PRELIMINARY DRAFT: PLEASE DO NOT QUOTE

Poverty Nutrition Trap in Rural India*

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May 2006

ABSTRACT

The contributions of the present report are as follows. Using data for rural India we test for the existence of a PNT in the case of two macronutrients – calories and protein - and select micronutrients (calcium, carotene, iron, riboflavin and thiamine) separately and for each category of wages – sowing, harvesting, and other – and for male and female workers separately. We use robust sample selection procedures to arrive at consistent estimates. It is discovered that the PNT exists in a number of cases. The paper also advances a number of policy conclusions from the analysis.

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* The UK Department for International Development (DFID) supports policies, programmes and projects to promote international development. DFID provided funds for this study as part of that objective but the views and opinions expressed are those of the author(s) alone. The authors would like to thank DFID for supporting this research.

I. Introduction

UNICEF (2006) has noted that as many as 57 million children under 5 are undernourished in India. While this is an immediate area of concern since reducing undernutrition forms one of the Millennium Development Goals, another important concern is whether such undernutrition impacts upon labour productivity, thus reducing the possibility that earnings from the labour market could be used to reduce undernutrition.

The effect of nutritional intake on labour productivity and wage rates has been an important area for research for economists and nutritionists for some time. This found initial expression in the form of the efficiency wage hypothesis developed by Leibenstein (1957) and Mazumdar (1959) and formalized and extended by Mirrlees (1975), Dasgupta and Ray (1986, 1987), and Dasgupta (1993), among others. Early surveys include Bliss and Stern (1978a, 1978b) and Binswanger and Rosenzweig (1984). The efficiency wage hypothesis postulated that in developing countries, particularly at low levels of nutrition, workers are physically incapable of doing hard manual labour. Hence their productivity is low which then implies that they get low wages, have low purchasing power and, therefore, low levels of nutrition, completing a vicious cycle of deprivation. These workers are unable to save very much so their assets –both physical and human – are minimal. This reduces their chances of escaping the poverty-nutrition trap (henceforth PNT).[1] Barrett and Swallow (2006) present a theoretical argument in support of the PNT emerging as the result of the existence of multiple dynamic equilibria.[2]

[1] In this paper we use the terms efficiency wage hypothesis and PNT interchangeably.
[2] For an analysis of how idiosyncratic and covariate shocks can lead to entrapment in a PNT in a dynamic framework see Lybbert et al. (2004).

There is a substantial literature on empirically testing for the existence of PNT.[3] Strauss (1986) models the effect of nutrition on farm productivity. He tests and quantifies the effects of nutritional status as measured by annual calorie intake on annual farm production and, hence, labour productivity using farm household level data from Sierra Leone. He finds significant and sizable effect of calorie intake on farm output, even after accounting for endogeneity. These effects are stronger at lower levels of calorie intake with this being determined through the presence of non-linear terms. Thomas and Strauss (1997) investigate the impact of four indicators of health (height, body mass index, per capita calorie intake and per capita protein intake) on wages of urban workers in urban Brazil. They discover that even after accounting for endogeneity issues and controlling for education and other dimensions of health, these four indicators have significant positive effects on wages. The effect of the nutritional variables - per capita calorie intake and per capita protein intake – was higher at low levels of nutrition, again determined through non-linear terms. In contrast Deolalikar (1988) finds in a (panel fixed effects) joint regression of the wage equation and farm production in rural South India that calorie intake does not affect either but a measure of weight-for-height does. He concludes that calorie intake does not affect wages or productivity indicating that the human body can adapt to short-run shortfalls in calorie intake. However, the fact that weight-for-height affects wages and productivity indicates that chronic undernutrition is an important determinant of productivity and wages. Barrett et al. (2006) provide empirical support for the dynamic multiple equilibrium analysis of PNT (along the lines of Barrett and Swallow 2006) in the case of Kenya and Madagascar.

[3] For a comprehensive review see Strauss and Thomas (1998).

The contributions of the present report are as follows. Using data for rural India we test for the existence of a PNT in the case of two macronutrients – calories and protein - and select micronutrients (calcium, carotene, iron, riboflavin and thiamine) separately and for each category of wages – sowing, harvesting, and other – and for male and female workers separately. We use robust sample selection procedures to arrive at consistent estimates. It is discovered that the PNT exists in a number of cases. The paper also advances a number of policy conclusions from the analysis.

The plan of this paper is as follows. In section II we motivate the analysis of PNT. Section III discusses the data and presents the estimation methodology. Section IV discusses the results and section V concludes.

II. Nutrition Poverty Traps

In Figure 1, a stylised version of the relationship between work capacity and nutrition is given.[4] The vertical axis represents a measure of work capacity and the horizontal axis income. Note first that work capacity is a measure of the tasks that an individual can perform during a period, say, the number of bushels of wheat that he can harvest during a day. Income is used synonymously with nutrition in the sense that all income is converted into nutrition. Nothing of importance changes if 70 or 80 per cent of income share is spent on nutrition.

The shape of the capacity curve requires an explanation. It is assumed here that much of the nutrition goes into maintaining the body's resting metabolism. This refers to the energy required to maintain body temperature, sustain heart and respiratory action, and to support the ionic gradients across cell membranes. For the

[4] The following exposition is based on Ray (1998).

"reference man" of the Food and Agriculture organisation (FAO)- a European male weighing 65 kg-the requirement is 1700 calories per day. Of course the requirement varies with the individual and the environment in which he lives. In the case of India Gopalan et al. (1971) indicate that for men doing sedentary, moderate and heavy work the calorie requirements per day are, respectively 2400, 2800 and 3900. A higher body mass, for example, raises resting metabolism. Another significant component is energy required to carry out physical labour. The FAO's estimate, applied to their reference man, for moderate work is typically lower than this. It is of course arguable that for the poor in developing countries this may be an underestimate. Once resting metabolism is taken care of, however, there is a marked increase in work capacity, as the bulk of the energy input goes into work. This phase is followed by a phase of diminishing returns, as the body's frame restricts conversion of nutrition into work capacity.

Figure 1 here

Assume that working in a labour market generates income, and that piece rates are paid. A piece rate, then, appears as a relationship between the number of tasks performed and the total income of a person. Using these assumptions, a supply curve of labour could be constructed that shows different quantities of labour supplied at different piece rates. Aggregation across individuals yields an aggregate supply curve, as shown in Figure 2.

Figure 2 here

At a piece rate of v_3 there is a gap in labour supply and a discontinuous jump. Introducing a downward sloping demand curve, an interesting case is that in which the demand curve passes through the dotted supply curve. If the piece rate is larger than v^*, there is excess supply, which lowers this rate. On the other hand, if the piece rate is lower than v^*, there is excess demand, so that wages rise. Note, however, that a piece rate of v^* is an equilibrium wage, provided we allow for unemployment.

Figure 3 here

Having some people work and restricting labour market access to others could fill the gap in labour supply. Those rationed out will be relatively undernourished. This completes the vicious cycle of poverty. Lack of labour market opportunities results in low wages and consequently low work capacity; a low work capacity feeds back by lowering access to labour markets. It is easy to show that higher non-labour assets (e.g. land) lead to higher wage incomes. Thus the poor without assets are doubly disadvantaged: not only do they not enjoy non-labour income but also have restricted access to labour market opportunities.

Note that nutritional status depends on both current consumption of nutrients (e.g. calories) and the history of that consumption. In the analysis that follows, we focus on the effects of differences in calorie intake.[5]

The essence of an empirical test for the PNT Hypothesis is the specification of a wage equation conditional on energy intake, for example, and control variables as:

$$w_h = f(calorie_h, p_1, p_2, p_3, p_4, X)$$

where w_h and 'calorie'[6] represents the wage and calorie intake of the h^{th} individual. p_i is the probability of being occupied in the ith occupation with i =1 indicating employment in agriculture, i=2 employment in non-agriculture, i=3 self employment and i = 4 other employment. This set of variables controls for labour market participation. 'X' represents control variables such as prices of various food products, income of the household from the non-agricultural sector, some household

[5] For critiques of PNT hypothesis, see Srinivasan (1994), and Subramaniam and Deaton (1996).
[6] The analysis here is motivated using 'calories' as the nutrient. In the remaining cases we use the other nutrients in the analysis.

characteristics as well as some regional dummies. The probabilities are taken as the control variables to incorporate the impact of labour market participation on wage rate. It is thus argued that the wage rate of the worker depends on his nutrition proxied as his energy intake, which in turn depends on his wages. Hence the wage rate and nutritional intake are both endogenous in this model.

III. Data and Methodology

The data used in this paper comes from the National Council for Applied Economic Research (NCAER). This data were collected through a multi-purpose household survey spread over six months, from January to June 1994. The data were collected using varied reference periods based on some conventional rules. The wage data used are that for harvesting, sowing and other occupations for male and female workers separately. Although the data are old, detailed data for a more recent year were not available. Further, in view of UNICEF (2006), the problem of undernutrition remains severe in India.

In view of the endogeneity mentioned above the empirical strategy followed in this paper is to predict the probabilities of labour market participation from a Maximum Likelihood Multinomial Logistic Regression (multi-logit) model (discussed next) and then use these in as determinants of the wage in an appropriately specified model of the PNT.

Multi Logit Model:

The polychotomous dependent variable *employed* takes four values: 1 if worker employed in agriculture, 2 if worker employed in non-agriculture, 3 if worker self-employed and 4 if worker employed in other sectors. The independent variables for the analysis can be broadly classified into two categories: Household level variables (which mainly include household characteristics) and Location Dummies to incorporate the role of regional disparity. These household and other variables are summarized in Table 1.

Table 1: Variables used in Analysis

Household Level Variables	
Variable Name	Variable Description
headage	Age of Household Head
headage2	Square of Age of Household Head
NO.ADULTMALE	no. of adult males in HH
NO.ADULTFEMALE	no. of adult females in HH
hhgrp	HH Group Dummy Variable 1 if SC/ST HH and 0 Otherwise
HINDU, MUSLIM, CHRISTIAN, SIKH, BUDDHIST, TRIBAL, JAIN, OTHERS	Religion dummies.
FEMALE_HHHEAD	Whether head of household is female.
HIGHESTFEMEDUPRIMARY	Highest level of education for any adult female in household is primary
HIGHESTFEMEDUMIDDLE	Highest level of education for any adult female in household is middle
HIGHESTFEMEDUMATRIC	Highest level of education for any adult female in household is matric
land_own	Land Owned in Acres
land_own2	Square of Land Owned
Other Variables	
RAINFALLINDEX	Rainfall Index (actual - normal rain fall) for

	agroclimatic zones.
bimaru	Dummy for Bimaru states (Bihar, Madhya Pradesh, Rajasthan, Uttar Pradesh)
coastal	Dummy for Coastal districts
landrain	Landowned*rainfall
pr_pulses	Price of Pulses
pr_gur_sugar	Price of Gur Sugar
pr_oil	Price of Oil
pr_milk	Price of Milk
Generated Variables	
Enepchat	Predicted value of calorie consumption per capita
Enepchat2	Predicted value of square of calorie consumption per capita
Propchat	Predicted value of protein consumption per capita
propchat2	Predicted value of square of protein consumption per capita
Calcpchat	Predicted value of calcium consumption per capita
Calcpchat2	Predicted value of square of calcium consumption per capita
Carothat	Predicted value of carotene consumption per capita
carothat2	Predicted value of square of carotene consumption per capita
ironpchat	Predicted value of iron consumption per capita
ironpchat2	Predicted value of square of iron consumption per capita
Ribopchat	Predicted value of riboflavin consumption per capita
ribopchat2	Predicted value of square of riboflavin consumption per capita
Thiapchat	Predicted value of thiamine consumption per capita
thiapchat2	Predicted value of square of thiamine consumption per capita

The predicted probabilities of participating in the labour market are calculated from the above regression and used subsequently in sample selection methods discussed next.

Tobit Analysis

The number of hours worked by an Agricultural labourer (AL) is a censored variable. The data is observed only for the individuals who actually work and not for the individuals who are willing to work but are unable to find employment. The efficiency wage hypothesis argues that, starting from a low base, the higher the nutritional intake of an individual the higher the probability that he/she would be employed, *ceteris paribus.* Given the low nutritional attainment of individuals in the sample it is no surprise that there are many households with unemployed individuals.

Hence there will be many zeroes in a random sample of wages of rural individuals. Our motivation for the analysis is to investigate the linkages of nutrition and wage rate for the whole sample rather than the sample comprising individuals who are employed. The conventional regression methods fail to account for the qualitative difference between limit (zero) observations and non-limit (continuous) observations.

Tobin (1958) suggested an estimation method suitable for the censored data. The regression model is referred as the censored regression model or the Tobit model discussed next.

The dependent variable is denoted by Y*, not Y. This is because the dependent variable is latent, and not observed. In theory, we do not observe wages below zero. Y* can be perceived as the desire to work. There is a threshold which one has to reach before one can start working. What we observe is Y, which is the amount an individual earned while working.

The Tobit model is generally represented in the following way. First, we postulate a latent variable, Y*, which depends on some independent variables and a disturbance term that is normally distributed with a mean of zero. But, we have a censoring at point *C,* which in our case, is zero. Thus we have an observed Y that equals Y* if the value of Y* is greater than 0, but equals 0 if the value of the unobserved Y* is less than or equal to 0. The observed model, therefore, has a dependent variable Y, with some independent variables and coefficients, and an error term. Because of the censoring, however, the lower tail of the distribution of Y_i, and of u_i, is cut off and the probabilities are piled up at the cut-off point. The implication is that the mean of Y_i is different from that of Y_i*, and the mean of u_i (the error term in the model with the observed variable) is different from the mean of $u*_i$ (the error term in the model with the latent variable; which is zero).

$$Y_i* = X_i'\beta + u*_i \qquad (1a)$$

We have censoring at C =0:

$$Y_i = Y_i* \; if \; Y_i* > C \qquad (1b)$$

$$Y_i = C \;\; if \; Y_i* \leq C \qquad (1c)$$

So the observed model is

$$Y_i = X_i'\beta + u_i \quad if \; Y_i > 0 \;\; and \;\; Y_i = 0, otherwise.$$

The procedure to estimate the above model has to take account of the censoring. We note that the entire sample consists of two different sets of observations. The first set contains the observations for which the value of *Y* is zero. For these observations we know only the values of the *X* variables and the fact that Y* is less than or equal to 0. The second set consists of all observations for which the values of both *X* and *Y** are known and the latter is positive. The likelihood function of the Tobit model consists of each of these two parts.

$$L = \sum_{Y_i>0} -\frac{1}{2}\left[\log(2\pi\sigma^2)\right] - \frac{1}{2}\sum_{i=1}^{n}\left(\frac{(Y_i - \beta' X_i)^2}{\sigma}\right) + \sum_{Y_i=0}\log\left[1-\Phi\left(\frac{\beta' X_i}{\sigma}\right)\right] \qquad (2)$$

where the first two terms constitute the first part of the likelihood function and the third is the second part.

The Tobit model has some notable limitations (Greene 2003, Smith and Brame 2003) that can be remedied by replacing it with a sample selection model. The first limitation is that in the Tobit model the same set of variables and coefficients determine both the probability that an observation will be censored and the value of the dependent variable. Second, the Tobit analysis is not based on a full theoretical explanation of why the observations that are censored are censored.

Sample selection models address these shortcomings by modifying the likelihood function. First, a different set of variables and coefficients determine the probability of censoring and the value of the dependent variable given that it is observed. These variables may overlap, to a point, or may be completely different. Second, sample selection models allow for greater theoretical development because the observations are said to be censored by some other variable, which we call *Z*. This allows us to take account of the censoring process, as we will see, because selection and outcome are not independent.

The Heckman Procedure

We now discuss the sample selection problem and its estimation methodology.

The problem of sample selection arises when the data in the survey is incidentally truncated or non-randomly selected. Our model determining wage nutrition relationship contains following main regression equation:

$$Y_i = \beta' X_i + \varepsilon_i \qquad (3)$$

where Y_i is the wage rate and X_i is a vector comprising the nutrition and other household characteristics. The model may imply a wage rate for all the individuals but we observe it only for those who are actually employed. Hence the model is truncated as the sample is selected on the basis of wages (in the agricultural sector).

Formally, the wages are observed only if:

$$Z_i^* = \gamma' W_i + u_i \qquad (4)$$

where W_i are independent variables that contribute to the employment probability of an individual. W_i may or may not overlap with the X_i. In our case it does.

Equation (4) is called the selection equation. The sample rule thus becomes that Y_i* (the wage rate) is observed only when Z_i*> 0 (or the person under consideration is employed in agricultural sector). We now discuss the estimation issues related to the observations in our sample (based on the above rule).

Estimation

OLS Estimates:

A simple OLS regression of the observed data produces inconsistent estimates of β Essentially because of omitted variables. Moreover, the disturbance term is heteroscedastic and hence the estimates will be inefficient.

Marginal Effects

The marginal effect of the regressors on Y_i has two components: direct effect on mean of Y_i which is β and the indirect effect through the regressor which is present in X_i. The problem of sample selection can lead the marginal effects to be overstated for the observed category (for which Z_i* > 0) and understated for the other category. For example, suppose that nutrition affects both the probability of working in agricultural sector and wage rate in either state (agricultural sector or non-agricultural sector). If we assume that the wages of the agricultural labourers (AL) is higher than that of otherwise identical non agricultural labourers (NAL), the marginal effects of nutrition has two parts: one due to its influence in increasing the probability of the individuals entering agricultural sector and one due to its influence on wage rate within the group.

Hence the coefficient on nutrition in the regression overstates the marginal effect of the nutrition of AL and understates it for the NAL. In the opposite case it would understate the marginal effect.

Heckman suggested a two step procedure for estimating the above model. The model is first reformulated to a probit form. It should be noted that although the variable Z_i* is not observed, one can infer its sign (for example whether an individual works in agricultural sector or not) but not the magnitude. Thus the model can be reformulated as follows:

Selection Mechanism:

$$Z_i{*} = \gamma' W_i + u_i \; \mathit{if} \; Z_i{*} > 0 \; \mathit{and}\, 0 \, \mathit{otherwise.}$$

Regression Model:

$$Y_i = \beta' X_i + \varepsilon_i \; \mathit{observed\, only\, if} \; Z_i = 1, (u_i, \varepsilon_i) \sim \mathit{bi}\,\mathrm{var}\,\mathit{iate\, normal}[0,0,1,\sigma_\varepsilon, \rho]$$

The parameters of the sample selection model can be estimated using Heckman’s two step estimation procedure discussed next.

Heckman’s two step procedure

Heckman’s two step estimation procedure (Heckman 1976, 1979) involves following steps:

• Step 1: Estimate the probit equation by maximum likelihood to obtain estimates of γ. For each model in selected sample compute the inverse Mills ratio:

$$\hat{\lambda}_i = \frac{\phi(\hat{\gamma} w_i)}{\Phi(\hat{\gamma} w_i)} \text{ and } \hat{\delta}_i = \hat{\lambda}_i (\hat{\lambda}_i + \hat{\gamma} w_i)$$

where ϕ *and* Φ are, respectively, the probability density function and the cumulative density function of a standard normal distribution.

• Step 2: Estimate β and $\beta_{\lambda} = \rho\sigma_{\varepsilon}$

by least squares regression of Y_i on X_i and $\hat{\lambda}$.

This methodology allows consistent estimates of the individual parameters. In this paper we present both Tobit and Heckman estimates for the wages for which we have a PNT.

IV. Results

In Table 2 we report results on the participation equation.

Table 2: Results on Multinomial Logit (Participation Equation)

Multinomial logistic regression		Number of obs =		7112
		Wald chi2(48) =	.	
Log pseudo-likelihood = .		Prob > chi2 =	.	
		Robust		
Employed	Coef.	Std. Err.	z	P>z
	1			
Headage	0.017842	0.114209	0.16	0.876
Headage2	-0.00017	0.00085	-0.2	0.838
NO.ADULTMALE	-0.09194	0.549474	-0.17	0.867
NO.ADULTFEMALE	-0.18747	0.202135	-0.93	0.354
SC/ST	1.201737	2.601734	0.46	0.644
HINDU	-0.84549	6.809308	-0.12	0.901
MUSLIM	-1.25798	9.687174	-0.13	0.897
CHRISTIAN	-0.0176	8.360935	0	0.998
SIKH	-1.4929	3.501264	-0.43	0.67
BUDDHIST	-167.967 .	.	.	
TRIBAL	1.890682	11.77738	0.16	0.872
land_own	0.034654	1.002856	0.03	0.972
land_own2	-6E-05	0.001693	-0.04	0.972

RAINFALLINDEX	0.00065	0.000261	2.49	0.013
Bimaru	-0.56459	1.02514	-0.55	0.582
FEMALE_HHHEAD	0.181989	2.022334	0.09	0.928
Coastal	-0.21157	2.031909	-0.1	0.917
_cons	3.266708	7.660754	0.43	0.67
	2			
Headage	0.020846	0.108413	0.19	0.848
Headage2	-0.00019	0.000824	-0.23	0.82
NO.ADULTMALE	-0.13012	0.496927	-0.26	0.793
NO.ADULTFEMALE	-0.07067	0.191068	-0.37	0.711
SC/ST	0.533542	2.345021	0.23	0.82
HINDU	-0.83303	6.507863	-0.13	0.898
MUSLIM	-0.83584	9.186911	-0.09	0.928
CHRISTIAN	-1.02427	8.026529	-0.13	0.898
SIKH	-3.60296	3.598008	-1	0.317
BUDDHIST	-181.351 .	.	.	
TRIBAL	-1.13723	11.08407	-0.1	0.918
land_own	0.003394	0.942384	0	0.997
land_own2	-2.3E-05	0.001501	-0.02	0.988
RAINFALLINDEX	0.000336	0.000294	1.14	0.254
Bimaru	-0.38736	0.892982	-0.43	0.664
FEMALE_HHHEAD	0.075132	1.87373	0.04	0.968
Coastal	0.067288	1.914682	0.04	0.972
_cons	1.042045	7.305637	0.14	0.887
	4			
Headage	-0.0389	0.146185	-0.27	0.79
headage2	0.000309	0.001232	0.25	0.802
NO.ADULTMALE	-0.43862	0.713786	-0.61	0.539
NO.ADULTFEMALE	-0.0976	0.378217	-0.26	0.796
SC/ST	2.138696	3.318063	0.64	0.519
HINDU	1.782214	6.932591	0.26	0.797
MUSLIM	2.646517	9.634771	0.27	0.784
CHRISTIAN	7.490437	10.70612	0.7	0.484
SIKH	-0.8308	3.651146	-0.23	0.82
BUDDHIST	42.48592 .	.	.	
TRIBAL	5.257467	14.74744	0.36	0.721
land_own	0.311153	1.031832	0.3	0.763
land_own2	-0.00097	0.001961	-0.49	0.622
RAINFALLINDEX	0.000635	0.000619	1.03	0.305
Bimaru	-1.25843	1.792535	-0.7	0.483
FEMALE_HHHEAD	2.201646	3.197906	0.69	0.491
Coastal	0.592066	2.167332	0.27	0.785
_cons	-4.50328	10.38256	-0.43	0.664

Comparison Group Employed ==3

P1 = probability of being employed in agriculture,
P2 = probability of being employed in non-agriculture,
P3 = probability of being self-employed,
P4 = probability of other employment.

It is interesting to note that rainfall positively and significantly affects the probability of being employed in agriculture and not the other forms of employment. In fact rainfall is the only significant determinant of agricultural employment.

In Table 3 we summarise evidence on the existence of PNT using the two techniques of Tobit and Heckman estimation, for men and women workers separately and for various categories of nutrients: calories, protein, and select micronutrients, viz., calcium, carotene, iron, riboflavin and thiamine.

Table 3: Existence of Poverty Nutrition Trap

Calories		
Wage Type	Estimation Technique	
Female Harvest	Tobit	Heckman
Male other	Tobit	
Male Harvest	Tobit	
Female other	Tobit	
Female Sowing		Heckman
Protein		
Wage Type	Estimation Technique	
Female Harvest		Heckman
Male Sowing		Heckman
Male Harvest		Heckman
Calcium		
Wage Type	Estimation Technique	
Female Harvest		Heckman
Carotene		
Wage Type	Estimation Technique	
Male Harvest		Heckman
Iron		
Wage Type	Estimation Technique	
Female Harvest	Tobit	Heckman

Female Other	Tobit	
Male other	Tobit	
Male Harvest	Tobit	Heckman
Riboflavin		
Wage Type	Estimation Technique	
Female Harvest		Heckman
Female Sowing		Heckman
Thiamine		
Wage Type	Estimation Technique	
Female Harvest	Tobit	Heckman
Female other	Tobit	
Male other	Tobit	
Male harvest	Tobit	Heckman
Female Sowing		Heckman

In Table 4 we report on the nutritional requirement to break out of the PNT. From the regression equation we compute the nutritional requirement to break the PNT. Thus if we use the Heckman method for female harvest wage we discover that the minimum daily calorie requirement is 3264.08. From the data the minimum annual per capita expenditure that can attain this is Rs. 3011. This is much higher than the per capita poverty line for that year which was Rs 2484 per year. As a percentage of the poverty line this gap is over 21 percent. In other cases (say Heckman female sowing for calories), however, expenditure at the poverty line should be sufficient to ensure adequate nutrition to break the PNT.[7]

[7] It should be noted that the calorie requirements in Table 4 could overstate the calorie requirements to break out of the PNT because these workers would not be performing the demanding tasks of harvesting or sowing throughout the year. However, since these workers are classified according to their primary functions, the extent of such overestimation may be limited. Furthermore, this view should be viewed with some scepticism since we do not have accurate estimates of the calorific requirements of the household and related work that these workers perform.

Table 4: Nutritional Requirement to break Poverty Nutrition Trap

Nutritional Category	Requirement to Break PNT	Minimum Equivalent Per Capita Expenditure per year
Calories (Calories/day)		
TFH	3,340.15	3142
HFH	3,264.08	3011
TMO	3,037.86	2068
TFO	3,212.47	1630.25
HFS	2,508.41	981.44
Protein (grams/day)		
HFH	415.32	4565
HFO	242.84	1056
HMS	329.93	1173
HMH	437.78	7065
HFS	189.64	904
Calcium (grams/day)		
HFH	524.45	555
Carotene (microgram/day)		
HMH	586.47	1197
Iron (milligram/day)		
TFH	65.69	927.5
HFH	188.22	2504
TFO	59.08	200
TMO	45.12	596
TMH	42.82	412.5
HMH	155.93	2038
Riboflavin (milligram/day)		
HFH	3.17	1790
HFS	1.50	110
HMH	8.13	2428
Thiamine (milligram/day)		
TFH	5.64	1056
HFH	9.35	4524
TFO	5.03	382
TMO	3.74	110
TMH	3.53	651
HFS	5.32	1633

N.B. The first letter in the acronyms used in this table refers to technique of estimation: "T" for Tobit and "H" for Heckman; the second refers to gender of workers "M" for male and "F" for female and the third refers to wage category: "H" for harvesting, "S" for sowing and "O" for other.

Results for the existence of PNT in respect of all categories are shown in Tables 5 to 11. In each of these cases the positive and significant sign of the predicted nutrient intake, say energy per capita, indicates the presence of PNT with respect to that nutrient. In other cases the PNT does not exist.

CALORIES (Table 5)

Table: 5a Female Harvest Wages

Tobit Model

Tobit estimates			Number of obs	=		4460
			LR chi2(23)	=		909.48
			Prob > chi2	=		0
Log likelihood =		-12008.6	Pseudo R2	=		0.0365
fem_harvest	Coef.		Std. Err.	t	P>t	
Enepchat		0.040015	0.019832	2.02		0.044
enepchat2		-5.99E-06	3.34E-06	-1.79		0.073
HIGHESTFEMEDUPRIMARY		1.696173	0.862424	1.97		0.049
HIGHESTFEMEDUMIDDLE		-2.25295	1.430465	-1.57		0.115
HIGHESTFEMEDUMATRIC		0.584347	1.095543	0.53		0.594
pr_pulses		-0.02928	0.13714	-0.21		0.831
pr_gur_sugar		-0.78259	0.551619	-1.42		0.156
pr_oil		-0.0286	0.03318	-0.86		0.389
pr_milk		-0.29046	0.074004	-3.92		0
Headage		0.074778	0.159995	0.47		0.64
headage2		-0.00142	0.001632	-0.87		0.384
NO.ADULTMALE		-3.3376	0.774961	-4.31		0
NO.ADULTFEMALE		2.119195	0.508672	4.17		0
Hhsize		0.429266	0.617263	0.7		0.487
SC/ST		5.271594	2.559148	2.06		0.039
HINDU		-1.38711	3.49791	-0.4		0.692
MUSLIM		-3.04744	3.681038	-0.83		0.408
CHRISTIAN		-6.50632	5.335768	-1.22		0.223
SIKH		-270.586	.	.	.	
BUDDHIST		-10.2865	10.28969	-1		0.318
p1		1.38726	2.168251	0.64		0.522
Bimaru		-14.4054	1.471021	-9.79		0
Coastal		2.953209	1.747631	1.69		0.091
_cons		-26.6075	20.76347	-1.28		0.2

Heckman Selection Model

Heckman selection	model -- two-step estimates	Number of obs	=		6594
(regression model	with sample selection)	Censored obs	=		2134
		Uncensored obs	=		4460
		Wald chi2(23)	=		1313.11

	Coef.	Std. Err.	z	P>z
		Prob > chi2	=	0
fem_harvest				
Bimaru	-8.31628	0.736491	-11.29	0
Enepchat	0.013905	0.004224	3.29	0.001
enepchat2	-2.13E-06	8.57E-07	-2.48	0.013
pr_pulses	-0.19393	0.06206	-3.12	0.002
pr_gur_sugar	-0.27138	0.161881	-1.68	0.094
pr_oil	0.068766	0.013702	5.02	0
pr_milk	-0.07809	0.034139	-2.29	0.022
Headage	0.054676	0.085533	0.64	0.523
Headage2	-0.00097	0.000869	-1.12	0.263
NO.ADULTMALE	-1.44647	0.28626	-5.05	0
NO.ADULTFEMALE	1.331039	0.28769	4.63	0
Hhsize	0.067531	0.229362	0.29	0.768
SC/ST	2.477348	0.769413	3.22	0.001
RAINFALLINDEX	0.002109	0.000495	4.26	0
Coastal	3.215776	1.01557	3.17	0.002
_cons	0.554281	4.368315	0.13	0.899
Select				
Headage	-0.00384	0.007484	-0.51	0.608
Headage2	2.98E-05	7.67E-05	0.39	0.698
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024
SC/ST	0.496191	0.036991	13.41	0
land_own	-0.00463	0.000427	-10.84	0
land_own2	-6.04E-08	1.77E-07	-0.34	0.734
RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087
Landrain	4.84E-06	6.13E-07	7.9	0
Bimaru	0.306848	0.041688	7.36	0
Coastal	1.004761	0.066374	15.14	0
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004
_cons	0.289162	0.166635	1.74	0.083
Mills				
Lambda	-0.5846	1.792234	-0.33	0.744
Rho	-0.04972			
Sigma	11.75735			
Lambda	-0.5846	1.792234		

Table 5b: Tobit Estimation (Male Other)

Tobit estimates		Number of obs	=	4460
		LR chi2(23)	=	444.67
		Prob > chi2	=	0
Log likelihood =	-13318.9	Pseudo R2	=	0.0164
male_other	Coef.	Std. Err.	t	P>t
Enepchat	0.12759	0.024289	5.25	0
enepchat2	-2.1E-05	4.07E-06	-5.26	0
HIGHESTFEMEDUPRIMARY	-0.93983	1.070373	-0.88	0.38

HIGHESTFEMEDUMIDDLE	-7.40146	1.755207	-4.22	0
HIGHESTFEMEDUMATRIC	-4.28813	1.352936	-3.17	0.002
pr_pulses	-0.05077	0.173378	-0.29	0.77
pr_gur_sugar	-4.10682	0.673587	-6.1	0
pr_oil	-0.05418	0.043246	-1.25	0.21
pr_milk	-0.45242	0.085801	-5.27	0
Headage	0.011706	0.19418	0.06	0.952
headage2	-0.00148	0.001969	-0.75	0.453
NO.ADULTMALE	-3.12002	0.959531	-3.25	0.001
NO.ADULTFEMALE	-1.23395	0.627521	-1.97	0.049
Hhsize	0.770679	0.778373	0.99	0.322
SC/ST	13.9435	3.137115	4.44	0
HINDU	9.550053	4.381092	2.18	0.029
MUSLIM	7.920399	4.569121	1.73	0.083
CHRISTIAN	-2.05174	6.692428	-0.31	0.759
SIKH	12.02454	23.24956	0.52	0.605
BUDDHIST	-41.1285	16.58411	-2.48	0.013
p1	16.63604	2.67558	6.22	0
Bimaru	2.449647	1.823549	1.34	0.179
Coastal	3.419991	2.182752	1.57	0.117
_cons	-98.5076	25.52251	-3.86	0

Heckman selection	model -- two-step estimates	Number of obs	=	6594
(regression model	with sample selection)	Censored obs	=	2134
		Uncensored obs	=	4460
		Wald chi2(23)	=	809.58
		Prob > chi2	=	0

Table 5c: Tobit estimation Male Average Wage

Tobit estimates		Number of obs	=		4460
		LR chi2(23)	=		366.57
		Prob > chi2	=		0
Log likelihood =	-14030.4	Pseudo R2	=		0.0129
male_harvest	Coef.	Std. Err.	T	P>t	
Enepchat	0.13315	0.024712		5.39	0
enepchat2	-2.3E-05	4.14E-06		-5.47	0
HIGHESTFEMEDUPRIMARY	-1.7414	1.093609		-1.59	0.111
HIGHESTFEMEDUMIDDLE	-7.16586	1.786374		-4.01	0
HIGHESTFEMEDUMATRIC	-0.16797	1.352849		-0.12	0.901
pr_pulses	-0.37957	0.178035		-2.13	0.033
pr_gur_sugar	-4.54938	0.685181		-6.64	0
pr_oil	0.133593	0.042548		3.14	0.002
pr_milk	-0.46705	0.087534		-5.34	0
Headage	-0.04772	0.197802		-0.24	0.809
headage2	-0.00092	0.002005		-0.46	0.646
NO.ADULTMALE	-2.60678	0.97838		-2.66	0.008
NO.ADULTFEMALE	-0.76422	0.638146		-1.2	0.231
Hhsize	0.452479	0.794815		0.57	0.569
SC/ST	16.48252	3.186224		5.17	0

HINDU	10.84056	4.460559	2.43	0.015
MUSLIM	10.16421	4.646328	2.19	0.029
CHRISTIAN	-2.7208	6.828537	-0.4	0.69
SIKH	5.951123	23.74172	0.25	0.802
BUDDHIST	-43.1493	16.80517	-2.57	0.01
p1	13.40297	2.722556	4.92	0
Bimaru	0.605786	1.85895	0.33	0.745
Coastal	-0.88646	2.221477	-0.4	0.69
_cons	-95.2693	25.96701	-3.67	0

Table 5d: Tobit Estimation Female other

Tobit estimates		Number of obs =		4460
		LR chi2(23) =		771.88
		Prob > chi2 =		0
Log likelihood =	-9631.27	Pseudo R2 =		0.0385
fem_other	Coef.	Std. Err.	t	P>t
Enepchat	0.056411	0.022607	2.5	0.013
enepchat2	-8.78E-06	3.84E-06	-2.28	0.022
HIGHESTFEMEDUPRIMARY	-0.79666	0.977675	-0.81	0.415
HIGHESTFEMEDUMIDDLE	-3.57068	1.612984	-2.21	0.027
HIGHESTFEMEDUMATRIC	-5.99079	1.322579	-4.53	0
pr_pulses	-0.06823	0.149076	-0.46	0.647
pr_gur_sugar	-0.44932	0.630553	-0.71	0.476
pr_oil	-0.09977	0.037604	-2.65	0.008
pr_milk	-0.24005	0.08298	-2.89	0.004
Headage	0.335991	0.180904	1.86	0.063
headage2	-0.00477	0.001873	-2.55	0.011
NO.ADULTMALE	-4.07252	0.852369	-4.78	0
NO.ADULTFEMALE	2.213834	0.574211	3.86	0
Hhsize	0.368468	0.658482	0.56	0.576
SC/ST	9.955164	2.942393	3.38	0.001
HINDU	-7.0041	3.707636	-1.89	0.059
MUSLIM	-8.19128	3.967677	-2.06	0.039
CHRISTIAN	-15.1956	5.767397	-2.63	0.008
SIKH	-282.793	.	.	.
BUDDHIST	-11.4231	10.95206	-1.04	0.297
p1	8.103186	2.469496	3.28	0.001
Bimaru	-14.2908	1.614675	-8.85	0
Coastal	3.516465	1.9533	1.8	0.072
_cons	-56.1509	23.43817	-2.4	0.017

Table 5e: Female Sowing - Heckman

Heckman selection	model -- two-step estimates	Number of obs	=		6594
(regression model	with sample selection)	Censored obs	=		2134
		Uncensored obs	=		4460
		Wald chi2(23)	=		1175.47
		Prob > chi2	=		0
	Coef.	Std. Err.	z	P>z	
fem_sowing					
Bimaru	-5.88153	0.627624	-9.37	0	
Enepchat	0.017007	0.003599	4.73	0	
enepchat2	-3.39E-06	7.30E-07	-4.65	0	
pr_pulses	-0.0691	0.05287	-1.31	0.191	
pr_gur_sugar	0.103302	0.137909	0.75	0.454	
pr_oil	-0.08489	0.011671	-7.27	0	
pr_milk	-0.07162	0.029082	-2.46	0.014	
Headage	0.180339	0.072909	2.47	0.013	
headage2	-0.00209	0.000741	-2.82	0.005	
NO.ADULTMALE	-0.73618	0.243956	-3.02	0.003	
NO.ADULTFEMALE	0.912363	0.245196	3.72	0	
Hhsize	-0.53584	0.195397	-2.74	0.006	
SC/ST	4.987092	0.655711	7.61	0	
RAINFALLINDEX	-0.00227	0.000422	-5.38	0	
Coastal	3.226689	0.8655	3.73	0	
_cons	-7.22458	3.722152	-1.94	0.052	
Select					
Headage	-0.00384	0.007484	-0.51	0.608	
headage2	2.98E-05	7.67E-05	0.39	0.698	
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044	
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024	
SC/ST	0.496191	0.036991	13.41	0	
land_own	-0.00463	0.000427	-10.84	0	
land_own2	-6.04E-08	1.77E-07	-0.34	0.734	
RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087	
Landrain	4.84E-06	6.13E-07	7.9	0	
Bimaru	0.306848	0.041688	7.36	0	
Coastal	1.004761	0.066374	15.14	0	
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004	
_cons	0.289162	0.166635	1.74	0.083	
Mills					
Lambda	0.867331	1.527327	0.57	0.57	
Rho	0.08649				
Sigma	10.02806				
Lambda	0.867331	1.527327			

PROTEIN (Table 6)

Table 6a: Heckman Result female_harvest

Heckman selection	model -- two-step estimates	Number of obs	=		6594
(regression model	with sample selection)	Censored obs	=		2134
		Uncensored obs	=		4460
		Wald chi2(23)	=		1315.19
		Prob > chi2	=		0
	Coef.	Std. Err.	z	P>z	
fem_harvest					
Bimaru	-9.2864	0.71706	-12.95	0	
Coastal	4.206494	0.905791	4.64	0	
Propchat	0.232581	0.068239	3.41	0.001	
propchat2	-0.00028	8.37E-05	-3.4	0.001	
pr_pulses	-0.14584	0.06932	-2.1	0.035	
pr_gur_sugar	-0.1527	0.1219	-1.25	0.21	
pr_oil	0.043658	0.014287	3.06	0.002	
pr_milk	-0.11161	0.034925	-3.2	0.001	
Headage	0.024553	0.079056	0.31	0.756	
headage2	-0.00075	0.000814	-0.92	0.359	
NO.ADULTMALE	-1.83027	0.317079	-5.77	0	
NO.ADULTFEMALE	1.390537	0.281073	4.95	0	
Hhsize	0.326839	0.183455	1.78	0.075	
SC/ST	1.766097	0.593562	2.98	0.003	
RAINFALLINDEX	0.002179	0.000499	4.37	0	
_cons	6.390909	3.655205	1.75	0.08	
Select					
Headage	-0.00384	0.007484	-0.51	0.608	
headage2	2.98E-05	7.67E-05	0.39	0.698	
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044	
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024	
SC/ST	0.496191	0.036991	13.41	0	
land_own	-0.00463	0.000427	-10.84	0	
land_own2	-6.04E-08	1.77E-07	-0.34	0.734	
RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087	

Landrain	4.84E-06	6.13E-07	7.9	0
Bimaru	0.306848	0.041688	7.36	0
Coastal	1.004761	0.066374	15.14	0
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004
_cons	0.289162	0.166635	1.74	0.083
Mills				
Lambda	-0.16357	1.772467	-0.09	0.926
Rho	-0.01392			
Sigma	11.74931			
lambda	-0.16357	1.772467		

Table 6b: Heckman result Female_other

Heckman selection	model -- two-step estimates	Number of obs	=		6594
(regression model	with sample selection)	Censored obs	=		2134
		Uncensored obs	=		4460
		Wald chi2(23)	=		1074.48
		Prob > chi2	=		0
	Coef.	Std. Err.	z	P>z	
fem_other					
Bimaru	-5.96193	0.59459	-10.03	0	
Coastal	3.115399	0.759028	4.1	0	
Propchat	0.035455	0.055482	0.64	0.523	
propchat2	-7.3E-05	6.79E-05	-1.08	0.282	
pr_pulses	-0.17129	0.056453	-3.03	0.002	
pr_gur_sugar	0.301379	0.099068	3.04	0.002	
pr_oil	-0.02948	0.011549	-2.55	0.011	
pr_milk	-0.04195	0.028369	-1.48	0.139	
Headage	0.083436	0.066928	1.25	0.213	
headage2	-0.00096	0.000689	-1.4	0.162	
NO.ADULTMALE	-0.79159	0.262302	-3.02	0.003	
NO.ADULTFEMALE	0.666752	0.234999	2.84	0.005	
Hhsize	-0.13229	0.149192	-0.89	0.375	
SC/ST	0.796208	0.49849	1.6	0.11	
RAINFALLINDEX	0.003095	0.000423	7.31	0	
_cons	9.39354	3.015734	3.11	0.002	
Select					
Headage	-0.00384	0.007484	-0.51	0.608	
headage2	2.98E-05	7.67E-05	0.39	0.698	
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044	
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024	
SC/ST	0.496191	0.036991	13.41	0	
land_own	-0.00463	0.000427	-10.84	0	
land_own2	-6.04E-08	1.77E-07	-0.34	0.734	

RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087
Landrain	4.84E-06	6.13E-07	7.9	0
Bimaru	0.306848	0.041688	7.36	0
Coastal	1.004761	0.066374	15.14	0
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004
_cons	0.289162	0.166635	1.74	0.083
Mills				
lambda	-5.25185	1.47235	-3.57	0
Rho	-0.51403			
sigma	10.21708			
lambda	-5.25185	1.47235		

Table 6c: Heckman Result Male_sowing

Heckman selection	model -- two-step estimates	Number of obs	=		6594
(regression model	with sample selection)	Censored obs	=		2134
		Uncensored obs	=		4460
		Wald chi2(23)	=		612.97
		Prob > chi2	=		0
	Coef.	Std. Err.	z	P>z	
male_sowing					
Bimaru	2.12997	0.904754	2.35	0.019	
Coastal	-4.8083	1.144635	-4.2	0	
Propchat	0.224351	0.085861	2.61	0.009	
propchat2	-0.00034	0.000105	-3.23	0.001	
pr_pulses	0.064957	0.087242	0.74	0.457	
pr_gur_sugar	-0.55918	0.153371	-3.65	0	
pr_oil	-0.04363	0.017962	-2.43	0.015	
pr_milk	-0.11961	0.043938	-2.72	0.006	
Headage	-0.09173	0.100054	-0.92	0.359	
headage2	0.000653	0.00103	0.63	0.526	
NO.ADULTMALE	-0.71741	0.39994	-1.79	0.073	
NO.ADULTFEMALE	-0.42532	0.35507	-1.2	0.231	
Hhsize	0.381966	0.230838	1.65	0.098	
SC/ST	2.202611	0.75032	2.94	0.003	
RAINFALLINDEX	-0.00146	0.000632	-2.31	0.021	
_cons	14.81886	4.608649	3.22	0.001	
Select					
Headage	-0.00384	0.007484	-0.51	0.608	
headage2	2.98E-05	7.67E-05	0.39	0.698	
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044	
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024	
SC/ST	0.496191	0.036991	13.41	0	

land_own	-0.00463	0.000427	-10.84	0
land_own2	-6.04E-08	1.77E-07	-0.34	0.734
RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087
Landrain	4.84E-06	6.13E-07	7.9	0
Bimaru	0.306848	0.041688	7.36	0
Coastal	1.004761	0.066374	15.14	0
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004
_cons	0.289162	0.166635	1.74	0.083
Mills				
lambda	-3.03921	2.23699	-1.36	0.174
Rho	-0.20355			
sigma	14.93091			
lambda	-3.03921	2.23699		

Table 6d: Heckman Result Male_harvest

Heckman selection	model -- two-step estimates	Number of obs =		6594
(regression model	with sample selection)	Censored obs =		2134
		Uncensored obs =		4460
		Wald chi2(23) =		860.72
		Prob > chi2 =		0
	Coef.	Std. Err.	z	P>z
Male_harvest				
Bimaru	-5.15814	0.982185	-5.25	0
Coastal	6.486343	1.247067	5.2	0
Propchat	0.29769	0.092592	3.22	0.001
propchat2	-0.00034	0.000113	-3	0.003
pr_pulses	-0.07242	0.094133	-0.77	0.442
pr_gur_sugar	-1.25071	0.16537	-7.56	0
pr_oil	0.128078	0.019333	6.62	0
pr_milk	-0.22794	0.047368	-4.81	0
Headage	-0.25433	0.109391	-2.32	0.02
headage2	0.002223	0.001126	1.97	0.048
NO.ADULTMALE	-1.05794	0.433818	-2.44	0.015
NO.ADULTFEMALE	-0.44635	0.386545	-1.15	0.248
Hhsize	0.705572	0.248954	2.83	0.005
SC/ST	4.354695	0.818086	5.32	0
RAINFALLINDEX	-0.00373	0.000691	-5.4	0
_cons	20.0689	4.994549	4.02	0
Select				
Headage	-0.00384	0.007484	-0.51	0.608
headage2	2.98E-05	7.67E-05	0.39	0.698
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024
SC/ST	0.496191	0.036991	13.41	0
Land_own	-0.00463	0.000427	-10.84	0

Land_own2	-6.04E-08	1.77E-07	-0.34	0.734
RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087
Landrain	4.84E-06	6.13E-07	7.9	0
Bimaru	0.306848	0.041688	7.36	0
Coastal	1.004761	0.066374	15.14	0
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004
_cons	0.289162	0.166635	1.74	0.083
Mills				
lambda	6.039267	2.429906	2.49	0.013
Rho	0.36651			
sigma	16.47772			
lambda	6.039267	2.429906		

Table 6e Heckman Result Female_Sowing

Heckman selection	model -- two-step estimates	Number of obs	=		6594
(regression model	with sample selection)	Censored obs	=		2134
		Uncensored obs	=		4460
		Wald chi2(23)	=		1161.64
		Prob > chi2	=		0
	Coef.	Std. Err.	z	P>z	
fem_sowing					
bimaru	-6.77068	0.61282	-11.05	0	
coastal	4.654086	0.775021	6.01	0	
propchat	0.098614	0.058195	1.69	0.09	
propchat2	-0.00026	7.14E-05	-3.65	0	
pr_pulses	-0.06629	0.059128	-1.12	0.262	
pr_gur_sugar	0.384532	0.103953	3.7	0	
pr_oil	-0.09555	0.012177	-7.85	0	
pr_milk	-0.0956	0.029782	-3.21	0.001	
headage	0.114295	0.067721	1.69	0.091	
headage2	-0.00145	0.000697	-2.08	0.038	
NO.ADULTMALE	-1.00458	0.270914	-3.71	0	
NO.ADULTFEMALE	0.886867	0.240433	3.69	0	
hhsize	-0.19023	0.156456	-1.22	0.224	
SC/ST	3.393028	0.507995	6.68	0	
RAINFALLINDEX	-0.00214	0.000428	-5.01	0	
_cons	3.761496	3.122126	1.2	0.228	
select					
headage	-0.00384	0.007484	-0.51	0.608	
headage2	2.98E-05	7.67E-05	0.39	0.698	
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044	
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024	
SC/ST	0.496191	0.036991	13.41	0	
land_own	-0.00463	0.000427	-10.84	0	
land_own2	-6.04E-08	1.77E-07	-0.34	0.734	

RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087
landrain	4.84E-06	6.13E-07	7.9	0
bimaru	0.306848	0.041688	7.36	0
coastal	1.004761	0.066374	15.14	0
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004
_cons	0.289162	0.166635	1.74	0.083
mills				
lambda	1.800704	1.515098	1.19	0.235
rho	0.17835			
sigma	10.0963			
lambda	1.800704	1.515098		

CALCIUM (Table 7)

Table 7: Female_Harvest Heckman

Heckman selection	model -- two-step estimates	Number of obs	=		6594
(regression model	with sample selection)	Censored obs	=		2134
		Uncensored obs	=		4460
		Wald chi2(23)	=		1308.29
		Prob > chi2	=		0
	Coef.	Std. Err.	z	P>z	
fem_harvest					
Bimaru	-7.17685	0.724717	-9.9	0	
Coastal	5.055971	0.866453	5.84	0	
Calcpchat	0.057689	0.021438	2.69	0.007	
Calcpchat2	-5.5E-05	2.64E-05	-2.08	0.037	
pr_pulses	-0.22183	0.060289	-3.68	0	
pr_gur_sugar	-0.11574	0.206103	-0.56	0.574	
pr_oil	0.029713	0.019033	1.56	0.119	
pr_milk	-0.06793	0.041575	-1.63	0.102	
Headage	0.011615	0.077976	0.15	0.882	
headage2	0.000281	0.0009	0.31	0.755	
NO.ADULTMALE	-1.93965	0.425108	-4.56	0	
NO.ADULTFEMALE	1.585221	0.279846	5.66	0	
Hhsize	-0.17335	0.144216	-1.2	0.229	
SC/ST	2.20168	0.889581	2.47	0.013	
RAINFALLINDEX	0.001665	0.000519	3.21	0.001	
_cons	10.76975	2.880375	3.74	0	
Select					
Headage	-0.00384	0.007484	-0.51	0.608	
headage2	2.98E-05	7.67E-05	0.39	0.698	
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044	
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024	
SC/ST	0.496191	0.036991	13.41	0	
Land_own	-0.00463	0.000427	-10.84	0	
Land_own2	-6.04E-08	1.77E-07	-0.34	0.734	
RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087	
Landrain	4.84E-06	6.13E-07	7.9	0	
Bimaru	0.306848	0.041688	7.36	0	
Coastal	1.004761	0.066374	15.14	0	
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004	

_cons	0.289162	0.166635	1.74	0.083
Mills				
Lambda	-0.83782	1.84359	-0.45	0.65
Rho	-0.07119			
Sigma	11.76923			
Lambda	-0.83782	1.84359		

CAROTENE (Table 8)

Table 8: Male_Harvest

Heckman selection (regression model	model -- two-step estimates with sample selection)	Number of obs =		6594
		Censored obs =		2134
		Uncensored obs =		4460
		Wald chi2(23) =		855.78
		Prob > chi2 =		0

	Coef.	Std. Err.	z	P>z
male_harvest				
Bimaru	-4.56189	0.838686	-5.44	0
Coastal	8.536757	1.247139	6.85	0
Carothat	0.042226	0.025161	1.68	0.093
carothat2	-3.6E-05	5.48E-05	-0.66	0.512
pr_pulses	-0.09016	0.081245	-1.11	0.267
pr_gur_sugar	-0.75888	0.167689	-4.53	0
pr_oil	0.07944	0.032429	2.45	0.014
pr_milk	-0.21556	0.045148	-4.77	0
Headage	-0.19455	0.129314	-1.5	0.132
headage2	0.001972	0.001283	1.54	0.124
NO.ADULTMALE	-0.33049	0.330673	-1	0.318
NO.ADULTFEMALE	-0.35287	0.415004	-0.85	0.395
Hhsize	0.16192	0.178945	0.9	0.366
SC/ST	3.456164	0.801135	4.31	0
RAINFALLINDEX	-0.00418	0.000706	-5.92	0
_cons	23.65583	4.10081	5.77	0
Select				
Headage	-0.00384	0.007484	-0.51	0.608
headage2	2.98E-05	7.67E-05	0.39	0.698
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024
SC/ST	0.496191	0.036991	13.41	0
land_own	-0.00463	0.000427	-10.84	0
land_own2	-6.04E-08	1.77E-07	-0.34	0.734
RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087
Landrain	4.84E-06	6.13E-07	7.9	0

Bimaru	0.306848	0.041688	7.36	0
Coastal	1.004761	0.066374	15.14	0
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004
_cons	0.289162	0.166635	1.74	0.083
Mills				
Lambda	5.950737	2.459262	2.42	0.016
Rho	0.3613			
Sigma	16.47056			
Lambda	5.950737	2.459262		

IRON (Table 9)

Table 9a: Female_Harvest Tobit-Heckman

Tobit estimates			Number of obs	=	4460
			LR chi2(23)	=	909.48
			Prob > chi2	=	0
Log likelihood =		-12008.6	Pseudo R2	=	0.0365
fem_harvest	Coef.		Std. Err.	t	P>t
Ironpchat		1.110126	0.621805	1.79	0.074
ironpchat2		-0.00845	0.004195	-2.01	0.044
HIGHESTFEMEDUPRIMARY		4.342896	1.563299	2.78	0.005
HIGHESTFEMEDUMIDDLE		0.577706	1.434878	0.4	0.687
HIGHESTFEMEDUMATRIC		1.135537	1.039506	1.09	0.275
pr_pulses		-0.08137	0.153108	-0.53	0.595
pr_gur_sugar		-0.12453	0.237171	-0.53	0.6
pr_oil		-0.08105	0.033083	-2.45	0.014
pr_milk		-0.30224	0.086669	-3.49	0
Headage		0.129601	0.180557	0.72	0.473
headage2		-0.00156	0.001717	-0.91	0.364
NO.ADULTMALE		-2.88108	0.796401	-3.62	0
NO.ADULTFEMALE		1.722835	0.562638	3.06	0.002
Hhsize		0.541801	0.648996	0.83	0.404
SC/ST		4.121839	1.834328	2.25	0.025
HINDU		-2.06715	4.291458	-0.48	0.63
MUSLIM		-2.56613	4.524056	-0.57	0.571
CHRISTIAN		-3.96387	5.4591	-0.73	0.468
SIKH		-277.589	.	.	.
BUDDHIST		-7.63189	10.45723	-0.73	0.466
p1		-0.545	1.589721	-0.34	0.732
Bimaru		-17.0828	2.227024	-7.67	0
Coastal		4.272284	1.239255	3.45	0.001
_cons		-3.20816	11.39614	-0.28	0.778

Heckman selection	model -- two-step estimates	Number of obs	=	6594
(regression model	with sample selection)	Censored obs	=	2134
		Uncensored obs	=	4460
		Wald chi2(23)	=	1307.95

	Coef.	Prob > chi2 Std. Err.	= z	0 P>z
fem_harvest				
Bimaru	-9.75545	0.768342	-12.7	0
Coastal	4.095827	0.949288	4.31	0
ironpchat	0.406556	0.156977	2.59	0.01
ironpchat2	-0.00108	0.001051	-1.03	0.303
Pr_pulses	-0.15073	0.060789	-2.48	0.013
Pr_gur_sugar	0.066958	0.104089	0.64	0.52
Pr_oil	0.053591	0.013637	3.93	0
Pr_milk	-0.1079	0.034045	-3.17	0.002
Headage	-0.00831	0.084869	-0.1	0.922
headage2	-0.00029	0.000861	-0.34	0.737
NO.ADULTMALE	-1.53716	0.288819	-5.32	0
NO.ADULTFEMALE	1.324359	0.296754	4.46	0
Hhsize	0.287801	0.190837	1.51	0.132
SC/ST	1.509875	0.658751	2.29	0.022
RAINFALLINDEX	0.002067	0.0005	4.13	0
_cons	5.353557	3.751462	1.43	0.154
Select				
Headage	-0.00384	0.007484	-0.51	0.608
headage2	2.98E-05	7.67E-05	0.39	0.698
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024
SC/ST	0.496191	0.036991	13.41	0
land_own	-0.00463	0.000427	-10.84	0
land_own2	-6.04E-08	1.77E-07	-0.34	0.734
RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087
Landrain	4.84E-06	6.13E-07	7.9	0
Bimaru	0.306848	0.041688	7.36	0
Coastal	1.004761	0.066374	15.14	0
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004
_cons	0.289162	0.166635	1.74	0.083
Mills				
Lambda	-0.13373	1.77995	-0.08	0.94
Rho	-0.01137			
Sigma	11.75714			
Lambda	-0.13373	1.77995		

Table 9b: Female-other Tobit

Tobit estimates		Number of obs	=	4460
		LR chi2(23)	=	771.88
		Prob > chi2	=	0
Log likelihood =	-9631.27	Pseudo R2	=	0.0385
fem_other	Coef.	Std. Err.	t	P>t

Ironpchat	1.408559	0.667528	2.11	0.035
ironpchat2	-0.01192	0.004784	-2.49	0.013
HIGHESTFEMEDUPRIMARY	3.085715	1.78645	1.73	0.084
HIGHESTFEMEDUMIDDLE	0.635784	1.614414	0.39	0.694
HIGHESTFEMEDUMATRIC	-5.1129	1.261171	-4.05	0
pr_pulses	-0.15294	0.165803	-0.92	0.356
pr_gur_sugar	0.50119	0.269105	1.86	0.063
pr_oil	-0.17106	0.037743	-4.53	0
pr_milk	-0.25025	0.09574	-2.61	0.009
Headage	0.419842	0.204514	2.05	0.04
headage2	-0.005	0.001968	-2.54	0.011
NO.ADULTMALE	-3.3514	0.861073	-3.89	0
NO.ADULTFEMALE	1.632886	0.636068	2.57	0.01
Hhsize	0.522208	0.692143	0.75	0.451
SC/ST	8.123458	2.085743	3.89	0
HINDU	-7.60442	4.552643	-1.67	0.095
MUSLIM	-7.1566	4.904148	-1.46	0.145
CHRISTIAN	-11.1623	5.820187	-1.92	0.055
SIKH	-292.266 .	.	.	
BUDDHIST	-7.03763	11.05516	-0.64	0.524
p1	5.200782	1.74981	2.97	0.003
Bimaru	-17.8157	2.383579	-7.47	0
Coastal	5.399223	1.363864	3.96	0
_cons	-21.6981	12.30622	-1.76	0.078

Heckman selection	model -- two-step estimates	Number of obs	=	6594
(regression model	with sample selection)	Censored obs	=	2134
		Uncensored obs	=	4460
		Wald chi2(23)	=	1072.6
		Prob > chi2	=	0

Table 9c: Male_other Tobit

Tobit estimates		Number of obs	=	4460
		LR chi2(23)	=	444.67
		Prob > chi2	=	0
Log likelihood =	-13318.9	Pseudo R2	=	0.0164

male_other	Coef.	Std. Err.	T	P>t
Ironpchat	2.438259	0.782535	3.12	0.002
ironpchat2	-0.02702	0.005137	-5.26	0
HIGHESTFEMEDUPRIMARY	8.564073	1.914845	4.47	0

HIGHESTFEMEDUMIDDLE	3.145154	1.759164	1.79	0.074
HIGHESTFEMEDUMATRIC	-1.82045	1.288592	-1.41	0.158
pr_pulses	-0.29629	0.193192	-1.53	0.125
pr_gur_sugar	-1.84787	0.289159	-6.39	0
pr_oil	-0.2028	0.043011	-4.71	0
pr_milk	-0.44489	0.102993	-4.32	0
Headage	0.232738	0.219471	1.06	0.289
headage2	-0.00216	0.002074	-1.04	0.297
NO.ADULTMALE	-1.11834	0.994177	-1.12	0.261
NO.ADULTFEMALE	-2.65398	0.694146	-3.82	0
Hhsize	1.09496	0.818559	1.34	0.181
SC/ST	8.792647	2.262152	3.89	0
HINDU	9.905032	5.398266	1.83	0.067
MUSLIM	11.96291	5.627803	2.13	0.034
CHRISTIAN	9.217868	6.892293	1.34	0.181
SIKH	-7.49648	23.45226	-0.32	0.749
BUDDHIST	-28.135	16.78453	-1.68	0.094
p1	9.218451	2.002519	4.6	0
Bimaru	-4.33039	2.803547	-1.54	0.123
Coastal	7.789419	1.567245	4.97	0
_cons	-13.5749	14.25597	-0.95	0.341

Table 9d: Male_harvest Tobit-Heckman

Tobit estimates		Number of obs	=		4460
		LR chi2(23)	=		366.57
		Prob > chi2	=		0
Log likelihood =	-14030.4	Pseudo R2	=		0.0129
male_harvest	Coef.	Std. Err.	t	P>t	
Ironpchat	2.414825	0.798624	3.02	0.003	
ironpchat2	-0.0282	0.005227	-5.4	0	
HIGHESTFEMEDUPRIMARY	8.302071	1.950424	4.26	0	
HIGHESTFEMEDUMIDDLE	4.019478	1.791013	2.24	0.025	
HIGHESTFEMEDUMATRIC	2.490877	1.284877	1.94	0.053	
pr_pulses	-0.64514	0.198289	-3.25	0.001	
pr_gur_sugar	-2.17307	0.293984	-7.39	0	
pr_oil	-0.0193	0.042252	-0.46	0.648	
pr_milk	-0.45388	0.105105	-4.32	0	
Headage	0.188392	0.223539	0.84	0.399	
Headage2	-0.00167	0.002112	-0.79	0.43	
NO.ADULTMALE	-0.45356	1.014218	-0.45	0.655	
NO.ADULTFEMALE	-2.26453	0.705468	-3.21	0.001	
Hhsize	0.786824	0.835847	0.94	0.347	
SC/ST	10.93234	2.297752	4.76	0	
HINDU	11.50813	5.504052	2.09	0.037	
MUSLIM	14.6782	5.729062	2.56	0.01	
CHRISTIAN	9.412393	7.037055	1.34	0.181	
SIKH	-14.0901	23.95737	-0.59	0.556	
BUDDHIST	-29.0562	17.01371	-1.71	0.088	

p1	5.514158	2.036634	2.71	0.007
Bimaru	-6.26285	2.861748	-2.19	0.029
Coastal	3.692646	1.597474	2.31	0.021
_cons	-5.41946	14.52939	-0.37	0.709

Heckman selection	model -- two-step estimates	Number of obs	=	6594
(regression model	with sample selection)	Censored obs	=	2134
		Uncensored obs	=	4460
		Wald chi2(23)	=	857.62
		Prob > chi2	=	0
	Coef.	Std. Err.	z	P>z
male_harvest				
Bimaru	-5.85683	1.05078	-5.57	0
Coastal	6.155161	1.304095	4.72	0
ironpchat	0.598753	0.213019	2.81	0.005
ironpchat2	-0.00192	0.001424	-1.35	0.176
pr_pulses	-0.08201	0.08254	-0.99	0.32
pr_gur_sugar	-1.01802	0.141314	-7.2	0
pr_oil	0.140011	0.018439	7.59	0
pr_milk	-0.22575	0.046168	-4.89	0
Headage	-0.28626	0.117056	-2.45	0.014
Headage2	0.002674	0.001188	2.25	0.024
NO.ADULTMALE	-0.75653	0.395835	-1.91	0.056
NO.ADULTFEMALE	-0.60186	0.40731	-1.48	0.14
Hhsize	0.713695	0.259034	2.76	0.006
SC/ST	4.249521	0.904818	4.7	0
RAINFALLINDEX	-0.00382	0.000692	-5.53	0
_cons	17.93737	5.123513	3.5	0
Select				
Headage	-0.00384	0.007484	-0.51	0.608
Headage2	2.98E-05	7.67E-05	0.39	0.698
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024
SC/ST	0.496191	0.036991	13.41	0
land_own	-0.00463	0.000427	-10.84	0
land_own2	-6.04E-08	1.77E-07	-0.34	0.734
RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087
Landrain	4.84E-06	6.13E-07	7.9	0
Bimaru	0.306848	0.041688	7.36	0
Coastal	1.004761	0.066374	15.14	0
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004
_cons	0.289162	0.166635	1.74	0.083
Mills				
Lambda	5.965028	2.438496	2.45	0.014
Rho	0.36217			
Sigma	16.47008			

Lambda		5.965028	2.438496	

Riboflavin (Table 10)

Table 10a: Female-Harvest Heckman

Heckman selection	model -- two-step estimates	Number of obs	=	6594
(regression model	with sample selection)	Censored obs	=	2134
		Uncensored obs	=	4460
		Wald chi2(23)	=	1315.04
		Prob > chi2	=	0
	Coef.	Std. Err.	Z	P>z
fem_harvest				
Bimaru	-8.69979	0.682973	-12.74	0
Coastal	4.856649	0.874654	5.55	0
Ribopchat	19.68506	5.33042	3.69	0
ribopchat2	-3.10063	0.884144	-3.51	0
pr_pulses	-0.32036	0.0766	-4.18	0
pr_gur_sugar	-0.46444	0.212682	-2.18	0.029
pr_oil	0.014812	0.019389	0.76	0.445
pr_milk	-0.07253	0.035181	-2.06	0.039
Headage	0.029473	0.078239	0.38	0.706
headage2	-0.00083	0.000812	-1.02	0.31
NO.ADULTMALE	-1.32507	0.254593	-5.2	0
NO.ADULTFEMALE	2.14764	0.326558	6.58	0
Hhsize	-0.45924	0.186634	-2.46	0.014
SC/ST	3.532966	0.917421	3.85	0
RAINFALLINDEX	0.001959	0.000498	3.93	0
_cons	17.70938	3.919207	4.52	0
Select				
Headage	-0.00384	0.007484	-0.51	0.608
headage2	2.98E-05	7.67E-05	0.39	0.698
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024
SC/ST	0.496191	0.036991	13.41	0
land_own	-0.00463	0.000427	-10.84	0
land_own2	-6.04E-08	1.77E-07	-0.34	0.734
RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087
Landrain	4.84E-06	6.13E-07	7.9	0

Bimaru	0.306848	0.041688	7.36	0
Coastal	1.004761	0.066374	15.14	0
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004
_cons	0.289162	0.166635	1.74	0.083
Mills				
Lambda	-0.93	1.805126	-0.52	0.606
Rho	-0.07905			
Sigma	11.76476			
Lambda	-0.93	1.805126		

Table 10b: Female_sowing Heckman

Heckman selection	model -- two-step estimates	Number of obs	=	6594
(regression model	with sample selection)	Censored obs	=	2134
		Uncensored obs	=	4460
		Wald chi2(23)	=	1163.96
		Prob > chi2	=	0

	Coef.	Std. Err.	z	P>z
fem_sowing				
Bimaru	-6.25982	0.582979	-10.74	0
Coastal	4.59119	0.746842	6.15	0
Ribopchat	7.953568	4.54607	1.75	0.08
ribopchat2	-2.65996	0.754095	-3.53	0
pr_pulses	-0.21417	0.065345	-3.28	0.001
pr_gur_sugar	0.025202	0.181411	0.14	0.89
pr_oil	-0.09891	0.016536	-5.98	0
pr_milk	-0.05186	0.030008	-1.73	0.084
Headage	0.111524	0.066825	1.67	0.095
headage2	-0.00146	0.000693	-2.1	0.035
NO.ADULTMALE	-0.57902	0.217344	-2.66	0.008
NO.ADULTFEMALE	1.540435	0.278725	5.53	0
Hhsize	-0.82952	0.159207	-5.21	0
SC/ST	5.095268	0.782903	6.51	0
RAINFALLINDEX	-0.00231	0.000426	-5.43	0
_cons	13.21408	3.344257	3.95	0
Select				
Headage	-0.00384	0.007484	-0.51	0.608
headage2	2.98E-05	7.67E-05	0.39	0.698
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024
SC/ST	0.496191	0.036991	13.41	0
land_own	-0.00463	0.000427	-10.84	0
land_own2	-6.04E-08	1.77E-07	-0.34	0.734

RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087
Landrain	4.84E-06	6.13E-07	7.9	0
Bimaru	0.306848	0.041688	7.36	0
Coastal	1.004761	0.066374	15.14	0
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004
_cons	0.289162	0.166635	1.74	0.083
Mills				
Lambda	1.255952	1.540643	0.82	0.415
Rho	0.12488			
Sigma	10.05737			
Lambda	1.255953	1.540643		

Table 10c: Male_harvest Heckman

Heckman selection	model -- two-step estimates	Number of obs	=	6594
(regression model	with sample selection)	Censored obs	=	2134
		Uncensored obs	=	4460
		Wald chi2(23)	=	855.85
		Prob > chi2	=	0

	Coef.	Std. Err.	z	P>z
male_harvest				
Bimaru	-5.02615	0.93709	-5.36	0
Coastal	7.754375	1.205664	6.43	0
Ribopchat	16.57579	7.224245	2.29	0.022
ribopchat2	-1.01885	1.1994	-0.85	0.396
pr_pulses	-0.11481	0.104198	-1.1	0.271
pr_gur_sugar	-0.99214	0.28879	-3.44	0.001
pr_oil	0.096188	0.026285	3.66	0
pr_milk	-0.21793	0.047769	-4.56	0
Headage	-0.26531	0.108266	-2.45	0.014
headage2	0.002524	0.001123	2.25	0.025
NO.ADULTMALE	-0.47042	0.349914	-1.34	0.179
NO.ADULTFEMALE	-0.06158	0.447569	-0.14	0.891
Hhsize	0.233556	0.253754	0.92	0.357
SC/ST	4.184962	1.254253	3.34	0.001
RAINFALLINDEX	-0.00401	0.00069	-5.81	0
_cons	24.6572	5.351575	4.61	0
Select				
Headage	-0.00384	0.007484	-0.51	0.608
headage2	2.98E-05	7.67E-05	0.39	0.698
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024

SC/ST	0.496191	0.036991	13.41	0
land_own	-0.00463	0.000427	-10.84	0
land_own2	-6.04E-08	1.77E-07	-0.34	0.734
RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087
Landrain	4.84E-06	6.13E-07	7.9	0
Bimaru	0.306848	0.041688	7.36	0
Coastal	1.004761	0.066374	15.14	0
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004
_cons	0.289162	0.166635	1.74	0.083
Mills				
Lambda	6.014543	2.472365	2.43	0.015
Rho	0.36493			
Sigma	16.4812			
Lambda	6.014543	2.472365		

THIAMINE (Table 11)

Table 11a: Female_harvest Tobit-Heckman

Tobit estimates		Number of obs	=	4460
		LR chi2(23)	=	909.48
		Prob > chi2	=	0
Log likelihood =	-12008.6	Pseudo R2	=	0.0365

fem_harvest	Coef.	Std. Err.	t	P>t
Thiapchat	11.62737	6.650008	1.75	0.08
Thiapchat2	-1.03045	0.515495	-2	0.046
HIGHESTFEMEDUPRIMARY	1.214845	0.927635	1.31	0.19
HIGHESTFEMEDUMIDDLE	-1.81797	1.300285	-1.4	0.162
HIGHESTFEMEDUMATRIC	-0.07383	1.17059	-0.06	0.95
pr_pulses	-0.49475	0.253295	-1.95	0.051
pr_gur_sugar	-1.24521	0.807585	-1.54	0.123
pr_oil	-0.08806	0.049257	-1.79	0.074
pr_milk	-0.17563	0.094793	-1.85	0.064
Headage	0.046095	0.13703	0.34	0.737
headage2	-0.00102	0.001403	-0.73	0.467
NO.ADULTMALE	-2.12879	0.59541	-3.58	0
NO.ADULTFEMALE	4.120241	1.018427	4.05	0
Hhsize	-1.37058	0.778105	-1.76	0.078
SC/ST	6.879477	3.24887	2.12	0.034
HINDU	4.24706	5.441555	0.78	0.435
MUSLIM	0.991118	5.272177	0.19	0.851
CHRISTIAN	1.573621	5.407049	0.29	0.771
SIKH	-272.165	.	.	.
BUDDHIST	2.564192	10.03085	0.26	0.798
p1	-0.01343	1.611666	-0.01	0.993
Bimaru	-13.6929	1.984611	-6.9	0
Coastal	6.399057	0.975127	6.56	0
_cons	24.31104	9.268185	2.62	0.009

Heckman selection	model -- two-step estimates	Number of obs	=	6594

(regression model	with sample selection)	Censored obs	=	2134
		Uncensored obs	=	4460
		Wald chi2(23)	=	1313
		Prob > chi2	=	0

	Coef.	Std. Err.	z	P>z
fem_harvest				
Bimaru	-9.05127	0.717627	-12.61	0
Coastal	4.730654	0.880668	5.37	0
Thiapchat	6.997471	2.034776	3.44	0.001
Thiapchat2	-0.37406	0.129869	-2.88	0.004
pr_pulses	-0.27722	0.077499	-3.58	0
pr_gur_sugar	-0.34702	0.212143	-1.64	0.102
pr_oil	0.026536	0.017349	1.53	0.126
pr_milk	-0.07771	0.036087	-2.15	0.031
Headage	0.013247	0.078387	0.17	0.866
headage2	-0.00062	0.000808	-0.76	0.445
NO.ADULTMALE	-1.28784	0.262139	-4.91	0
NO.ADULTFEMALE	2.030463	0.334037	6.08	0
Hhsize	-0.3516	0.208711	-1.68	0.092
SC/ST	3.131536	0.934811	3.35	0.001
RAINFALLINDEX	0.00204	0.000495	4.12	0
_cons	14.79265	4.084994	3.62	0
Select				
Headage	-0.00384	0.007484	-0.51	0.608
headage2	2.98E-05	7.67E-05	0.39	0.698
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024
SC/ST	0.496191	0.036991	13.41	0
land_own	-0.00463	0.000427	-10.84	0
land_own2	-6.04E-08	1.77E-07	-0.34	0.734
RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087
Landrain	4.84E-06	6.13E-07	7.9	0
Bimaru	0.306848	0.041688	7.36	0
Coastal	1.004761	0.066374	15.14	0
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004
_cons	0.289162	0.166635	1.74	0.083
Mills				
Lambda	-0.57224	1.789614	-0.32	0.749
Rho	-0.04867			

Table 11b: Female_other Tobit

Tobit estimates		Number of obs =		4460
		LR chi2(23) =		771.88
		Prob > chi2 =		0
Log likelihood =	-9631.27	Pseudo R2 =		0.0385

fem_other	Coef.	Std. Err.	t	P>t
Thiapchat	14.66391	7.123054	2.06	0.04
Thiapchat2	-1.45891	0.588611	-2.48	0.013
HIGHESTFEMEDUPRIMARY	-1.43776	1.051046	-1.37	0.171
HIGHESTFEMEDUMIDDLE	-2.91902	1.458096	-2	0.045
HIGHESTFEMEDUMATRIC	-6.86496	1.407551	-4.88	0
pr_pulses	-0.74191	0.289163	-2.57	0.01
pr_gur_sugar	-1.13061	0.92524	-1.22	0.222
pr_oil	-0.16882	0.053762	-3.14	0.002
pr_milk	-0.07061	0.108042	-0.65	0.513
Headage	0.281044	0.156117	1.8	0.072
headage2	-0.00407	0.001617	-2.52	0.012
NO.ADULTMALE	-2.36713	0.664038	-3.56	0
NO.ADULTFEMALE	4.998936	1.164864	4.29	0
Hhsize	-2.11491	0.892971	-2.37	0.018
SC/ST	12.14597	3.722716	3.26	0.001
HINDU	1.402116	6.027062	0.23	0.816
MUSLIM	-2.13104	5.857406	-0.36	0.716
CHRISTIAN	-3.38423	5.867901	-0.58	0.564
SIKH	-284.354	.	.	.
BUDDHIST	6.972183	10.72618	0.65	0.516
p1	6.102622	1.823642	3.35	0.001
Bimaru	-13.1289	2.187224	-6	0
Coastal	8.064325	1.063431	7.58	0
_cons	16.474	10.44469	1.58	0.115

Table 11c: Male_other Tobit

Tobit estimates		Number of obs =		4460
		LR chi2(23) =		444.67
		Prob > chi2 =		0
Log likelihood =	-13318.9	Pseudo R2 =		0.0164

male_other	Coef.	Std. Err.	t	P>t
Thiapchat	24.90991	8.376703	2.97	0.003
Thiapchat2	-3.32967	0.630799	-5.28	0

HIGHESTFEMEDUPRIMARY	-2.21087	1.150554	-1.92	0.055
HIGHESTFEMEDUMIDDLE	-5.74373	1.597992	-3.59	0
HIGHESTFEMEDUMATRIC	-6.00877	1.44045	-4.17	0
pr_pulses	-1.65811	0.309734	-5.35	0
pr_gur_sugar	-5.78695	0.985732	-5.87	0
pr_oil	-0.13974	0.063294	-2.21	0.027
pr_milk	-0.03309	0.111206	-0.3	0.766
Headage	-0.18193	0.165016	-1.1	0.27
headage2	0.000748	0.001681	0.44	0.656
NO.ADULTMALE	0.743403	0.730652	1.02	0.309
NO.ADULTFEMALE	4.894129	1.244076	3.93	0
Hhsize	-4.58852	0.948903	-4.84	0
SC/ST	18.53596	3.985274	4.65	0
HINDU	30.77881	6.719736	4.58	0
MUSLIM	23.38136	6.489964	3.6	0
CHRISTIAN	26.67488	6.772201	3.94	0
SIKH	11.66411	23.93473	0.49	0.626
BUDDHIST	1.813028	16.31345	0.11	0.912
p1	11.98701	2.005247	5.98	0
Bimaru	5.830053	2.458912	2.37	0.018
Coastal	12.22539	1.244193	9.83	0
_cons	69.78708	11.37014	6.14	0

Table 11d: Male_harvest Tobit Heckman

Tobit estimates		Number of obs	=		4460
		LR chi2(23)	=		366.57
		Prob > chi2	=		0
Log likelihood =	-14030.4	Pseudo R2	=		0.0129
male_harvest	Coef.	Std. Err.	t	P>t	
Thiapchat	24.56311	8.550139	2.87	0.004	
Thiapchat2	-3.47997	0.641753	-5.42	0	
HIGHESTFEMEDUPRIMARY	-3.03678	1.174967	-2.58	0.01	
HIGHESTFEMEDUMIDDLE	-5.404	1.626831	-3.32	0.001	
HIGHESTFEMEDUMATRIC	-1.91908	1.443646	-1.33	0.184	
pr_pulses	-2.07145	0.316211	-6.55	0	
pr_gur_sugar	-6.32688	1.002707	-6.31	0	
pr_oil	0.056559	0.06351	0.89	0.373	
pr_milk	-0.02318	0.113174	-0.2	0.838	
Headage	-0.26183	0.168027	-1.56	0.119	
headage2	0.001513	0.001712	0.88	0.377	
NO.ADULTMALE	1.426087	0.743739	1.92	0.055	
NO.ADULTFEMALE	5.601207	1.266322	4.42	0	
Hhsize	-5.09557	0.96511	-5.28	0	
SC/ST	21.2122	4.049735	5.24	0	
HINDU	33.37883	6.837352	4.88	0	
MUSLIM	26.60322	6.598696	4.03	0	
CHRISTIAN	27.60671	6.905602	4	0	
SIKH	6.125165	24.44274	0.25	0.802	

BUDDHIST	1.895256	16.51912	0.11	0.909
p1	8.529798	2.038418	4.18	0
Bimaru	4.264037	2.506281	1.7	0.089
Coastal	8.045774	1.270627	6.33	0
_cons	81.05923	11.57238	7	0

Heckman selection	model -- two-step estimates	Number of obs	=	6594
(regression model	with sample selection)	Censored obs	=	2134
		Uncensored obs	=	4460
		Wald chi2(23)	=	857.87
		Prob > chi2	=	0

	Coef.	Std. Err.	z	P>z
male_harvest				
Bimaru	-5.69569	0.984831	-5.78	0
Coastal	7.805282	1.215557	6.42	0
Thiapchat	6.437212	2.758467	2.33	0.02
Thiapchat2	-0.0082	0.176281	-0.05	0.963
pr_pulses	-0.02868	0.105445	-0.27	0.786
pr_gur_sugar	-0.77659	0.288127	-2.7	0.007
pr_oil	0.100326	0.023506	4.27	0
pr_milk	-0.24395	0.048985	-4.98	0
Headage	-0.28335	0.108714	-2.61	0.009
headage2	0.002729	0.001121	2.43	0.015
NO.ADULTMALE	-0.61864	0.36063	-1.72	0.086
NO.ADULTFEMALE	-0.34556	0.458259	-0.75	0.451
Hhsize	0.538432	0.283913	1.9	0.058
SC/ST	3.371457	1.279248	2.64	0.008
RAINFALLINDEX	-0.00389	0.000687	-5.66	0
_cons	18.99829	5.58184	3.4	0.001
Select				
Headage	-0.00384	0.007484	-0.51	0.608
headage2	2.98E-05	7.67E-05	0.39	0.698
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024
SC/ST	0.496191	0.036991	13.41	0
land_own	-0.00463	0.000427	-10.84	0
land_own2	-6.04E-08	1.77E-07	-0.34	0.734
RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087
Landrain	4.84E-06	6.13E-07	7.9	0
Bimaru	0.306848	0.041688	7.36	0
Coastal	1.004761	0.066374	15.14	0
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004
_cons	0.289162	0.166635	1.74	0.083

Mills Lambda	6.377306	2.454175	2.6	0.009
Rho	0.38555			
Sigma	16.54083			
Lambda	6.377306	2.454175		

Table 11e: Female_sowing Heckman

Heckman selection (regression model	model -- two-step estimates with sample selection)	Number of obs	=		6594
		Censored obs	=		2134
		Uncensored obs	=		4460
		Wald chi2(23)	=		1161.76
		Prob > chi2	=		0

	Coef.	Std. Err.	z	P>z
fem_sowing				
Bimaru	-6.71154	0.612547	-10.96	0
Coastal	4.516915	0.752	6.01	0
Thiapchat	4.062358	1.735448	2.34	0.019
Thiapchat2	-0.3821	0.110773	-3.45	0.001
pr_pulses	-0.16762	0.066114	-2.54	0.011
pr_gur_sugar	0.094087	0.180957	0.52	0.603
pr_oil	-0.10361	0.014797	-7	0
pr_milk	-0.06626	0.030781	-2.15	0.031
Headage	0.089459	0.066956	1.34	0.182
Headage2	-0.00125	0.00069	-1.81	0.071
NO.ADULTMALE	-0.59356	0.223791	-2.65	0.008
NO.ADULTFEMALE	1.568734	0.285119	5.5	0
Hhsize	-0.77374	0.178048	-4.35	0
SC/ST	5.064527	0.797781	6.35	0
RAINFALLINDEX	-0.00236	0.000423	-5.59	0
_cons	10.62989	3.485853	3.05	0.002
Select				
Headage	-0.00384	0.007484	-0.51	0.608
Headage2	2.98E-05	7.67E-05	0.39	0.698
NO.ADULTMALE	-0.03827	0.019037	-2.01	0.044
NO.ADULTFEMALE	0.049924	0.022145	2.25	0.024
SC/ST	0.496191	0.036991	13.41	0
land_own	-0.00463	0.000427	-10.84	0
land_own2	-6.04E-08	1.77E-07	-0.34	0.734
RAINFALLINDEX	8.92E-05	0.000052	1.71	0.087
Landrain	4.84E-06	6.13E-07	7.9	0
Bimaru	0.306848	0.041688	7.36	0
Coastal	1.004761	0.066374	15.14	0
FEMALE_HHHEAD	0.246493	0.085797	2.87	0.004

_cons	0.289162	0.166635	1.74	0.083
Mills Lambda	1.121481	1.527492	0.73	0.463
Rho	0.11156			
Sigma	10.05244			
Lambda	1.121481	1.527492		

IV. Conclusions

The possibility that when workers are acutely under-nourished they may not be able to exert sufficient effort so that their wages remain low which then leads to further poor nutritional outcomes has been known in the literature for almost fifty years now. A number of authors have tried to empirically test for this existence of this trap but none has been able to establish unambiguously that this holds for a subset of the working population and not the whole.

This paper has attempted to quantify and formally test for the presence of PNT in rural India. It outlines a methodology that can identify the impact of energy consumption, protein and micronutrients on wage rates, even in the presence of mutual endogeneity. This paper has an important policy implication in that it argues that if a minimum wage has to be set in agriculture it must be adequate to ensure that workers are not caught in the poverty-nutrition trap.

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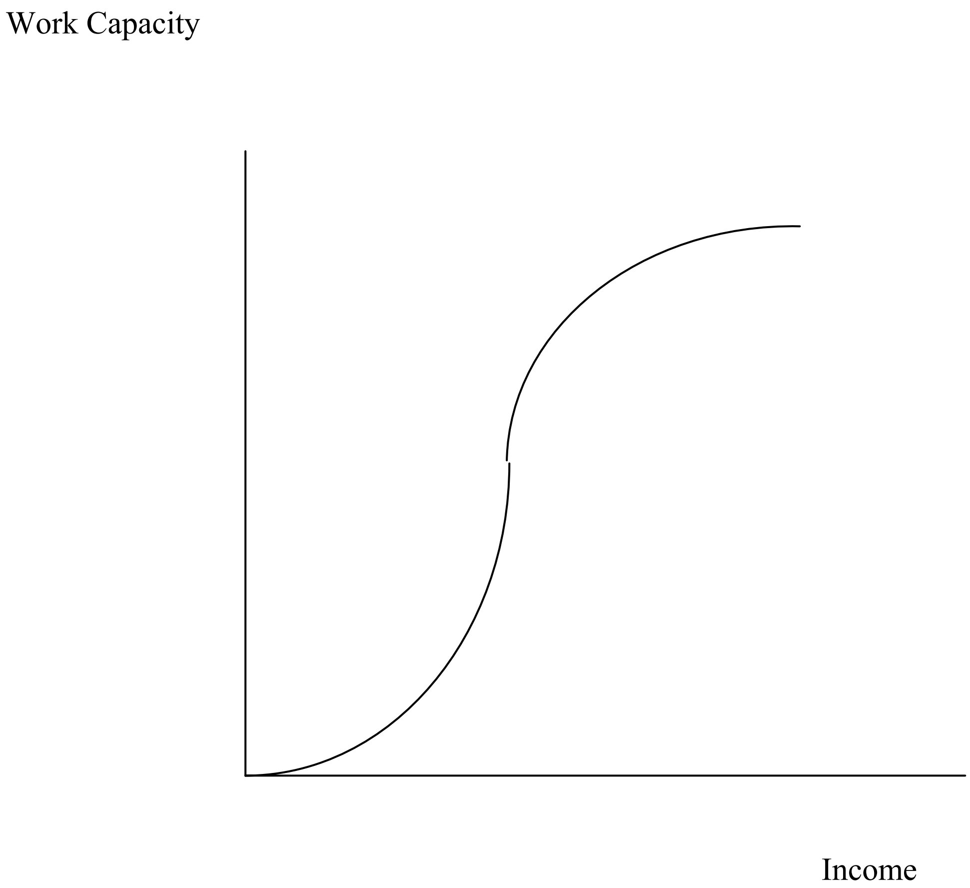

Figure 1: The Capacity Curve

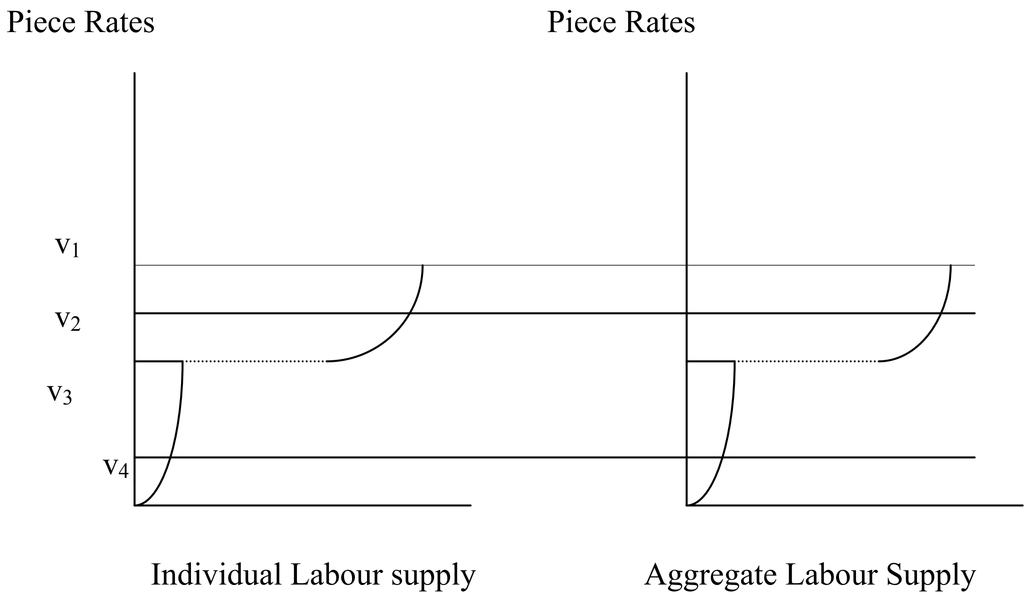

Figure 2: Individual and Aggregate Labour Supply

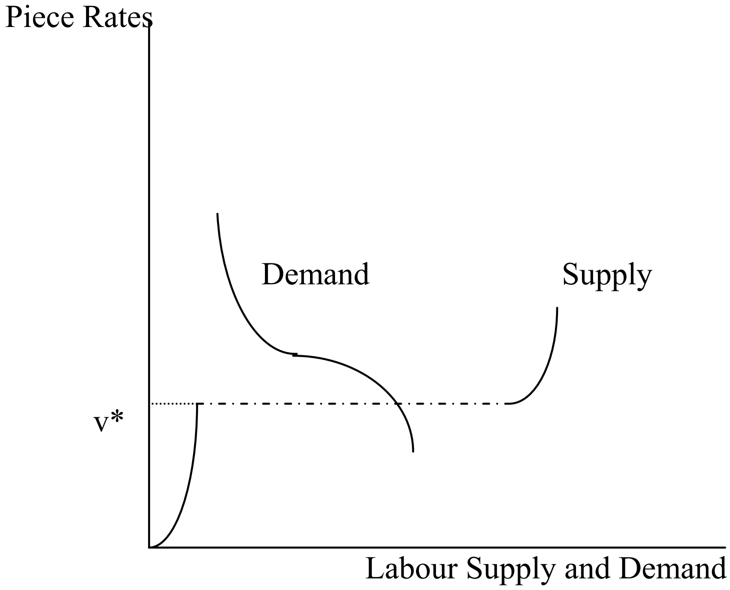

Figure 3: “Equilibrium” in the Labour Market

Source: Ray (2004).