

Leveraging Non-Farm Income: Micro-evidence of Occupational Choice for Rural Households in India

Mukherjee, Swayambhu and Kar, Saibal

Centre for Studies in Social Sciences, Calcutta, IZA, Bonn

6 March 2020

Online at https://mpra.ub.uni-muenchen.de/109940/ MPRA Paper No. 109940, posted 28 Sep 2021 04:59 UTC

Leveraging Non-Farm Income: Micro-evidence of Occupational Choice for Rural Households in India

Swayambhu Mukherjee*

Saibal Kar** Centre for Studies in Social sciences, Calcutta and IZA, Bonn

April 2020

* This paper is partly drawn from the M. Phil Dissertation towards award of the degree at the Department of Economics, Calcutta University.

** **Corresponding Author**: Centre for Studies in Social Sciences, Calcutta. R1, B P Township, Kolkata 700094, India. Ph: +91-33-2462-6183. E-mail: saibal@cssscal.org

Acknowledgements: The authors thank seminar participants at Calcutta University for comments and the Chief Editor, Prof. Narayana at FPI, Bengaluru for the invitation to contribute. The usual disclaimer applies.

1. Introduction and Related Literature

Recent reports from the World Bank (2017) indicated that agriculture still accounts for one-third of the global gross domestic product (GDP) as of 2014. A majority of the world's population inhabits the rural areas, and especially so in the developing economies. Quite evidently, a significant part of this population is directly engaged with agriculture for their livelihood. Indeed, related statistics (World Bank, 2012) showed that among the world's 7.1 billion people then, an estimated 1.3 billion (19%) were directly engaged in farming. In fact, it helps to redefine the sector as agriculture and allied, since the output supplied provides much more than just the required quantity of food for direct human consumption. It produces significant amount of feed for livestock, fuel (for transportation and energy production including household kitchen fires), fibre (for clothing), and agriculture biomass increasingly being used for production purpose in a host of chemical and material producing units (Alston and Pardey, 2014). A large section of the rural workforce seems to be engaged with both farm and non-farm activities exploring some of the above production characteristics and advantages. This paper is an attempt to investigate empirically the major factors that influence choices between farming and non-farming activities as exclusive occupations, vis-à-vis diversification, across a large sample of rural households in India. A detailed survey of the extant literature reveals that the evidence on occupational choice among rural households as function of several factors is not too common. In addition, utilizing two subsequent rounds of micro-data from IHDS (India Human Development Survey) database for India is rare, thereby offering enough room for this specific

inquiry.¹

It is well-known that gradually the share of agriculture as the major income provider started diminishing. For the developed world, such as that in the United States one of the most remarkable changes in the era has been the abandoning of farming as a means of livelihood. This stands true not only across the farmers practicing agriculture on a mass scale but also the small and marginal farmers. The proportion of population engaged in farming was 2% at the beginning of the 20th century and 90% of their income was sourced by non-farm practices (Reardon, *et al.* 1992; Lobao & Meyer, 2001; Reardon et al., 2001). However, low income from farming activities turned out to be one of the crucial factors influencing withdrawal of participation from the farm sector. Consequently, the number of farms in the US declined from 6.4 million in 1920 to 2.2 million in 2006 (Mishra et al., 2008, 2002). With the number of large scale farms gradually declining, farmers in larger proportion opted for non-farm activities as a potential alternative. In comparison, India despite being predominantly agrarian for a long time, the net domestic product for agriculture still declined both in absolute terms and in terms of the growth rate -- 2.8% in the 1990s as compared to 3.5% in 1980s. It further dipped to 1.3% in 1999-2000 and also exhibited negative growth rate during 2001-02 (Majumder, 2002). Subsequently, agriculture has been termed as the "relatively unrewarding profession" by the National Agricultural Policy already in the year 2000 (Gupta, 2005).

Rural Non-Farm Sector

Not surprisingly therefore, in the recent past the role of non-farm activities as a major source of income has gained significance across all rural economies in the developing world.

¹ See https://www.ihds.umd.edu/papers-using-ihds-public-data for papers utilizing IHDS database for various questions. Accessed, June 12, 2019.

Rural economies are no more considered completely agricultural in terms of occupational classifications. The rising importance of non-farm activities in the traditionally agricultural societies is attributed to the structural changes in the recent years aided by mechanization and higher labor productivity. Income from non-farm sources exhibits a rising trend in terms of their share in total income of rural households (Imai et al, 2015). On the higher side for example, evidence from Mexico suggests that rural non-farm activities generate more than half of the household's income on average. In general, it seems that the education level of the individual and growth in non-farm employment influence higher participation in the non-farm sector (Janvry and Sadoulet, 2001). Not long before, the rural non-farm activities were believed to be part of a low-productivity 'residual' sector, which however, changed from the 1990's onwards as a crucial source to eliminate rural poverty and inequality in developing countries (Lanjouw and Lanjouw, 2001; Hazell et al., 2007, Diechmann et al. 2009; etc). There should be little doubt that the rural non-farm sector has been quite potent in generating employment, particularly for women and the rural poor (Hazell, et al. 2010; Imai et al., 2015). Evidence suggests that income from rural non-farm consists of 51% of the total income in Asia, followed by 47% in Latin America and 34% in Africa. For India specifically, till the 1980s as we have already hinted above, low participation was common with fewer than 12 Indian states reporting rural non-farm activities less than 20% of the total share. However, the entire situation underwent a dramatic change in the next 20 years. Rural non-farm activities have followed a path of moderate to high growth during this time. Since non-farm activities include animal husbandry to a large extent, the following example regarding growth rates is instructive. It typically shows that animal husbandry as a branch of rural nonfarm activities has grown steadily over time with its own share within the agricultural GDP rising up to 27% around 2012-13. The statistics supports the claim that rural

non-farm activities have become a viable source of income across states with a growth rate almost double that of farm output. The occupational distribution naturally will reflect these changes as we discus shortly.

Share in GDP (%)			Share of Animal	Cumulative Annual Growth Rates of Output			
			husbandry in Agri-	in Crop Hus	bandry and	Animal Hus	sbandry
Year	Agri.	Animal	cultural GDP (%)	Year	Food	Milk	Egg
	-	husbandry			grain		
1000.01 24	24.72	4.82	12.99	1980-81 -	3.50	5.48	7.69
1980-81	34.72		13.88	1990-91			
1000.01	28.20	6.45	22.79	1990-91 -	2.00	4 1 1	5.67
1990-91	28.30	6.45 22.78		2000-01	2.06	4.11	5.67
2000-01 21.	21.24	21.24 5.44	25.61	2000-01 -	2.50	4.22	5.58
	21.24		25.61	2010-11			
2010 11	15 77	2.04	24.00	2010-11 -	1.00	4.05	5 10
2010-11	15.77	3.94	24.99	2012-13	1.98	4.25	5.19
2012-13	15.10	4.11	27.25		-	•	•

 Table 1.
 Share and Growth of Rural Farm and Non-Farm Activities in India

Source: Basic Animal Husbandry Statistics, Department of Animal Husbandry, Ministry of Agriculture, GoI. National Accounts Division, Central Statistical Office, MoSPI, Government of India

Available discussion suggests that household wealth, caste, village level conditions and population density, etc. significantly influence the occupational distribution. Although non-farm activities cannot reduce poverty directly owing to poor asset holding by most of the rural households, it acts as a crucial mediator in pushing up the wage rates in the agricultural sector. So, on average do non-farm activities present a choice to a rural household in terms of distribution of labor between main and subsidiary occupations? Based on evidences from Asia, Africa and Latin America it seems that the role of non-farm sector as leverage against shocks in the farm sector has mixed success. Similarly, the ability of the non-farm sector in lowering income inequality by creating more jobs in these countries is not quite uniform. This can be attributed to the fact that entry barriers to rural non-farm activities exist which the poor people are unable to overcome. The major obstacle lies in the ability to invest in rural non-farm activities and relaxing credit constraints via financial intermediation might be useful (Reardon *et al.* 2000).

Yet, diversification of occupation, generally defined as a process by which the rural households engage in a diverse portfolio of activities for the sake of survival and improvement in their standards of living (Ellis, 1998), remains fairly predominant in a large class of samples over several rounds of surveys conducted on such matters. The general pattern is one of complementary activities between sectors for farm households thereby adjusting for price fluctuations, climate and output shocks and generally managing the risk of investments between farm and non-farm produces (see, Benjamin, 1994; Kelly and Illberry, 1995; Dercon, 1996; Hearn *et al.*, 1996, etc).

We, therefore look at the occupational status of individuals between farm, non-farm and diversified portfolios as function of a set of parameters. The empirical exercise has been conducted for the individuals belonging to the rural community of India using IHDS data. The econometric methodology adopted for conducting the analytical exercise is multinomial logit, the justification for which is discussed in the sections that follow. In section 2, we provide an insight into the IHDS dataset. In section 3, we discuss the empirical methodology and specifications. Section 4 offers the empirical results from the multinomial logit regression and we conclude in section 5.

2. Description of Data and Choice of Variables

The India Human Development Survey (IHDS) is a nationally representative multi-topic survey initially conducted with 41,554 households in 1503 villages and 971 neighborhoods

across India. It covered all major 28 states and union territories. IHDS has been jointly organized by researchers from the University of Maryland and the National Council of Applied Economic Research (NCAER), New Delhi. The IHDS Survey consists of two rounds – the first round of survey was conducted in 2005 and the second round of survey was conducted in 2012. About 83% of the households who were interviewed during the first round were re-interviewed during the second round, in addition to some new households. The total number of households interviewed in the second round was 42,152. The individual data for the first round consists of information on 215,754 individuals while it contains information on 204,569 individuals in the second round of the survey. The households and consequently individuals have been categorized as residents of the urban and rural community based on the information from the Census of 2001 for the first round (2005) and Census of 2011 for the second round (2012).

The IHDS data set provides a unique opportunity to explore the sources of income of the rural households in India. In the survey, the households were asked about their primary source of income, whether they possess cultivable land, what proportion of that is cultivated, share cropped or rented. The information on the land size in terms of local units and the number of livestock owned by them was also captured. Individuals were enquired about their participation in any other activity apart from lending labor to their family farms and every single details related to their wage employment status was recorded. This included, the number of days spent in that work, number of hours worked in a day, and annual income from the wage employment. Information as to whether the household has any non-farm business was also captured in the IHDS data in addition to the information as to which particular individual of the household participated in the non-farm business. The information on the income of the individuals from government benefit and pension schemes were also taken into account. Individuals were

questioned regarding their literacy, reading and writing skills, educational qualification, vocational training and the discipline of higher education (if any). The responses received have helped in segregating the participation of the individuals in various sectors under broader categorizations, namely farm, non-farm and diversification, directly amenable to various explanations behind the observed patterns.

For the aforementioned purpose we retain the information pertaining to the individuals in the rural sector only. The data set now consists of 143,374 individuals from the first round and 135,119 individuals from the second round. Based on this, the various occupational categories were generated. An individual who works in the family farm as an entrepreneur or in the wage market as an agricultural laborer or in both is considered to be participating in the farm sector (Sector=1). An individual who works in the family non-farm business or works as wage labor in any other sector other than agriculture or both, has been considered as a participant in the nonfarm sector (Sector=2). An individual who participates in the family farm as well as work as a wage laborer other than agricultural laborer (welders, construction workers, teachers, etc.) has been considered to diversify between the two sectors. An individual working in the family nonfarm business and working as a wage laborer in the agricultural sector is also treated as diversifying. Any individual participating in both family farm and family non-farm businesses has similarly been deemed as diversifying (Sector=3). Initially, this segregation was done using the individual data sets for both rounds: 2005 and 2012. Subsequently, the individual data files were merged with the household data files for each individual round of 2005 and 2012, which was later appended to generate a pooled data set.

While generating the categorical outcomes for each sector, a fourth category was also generated (Sector=0) which is indicative of individuals who do not belong to any of the broad

8

classifications mentioned above. As the study addresses the participation decision of individuals who are in the labor force, the fourth category was eliminated for the sake of simplicity of the analysis.

A simple comprehensive exercise from the two rounds separately reflect the following:

Sectors	Number of participants	Percentage
Farm (Sector=1)	42,628	51.93
Nonfarm (Sector=2)	31,714	38.63
Diversification (Sector=3)	7,747	9.44
Total	82,089	100.00

 Table 2: Distribution of Participation in Round 1

Authors' Estimation from IHDS Data.

Sectors	Number of participants	Percentage
Farm (Sector=1)	39,088	58.46
Nonfarm (Sector=2)	15,390	23.02
Diversification (Sector=3)	12,385	18.52
Total	66,863	100.00

Table 3: Distribution of Participation in Round 2

Authors' Estimation from IHDS Data.

A comparison of the two rounds reveals that the proportion of individuals opting for diversification has increased significantly over time as opposed to participating solely in the farm or the non-farm sector. The distribution of participation of individuals in the various sectors however suggests that farming continues to be the dominant choice of the individual in India. However, individuals have also opted to pursue non-farm activities along with farming rather than shifting completely to non-farm. Obviously, the important question in this matter is what proportion of the agricultural work force does both and what influences such decisions. The IHDS data set allows us to accommodate all such variables or factors that determine the distribution of participation of the individuals in the said categories of occupation. The proposed relation can be formalized as

Participation^j_{it}

= f (Income variation_t, Highest level of education, Literacy, Vocational training)

Where, i = Farm, Nonfarm, Diversification and j = individual

The information on the required explanatory variables have been listed in table 4 (see appendix) to get an overview of the sample.

In table 4 Education (Literacy), Education (College/Vocational Training), Education (Highest Degree) are all dummy variables. Education (Literacy) is a binary choice variable which has captured responses only in terms of Yes/No. In case of Education (College/Vocational Training), 0 denotes that the individual never went to college or received vocational training, 1 denotes that the individual attended college and 2 denotes that the individual has received technical training. Education (Highest Degree) consisted of categories ranging from 0 to 9 which represents different levels of educational attainments by an individual.

However, while undertaking the regression exercise, we use the mean differences in earnings for respective sectors as the explanatory variables instead of just the sector-specific income. Mean difference in earnings has been generated as:

Mean difference =
$$Y_{jt} - \frac{\sum Y_{jt}}{n}$$
 (2)

10

where j = individual and n = sample size

All other independent variables used in the regression retain the similar forms as listed in the table.

3. Empirical Method and Specification

The econometric method adopted for carrying out the analysis is multinomial logit model. Multinomial logit models are used when we have to choose from among several discrete alternatives. Multinomial logistic regression is the commonly used strategy when the categories are unordered. It is nothing but a manifestation of the binary logistic regression with the provision of more than two categories of dependent variables, unlike the binary case, being considered. Multinomial logistic regression helps in predicting the probability of the categorical placement of the dependent variable, which in turn depends on multiple explanatory variables. Moreover, it does not make any assumptions regarding normality, linearity or homoscedasticity (Starkweather & Moske, 2011).

Multinomial logistic regression can be deemed appropriate for the dataset used in the current study as it satisfies the aforementioned criteria. In this case, the dependent variable consists of more than two categorical outcomes which are unordered in form. And, it is required to predict the probability of occurrence of each of these outcomes of the dependent variables as function of more than one explanatory variable as already mentioned in the previous section. The probability of an individual choosing one particular alternative is referred to as the response probability. The response probabilities from all the alternatives must add up to 1. In our case with three alternative choices we determine two probabilities that would automatically determine the third.

If we assume that X_i is one of the factors that influence the probability of choosing one particular alternative, then the multinomial logit model can be represented as:

$$\pi_{ij} = \frac{e^{\alpha_j + \beta_j X_i}}{\sum_{i=1}^3 e^{\alpha_j + \beta_j X_i}}$$
(3)

The subscript *j* attached to α and β represents different values of the coefficient that varies from one choice to the other. Presently, *X* denotes a vector of explanatory variables while β represents a vector of coefficients. In case of multiple explanatory variables, one particular category is chosen as the reference or base category and the coefficients of the base category are set as zero. If the first category is chosen as the base category, then $\alpha_1 = 0$ and, $\beta_1 = 0$. The probabilities are estimated as:

$$\pi_{i1} = \frac{1}{1 + e^{\alpha_2 + \beta_2 X_i} + e^{\alpha_3 + \beta_3 X_i}} \quad (4)$$

$$\pi_{i2} = \frac{e^{\alpha_2 + \beta_2 X_i}}{1 + e^{\alpha_2 + \beta_2 X_i} + e^{\alpha_3 + \beta_3 X_i}} \quad (5)$$

$$\pi_{i3} = \frac{e^{\alpha_3 + \beta_3 X_i}}{1 + e^{\alpha_2 + \beta_2 X_i} + e^{\alpha_3 + \beta_3 X_i}} \quad (6)$$

These are often referred to as the odds ratio in favor of one outcome as opposed to the other. To put these in perspective, for the present paper, occupation in the farm sector denoted by Sector=1 has been taken as the reference or base category. The Wald and likelihood ratio tests confirms the validity of the model for the categories Sector=2 and Sector=3 in a combined manner. The empirical results follow.

4. The Empirical Results

The result obtained from the multinomial logistic regression model is represented with the help of Table (4). It shows the estimated coefficients, the standard error, and the measure of goodness of fit of the model. The model is significant at a level of 1% as given by the likelihood ratio test.

Explanatory Variables	Non-Farm Sector = 2	Diversification = 3	
	Coefficients	Coefficients	
	(Col-1)	(Col-2)	
Farm Sector Income	0000173**	-7.21e-06**	
Mean Difference	(1.63e-06)	(8.07e-07)	
Non-Farm sector Income	.0000604**	.000019**	
Mean Difference	(3.36e-06)	(2.09e-06)	
Diversification Income	0000243**	7.05e-06**	
Mean Difference	(3.22e-06)	(8.08e-07)	
Govt. Benefit Income	.000016*	.0000334*	
	(.0000157)	(.0000178)	
Land Holding Size	3163152**	0274871**	
	(.0261794)	(.0054493)	
Total Livestock	0791282**	.008785**	
	(.0078645)	(.001796)	
Education Literacy	.5744327**	.375394**	
Education Literacy	(.0223417)	(.025892)	
		· · ·	
Vocational Training	.4301389**	.0024706**	
	(.0552472)	(.0613186)	
Highest Degree	.2206986**	.2418621**	
	(.0274557)	(.028423)	
Intercept	4671651**	-1.440547**	
	(.0529145)	(.041135)	

Table 3: Results of Multinomial Logistic Regression

Source: Authors' Estimation from IHDS Data. Note: Number of observation = 148,910. Wald chi2(18) = 3086.62Prob> chi2 = 0.0000. Log pseudolikelihood = -5.990e+08 Pseudo R2 = 0.2070 Table (4) shows the impact of the independent variables in influencing the participation of individuals in one occupation category as opposed to the other, the categories being farm, non-farm, and diversification (which is a combination of both farm and non-farm). It is evident from the table that the mean difference in earnings from the farm sector; the mean difference in earnings from the non-farm sector; the mean difference in earnings from diversification between farm and non-farm; land size owned by the individual; livestock owned by the individual; literacy level of the individual; whether the individual attended college or vocational training; and the highest educational qualification; all significantly influence the decision to choose non-farm sector in terms of occupation in the face of the choice to opt for the farm sector.

Note that, we have also included a standard determinant of labor supply and occupation choice in the empirical specification, namely, public income transfers, because non-income support usually affects individual decision significantly in this regard. However, we find that the transfers from various government benefit schemes such as Annapurna, old-age pension, maternity benefits, etc. is relatively less significant in influencing the decision of the individual to participate in the non-farm sector. The results for these explanatory variables have been clearly indicated in column (1) of the table.

For further detail, we find that the effect of the mean difference in earnings from the farm sector is negative, implying that greater is the value of the explanatory variable in question lesser is the likelihood that the individual will opt for the non-farm sector. In other words, higher is the mean difference in income from the farm sector, quite naturally, greater is the chance of the individual to venture into the farm sector. Mean difference of earnings partly explain the variances or fluctuations in income and a positive fluctuation usually promotes higher participation. Generally, a higher mean income and a high variance reflect some degree of risk taking ability on the part of the individual. A negative likelihood ratio for the mean difference in earnings from diversification is indicative of the fact that greater the variation in earnings from diversification, less likely it is for the individual to opt for the non-farm sector. We also find that greater is the size of the landholding as 'owned' by the individual, less likely it is for the person to pursue occupation in the non-farm sector as opposed to the farm sector. This can be explained with the help of the fact that if the area of cultivable land owned by the individual is larger, she will prefer to practice cultivation on a higher scale. A negative coefficient for total livestock actually influences individuals to choose the diversification mode significantly and avoid being on the non-farm sector exclusively. It is also indicative of some degree of complementarity, wherein, livestock being crucial for farming a greater stock can fetch higher income from the farm sector as well. However, the effects of literacy, attending college or vocational training, and the educational qualification of the individual are positive in influencing the decision of the individual to choose non-farm sector over farm sector, significantly. While we do not have the scope to explore this presently, but in general the intergenerational mobility of occupation (see Nandi and Kar, 2015 viz.) away from traditional farming associate strongly with social stigma with certain occupations, lack of dignity of labor in Indian societies, etc. A positive likelihood ratio indicates that if the individual is literate, and he or she has a higher educational qualification having attended college or vocational training, then it is more likely that the individual will prefer to seek occupation in the non-farm sector as opposed to venturing in the farm sector. Higher education has always been linked to occupations other than those involving agricultural activities, especially in the absence of land holdings and other assets. Evidences

clearly and significantly indicate that secondary schooling or beyond are more likely to push individuals into non-agricultural activities as the present results confirm.

In Column (3) of table 4 we show how each of these elements affect the decision to choose a diversified portfolio as compared to farming as the benchmark choice. In each case the coefficients are statistically significant with expected signs to help us argue that shifting to a mixed portfolio is associated with diversifying risk as well. This is common for most applications of choice under uncertainty. Note that, all farm and non-farm activities are exposed to uncertain turn of events owing to natural shocks and therefore, the income determination process engages with risk taking ability of individuals. While we do not measure risk explicitly, the choice of occupation acts as a proxy.

5. Concluding Remarks

According to the Census of India, 2011, 69% of the population continues to live in the rural areas of the country and depend largely on agricultural and non-agricultural sources of income. Despite significant growth in the process of urbanization in the country, dependence on rural activities is still significant and approximately 42.7% of the workforce earns their livelihood from farm and non-farm activities as the primary source. However, within the agricultural sector, broadly defined, there is substantial lack of mobility between alternative occupations. In earlier attempts it has been shown that individuals (men) who leave rural residence for shorter stays as migrant in urban areas and work in non-agricultural sectors often choose to engage with non-farm activities on return. Otherwise, the rigidity of occupational choice is quite strong among most individuals. Yet, as per the development policies adopted by the country, it is often the case that incentives are offered to diversify between sub-sectors in the

rural area mainly in order to cope with income shocks. It is well known that dependence on the vagaries of nature and unanticipated shocks in demand both contribute to significant income variances for those associated with agricultural activities. The public policies are often directed towards allowing individuals to choose animal husbandry as a major alternative to farming activities, but there are many more such activities within the larger ambit of the unorganized sector. We will discuss the possibilities available from such options briefly, before we conclude, essentially as a future direction the present evidence may take in view of more detailed classification of non-farm activities in the rural areas.

As discussed before, primarily four basic factors are deemed as rather influential in determining occupational choices, namely, risk and uncertainty, financial constraint and wealth endowment, human capital of individuals, and certain demographic and socio-economic factors. As a reminder, the agricultural income (GDP at factor cost) consists of income from crop output (field and plantation crops), livestock, fisheries and forestry. The growth of agricultural income during the '90s was not only satisfactory and significant; it was even marginally higher than the corresponding rate of growth in the '80s. The income trend for allied activities was encouraging. In case of livestock, although the income growth is the highest among all allied activities, the growth rate in the '90s declined over the previous decade. Since the 1980s, livestock has been growing at a rate of more than 4 per cent. As a result of high growth the livestock output is now more than one-fourth of the agricultural (crop and plantation) output; the corresponding figure in the year 1980-81 was less than one-seventh. Livestock sector grew at an annual rate of 5.3% during 1980s, 3.9% during 1990s and 3.6% during 2000s. Despite deceleration, growth in livestock sector remained about 1.5 times larger than in the crop sector which implies its critical role in cushioning agricultural growth.

However, even conservative estimates show that in order to accommodate the entry into the labor force while transiting into a demographically young society, the growth of agricultural production has to be multiple times what it is now, lack of which suggesting that diversification into other activities is unavoidable. The present paper was an attempt to investigate the influence of factors that would drive this outcome. We do find results largely in conformity with what one would expect in terms of the probability to switch sectors completely or at least diversify. However, we are also mindful of the concern that we do not engage with some other variables that could also add to the explanatory power of our specification and therefore, might be suffering from omitted variables bias to some extent. We hope to include a bigger set of variables in future, while also adding newer information at the individual level.

References

Alston J and Pardey, P (2014). Agriculture in the Global Economy. *Journal of Economic Perspectives*, 28(1),121-146 pp.

Benjamin, C., (1994). The Growing Importance of Diversification Activities for French Farm Households, *Journal of Rural Studies*, 10, 4, pp. 331-42.

Deichmann, U, F. Shilpi and R. Vakis (2009). Urban Proximity, Agricultural Potential and Rural Non-farm Employment: Evidence from Bangladesh, *World Development*, 37(3), pp. 645-660.

Dercon, S. (1996). Risk, Crop Choice and Savings: Evidence from Tanzania. *Economic Development and Cultural Change*, 44(3), pp. 485-513.

Ellis, F. (1998). Household strategies and rural livelihoodDiversification, The Journal of Development Studies, 35:1, 1-38.

Gupta, D. (2005). Whither the Indian Village: Culture and Agriculture in 'Rural' India, *Economic and Political Weekly*, Vol. 40, No. 8 (Feb. 19-25, 2005), pp. 751-758.

Hazell, P. B.R., Haggblade, S and Reardon, S (2007). Structural Transformation of the Rural Non-farm Economy, in S. Haggblade, P.B.R. Hazell, and T. Reardon, eds., *Transforming the Rural Non-farm Economy* (Baltimore: Johns Hopkins University Press).

Hazell, P. B.R., Haggblade, S and Reardon, T (2010). The Rural Non-farm Economy: Prospects for Growth and Poverty Reduction. *World Development*. 38(10), pp. 1429-1441.

Hearn, D, K. McNamara and L. Gunter (1996), Local Economic Structure and Off-Farm Labour Earnings of Farm Operators and Spouses, *Journal of Agricultural Economics*, 47, 1, pp. 28-36.

Imai, K, R. Gaiha and G. Thapa (2015), Does non-farm sector employment reduce rural poverty and vulnerability? Evidence from Vietnam and India, *Journal of Asian Economics*, 36(C), pp. 47-61.

Janvry, A and Sadoulet, E (2001). Income Strategies Among Rural Households in Mexico: The Role of Off-farm Activities. *World Development*, 29 (3), pp. 467-480.

Kelly, C. and B. W. Ilbery, (1995), Defining and Examining Rural Diversification: A Framework for Analysis, *Tijdschriftvoor Economische en Sociale Geografie*, 85, 2, pp.177-85.

Lanjow, J and P. Lanjow (2001). The rural non-farm sector: issues and evidence from developing countries, *Agricultural Economics*, 26, pp.1–23.

Lobao, L., and K. Meyer (2001). The Great Agricultural Transformation: Crisis, Change, and Social Consequences of Twentieth Century US Farming, *Annual Review of Sociology*, 27: pp. 103–24.

Mishra, A., Morehart, M., El-Osta, H. S., Johnson, J. D., & Hopkins, J. W. (2002). Income, wealth, and well-being of farm operator households. *Agricultural Economics Report* No. 812, Economic Research Service, U.S. Department of Agriculture, Washington, DC.

Mishra, A.K. and H. El-Osta (2008). Effect of agricultural policy on succession decisions of farm households, *Review of Econ Household* (2008) 6:285–307.

Mujumdar, N (2002). 'Rural Development: New Perspectives', *Economic and Political Weekly*, Vol 37, pp 3983-87.

Nandi, T and S. Kar (2015), Short-term Migration and Inter-generational persistence of Industry in India, *IZA Discussion Paper # 9283*. IZA, Bonn.

Reardon, T., C. Delgado, and P. Matlon (1992). Determinants and effects of income diversification amongst farm households in Burkina Faso. *The Journal of Development Studies*, 28 (2).

Reardon, T., J. Taylor, K. Stamoulis, P. Lanjouw, and A. Balisacan (2000). Effects of Non-Farm Employment on Rural Income Inequality in Developing Countries: An Investment Perspective, *Journal ofAgricultural Economics*, 51, 2, pp. 266-288.

Reardon, T., Berdegue, J., Escobar, G. (2001). Rural Nonfarm Employment and Incomes in Latin America: Overview and Policy Implications. *World Development*, 29 (3), pp. 395-409.

Starkweather, J. & Moske, A. K. (2011). Multinomial LogisticRegression. Retrieved from http://www.unt.edu/rss/class/Jon/Benchmarks/MLR_JDS_Aug2011.pdf.

World Bank (2017), Annual Report: 2017. Washington DC. The World Bank.

World Bank (2012), Annual Report: 2012. Washington DC. The World Bank.

Appendix1:

Variables	Mean	Std. Dev	Min	Max
Farm Income (inRs.)	30029.1	113411.5	-909625	1.10e+07
Non-Farm Income (in Rs.)	18713.86	68059.94	-106000	6190000
Diversification Income (in Rs.)	14971.83	88832.4	-869825	1.12e+07
Government Transfers (in Rs.)	91.2235	699.6431	0	40000
Land Holding (in ha)	2.302094	5.99751	-56	400
Total Livestock	3.147994	6.181872	-2	301
Education (Literacy)	0.654543	0.4755186	0	1
Education (College/VocTraining)	0.0856316	.3113461	0	2
Education (Highest Degree)	0.135829	0.6557591	0	9

Table 4: Description of independent explanatory variables

Authors' Estimation with IHDS Data.