

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