

# **Rural Non-Farm Employment Diversification in India: Determinants and Effect on Wages and Household Consumer Expenditure**

A thesis submitted to Indian Institute of Technology Guwahati in partial  
fulfilment of the requirements for the degree of  
Doctor of Philosophy.



By

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Guwahati- 781039

India

September 2023



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*Dedicated to*

My Parents and Sister

# Indian Institute of Technology Guwahati

Department of Humanities and Social Sciences

Guwahati- 781039, Assam, India



## Declaration

I hereby declare that the thesis entitled “Rural Non-Farm Employment Diversification in India: Determinants and Effect on Wages and Household Consumer Expenditure”, is my original research work carried out by me in the Department of Humanities and Social Sciences, Indian Institute of Technology Guwahati, India, under the supervision of Dr. Amarjyoti Mahanta, Assistant Professor (Economics), Department of Humanities and Social Sciences, Indian Institute of Technology Guwahati.

In keeping with the general practice of reporting observations, due acknowledgement has been made wherever the work described is based on the findings of other investigations.

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## **Certificate**

This is to certify that the thesis entitled “Rural Non-Farm Employment Diversification in India: Determinants and Effect on Wages and Household Consumer Expenditure”, submitted by Ms. Kashmiri Das for the degree of Doctor of Philosophy in Economics in the Department of Humanities and Social Sciences, Indian Institute of Technology Guwahati, embodies bonafide record of research work carried out under my supervision and guidance. The collection of data from secondary sources has been done by Ms. Kashmiri herself. All assistance received has been duly acknowledged.

The present thesis or any part thereof has not been submitted to any other University for the award of any degree or diploma.

(Dr. Amarjyoti Mahanta)

Supervisor

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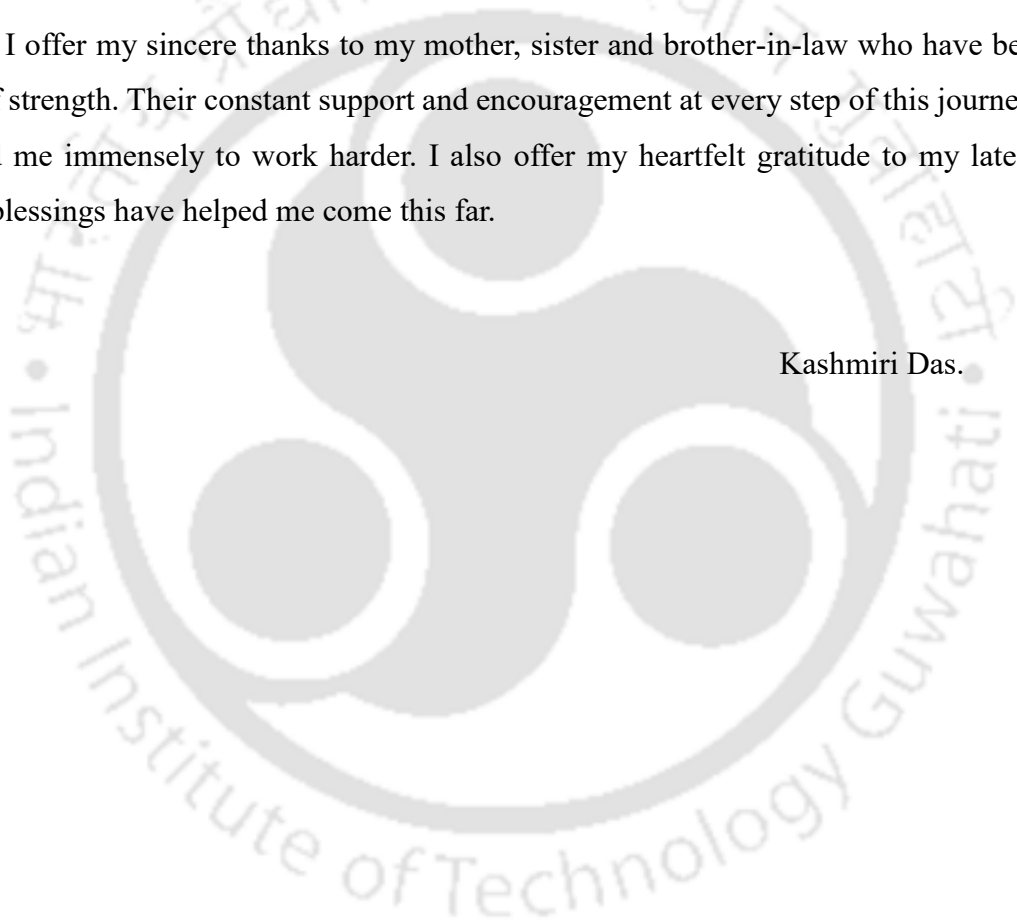
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Kashmiri Das.



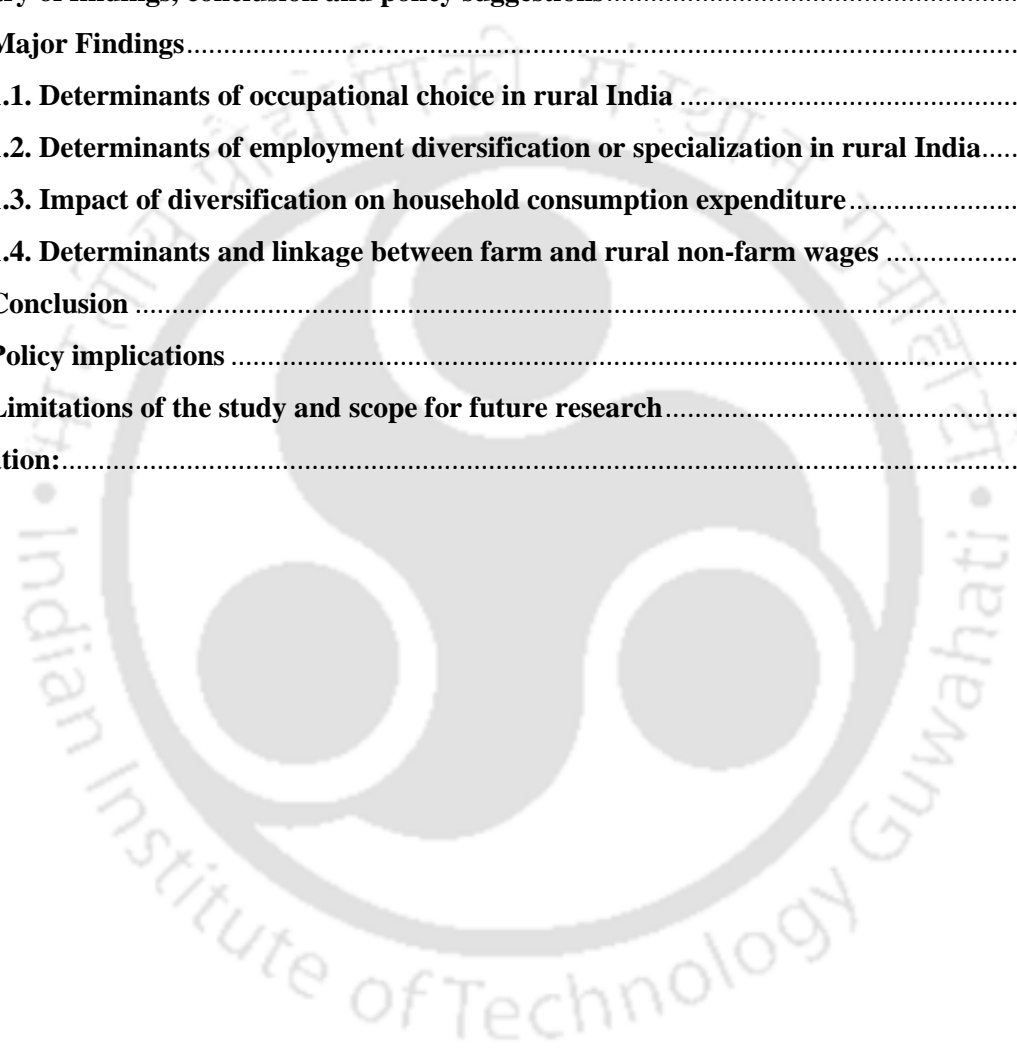


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## Abbreviation

ATE	: Average Treatment Effect
ATT	: Average Treatment Effect on the Treated
ATU	: Average Treatment Effect on the Untreated
CIA	: Conditional Independence Assumption
CPI	: Consumers Price Index
DID	: Differences in Difference
EUS	: Employment and Unemployment Survey
GDP	: Gross Domestic Product
GHS	: Ghanaian Sedi
GOI	: Government of India
GSDP	: Gross State Domestic Product
IHDS	: India Human Development Survey
IMD	: India Meteorological Department
IIA	: Independence of Irrelevant Alternatives
LUS	: Land Use Statistics
MGNREGA	: Mahatma Gandhi National Rural Employment Guarantee Act
MRM	: Multinomial Regression Model
NCAER	: National Council of Applied Economic Research
NIC	: National Industrial Classification
NSSO	: National Sample Survey Organization
OBC	: Other Backward Classes
OLS	: Ordinary Least Squares
PLFS	: Periodic Labour Force Survey
PMGSY	: Pradhan Mantri Gram Sadak Yojana
PSM	: Propensity Score Matching
PS	: Principal Status
RNFS	: Rural Non-Farm Sector
SC	: Schedule Caste
SD	: Standard Deviation
SDG	: Sustainable Development Goal
SE	: Standard Error

SID	: Simpson Index of Diversification
SLF	: Sustainable Livelihood Framework
SS	: Subsidiary Status
ST	: Schedule Tribe
UPSS	: Usual Principal and Subsidiary Status
US	: United States



## Abstract

Mounting evidence on rural livelihoods point towards a gradual transition of households from agriculture to rural non-farm sector (hereafter RNFS) with employment in the former sector now has become rarely a sufficient means of living (Barrett, Reardon and Webb, 2001; Ellis, 1998; Haggblade, Hazell and Reardon, 2010; Lanjouw and Shariff, 2004; Lanjouw and Lanjouw, 2001; Nakajima, Otsuka and Yamano, 2018). Although the RNFS was envisioned to wither away with economic growth, this residual sector, in turn, has transformed into an important livelihood strategy with its substantial contribution to employment and income. Its share of employment ranges from 32 per cent in Asia, 40 per cent in Latin America and 42 per cent in Africa (Reardon, 1997) and share of income accounts for 35 to 50 per cent (Haggblade *et al*, 2010).

In case of India, the importance of RNFS as a source of livelihood gained momentum due to continuous fall in farm productivity, increased marginalization of land holding and a stunted nature of structural transformation, resulting in a lower labor absorption capacity by both agriculture as well as urban industrial and services sector (Binswanger-Mkhize, 2013). Poverty and unemployment are, thus more widespread in rural compared to urban India (Nakajima *et al*, 2018). But unlike agriculture, the RNFS is characterized by heterogeneity with high paying formal sector jobs in modern enterprises on one hand, and availability of low paying menial jobs on the other hand (Start, 2001). As such, various demographic, household and locational factors affect an individual's probability of joining a particular non-farm occupation. This heterogeneity which remained undermined in existing literatures, is addressed in our study as ignoring this aspect may mask many differences that exists between them (Lanjouw & Lanjouw, 2001; Fisher *et al*, 1997; Unni, 1998).

Again, this diversified livelihood strategy adopted by rural households, particularly farm households are not only for employment purpose but also to benefit out of this process. These benefits accrue in terms of increased consumption expenditure and dietary diversity, reduction in poverty and vulnerability and utilization of non-farm income for farm investments. Although rural farm households benefit from diversification as established in existing literatures, yet these benefits might vary between cultivator and casual farm households as cultivators, being the food producers are more food secure and economically well off compared to casual farm households (Dzanku, 2018; Chandrasekhar, Dev & Pandey, 2014; Rahman & Mishra, 2020). Hence, we address this aspect of diversification in our thesis where benefits of diversification in terms of magnitude and share of food and non-food consumption expenditure are estimated

separately for cultivator and casual farm households. Implications of diversification by non-farm households towards agriculture are also analyzed to shed light on whether non-farm sector is still used as a supplementary occupation or can be pursued as the major income source.

Again, the welfare of rural workers also depends on the prevailing wage rates where wages can be broadly categorized into farm and non-farm wages. As movement of labor from one sector to the other occurs, there may be linkages between farm and non-farm wages which is studied here. Moreover, not only 70 million rural workers constitute wage workers but it also represents the low economic status of those involved. Particularly farm wage workers constitute the most marginalized group (Himanshu & Kundu, 2016; Himanshu, 2018) and any upward movement of wages due to diversification would contribute significantly to poverty reduction and economic upliftment. Although studies have examined the demand and supply framework of farm wage rate determination together with the impact of other growth factors, the role of non-farm wages in influencing farm wages have remained unexplored. Hence, our thesis attempts to study the determinants and linkage between rural farm and non-farm wages to analyze the responsiveness of a change in wage rates in one market on the other.

Hence, the broad objectives of this thesis include the determinants of rural non-farm employment diversification, welfare implication of diversification on rural households and the determinants and linkage between rural farm and non-farm wages. To fulfil these objectives, national level secondary data on employment and unemployment of NSSO is utilised for three time periods that includes 61<sup>st</sup> (2004–05), 66<sup>th</sup> (2009–10) and 68<sup>th</sup> (2011–12) round. Non-availability of recent employment data by NSSO resulted in restriction of data use till 2011–12. Although Periodic Labour Force Survey (PLFS) data are available, yet they lack information on some crucial variables such as the principal activity and occupation of the household, information on land and a lack of detailed information on the household's spending on various food and non-food items (Jajoria & Jatav, 2020) which practically limits its use for our thesis.

We applied a multinomial logistic regression model to estimate the determinants of non-farm employment choice compared to agriculture activities where heterogeneity of RNFS is addressed through proper segregation of this sector into various sub-categories. We broadly consider the effect of individual, household and locational factors on diversification probabilities with emphasis on the role of education, caste and land ownership on employment diversification across gender. Our findings demonstrate a positive impact of education and

vocational training on employment in manufacturing, trade and service activities while having an adverse impact on construction employment. We also observe that education enabled rural females to diversify towards manufacturing and construction sector employment and their probability to join trade and service activities further increases if they belong to land owning households. Non-farm employment is also preferred by low caste ST, SC and OBC workers who are not only deprived of physical endowments but also lack adequate human capital. On the other hand, land owning households are less likely to diversify and more likely to engage in cultivation. Also, we found that the tendency to join non-farm activities rises with an increase in dependency ratio while it falls with a rise in household size. This might reflect a distress induced process where diversification is adopted as a survival strategy. Ebaidalla (2022) also observed that households with more dependents diversify to non-farm activities in rural Sudan to meet the household income requirements.

Again, diversification also refers to a situation where individuals combine more than one economic activity and to examine this aspect of diversification separately for rural farm and non-farm workers, we applied a binary logit regression model and pooled the data for all the three time periods. We also focused on the direction of diversification where diversification from farm to non-farm occurs when farm workers whose principal occupation is in agriculture also engage in non-farm activities as a subsidiary worker. Similarly, non-farm workers are regarded as diversified when they also supply labor in farm activities. Workers who engage in only one activity form the non-diversified group. Here, we try to analyze the nature and characteristics of workers who diversify from farm to non-farm and those who diversify from non-farm to farm. The results show that older people are less likely to combine multiple economic activities whether they are farm workers or non-farm workers. Specialization in either activity is also preferred by educated individuals who can earn high returns through utilisation of their skills. Our findings demonstrate the significance of non-farm employment for low caste workers who not only specialise in non-farm activities but also diversify to non-farm activities even if their principal occupation is in agriculture. We further found that diversification strategy varies between males and females. While diversification from farm to non-farm employment has increased for rural female workers, males are more likely to diversify from non-farm to farm. Inheritance of land mostly by male members might increase their chance of working on the field. Diversification is also more likely to happen in regions where unemployment rate is high signifying that workers try to engage in work other than their principal occupation when there is an overall fall in income levels. Therefore, we observe that

workers combine multiple activities only as a response to cope with push factors like high dependency ratio and high unemployment rate.

Furthermore, for analysing the well-being of diversified rural households, we applied Propensity Score Matching (PSM) method. We observe that both rural farm and non-farm households are in a better position in terms of higher spending on food and non-food items due to diversification. For instance, diversified casual farm households could spend rupees 276 and rupees 593 more on food and non-food during 2011–12. However, benefits differ for cultivator and casual farm households when they completely shift towards non-farm employment. A complete shift of cultivator households to non-farm self-employment lowers their spending on food and non-food while for casual farm households, switching to casual non-farm activities resulted in a gain in their consumption expenditure. The findings demonstrate the low economic status of casual farm households which can be improved either through combining farm with non-farm activities or by shifting completely to casual non-farm employment. Similarly, for casual non-farm households, diversification to farm activities results in greater consumption expenditure but for self-employed non-farm households, diversification significantly enhances the magnitude of food expenditure only, without having any impact on non-food expenditure. Therefore, we say that an overall increase in consumption spending has occurred for self-employed non-farm households because of diversification. In addition to this, diversification also affects the household's pattern of food and non-food spending where cultivator households tend to spend a greater share of income on non-food items like durable goods, education and health and lowers their expenditure share on food. For casual farm and casual non-farm households, diversification significantly reduces their food expenditure share without having any impact on non-food share. Again, for self-employed non-farm households, diversification augments only their food expenditure share while reducing their share of non-food expenditure. Thus, it is observed that occupational diversification can be a welfare enhancing process, particularly for casual households who are at the low level of income strata. However, this livelihood strategy does not have a uniform impact on welfare and depends crucially on the household type and nature of diversification strategy adopted.

Lastly, we estimated the determinants of rural farm and non-farm wages where wage rates are calculated at the state region level of NSSO forming a panel data for three time periods. We applied fixed effects panel model due to absence of any simultaneity issue related to farm and non-farm wage determination. We observe a close association between rural farm and non-farm wages where a rise in wage rate in one market led to an increase in wages in the other

market. We find a direct positive effect of a rise in real non-farm wage on farm wages and a positive impact of farm wage on non-farm wages. For instance, a one-rupee increase in non-farm wage increases wages of casual farm workers by 0.220 rupees. Similarly, increase of farm wage by one rupee increases non-farm wage by 0.243 rupees. This indicates that any rise in non-farm wages acts as a pull factor for daily wage workers in agriculture which results in a shift of workforce from farm to non-farm sector. This shift of workers creates a situation of labor scarcity in agriculture leading to an increase in farm wages as well. Apart from non-farm wages, rural farm wages also respond positively to a rise in irrigation intensity and share of farm wage workers. We also observe an increasing trend in the movement of both farm and non-farm wages over time but since the magnitude of a rise in non-farm wage is higher than that of farm, therefore, we do not observe any convergence of farm and non-farm wages for these time periods.

Based on the above findings, the study suggests that employment in remunerative non-farm jobs not only requires adequate human capital but also availability of jobs as well. Since education also favor rural females to engage in work outside agriculture, therefore, policies should focus on easy accessibility of formal and vocational training facilities. Skill training programs would particularly benefit women to compete for non-farm jobs. Also, expansion of infrastructure facilities like all-weather roads, electricity, and telecommunications and even a well-functioning financial market would better serve the diverse employment requirements of the people. We also observe a positive linkage between rural farm and non-farm sectors not only through its favourable effect on household consumption expenditure but also through wages. As such policies should focus on strengthening the growth linkage between these two sectors. Investments in agricultural technology, transport and communication and electrification would encourage development of non-farm businesses as well.

## Chapter 1

### Introduction

#### 1.1. Background of the study

Till the 1960s and 1970s, agriculture predominated as the major source of income and employment in most of the emerging economies. But development theorists envisioned that with economic growth and development, the process of structural transformation would shift the growth trajectory from agriculture to the industrial sector which would later be led by the services sector (Binswanger-Mkhize, 2013; Panda, 2017). As a result of structural transformation, the surplus labor force from the traditional sector could be easily absorbed by the modern industrial sector due to its increased productivity. Such a pattern of structural transformation can be observed in almost all countries at varying degrees. For instance, in case of China, the manufacturing sector is the dominant sector both in terms of employment generation and its share in GDP. Employment in the manufacturing sector increased from 17 million to over 60 million from 1977-78 to 1999-00 after attaining self-sufficiency in agriculture (Mukherjee and Zhang, 2006). Its share of GDP is also substantial at 33%. On the contrary, studies have also pointed out issues of urban unemployment, growth of urban informal jobs with no job security and urban congestion because of the migration of workers from rural to urban manufacturing and services sector in search of a better livelihood (Jatav & Sen, 2013; Panda, 2017). Hence, nations have now prioritized generation of employment opportunities within the rural periphery and their focus has shifted from agriculture to the rural non-farm sector (hereafter RNFS).

Unlike China and other nations where structural transformation became successful, India witnessed not only issues related to migration in urban regions, but the structural transformation is itself atypical or stunted in nature where economic growth is mainly driven by the services sector without having any significant role of manufacturing sector in the growth process (Binswanger-Mkhize, 2013). Although the services sector accrues higher returns, it is not a labour-intensive sector and the rate of employment generation is very low. On the contrary, performance of the manufacturing sector was disappointing both in terms of growth and generation of adequate employment opportunities (Binswanger-Mkhize, 2013). The share of workers in the manufacturing sector increased from 14 million to only 22 million from 1977-78 to 1999-00 (Mukherjee and Zhang, 2006). The share of manufacturing to GDP is only 16% while it is 50% for services. Moreover, a limited number of urban sector jobs with social

security benefits discourages unskilled and semi-skilled workers including women from migrating to urban regions (Binswanger-Mkhize, 2013). This led to a situation of stunted structural transformation where rural labor force has started shifting from agriculture to the RNFS instead of migrating to high productivity sectors in urban regions. No doubt agriculture still employs more than half of the rural population in India but its falling productivity over time makes it an unviable source of livelihood in the long run. The share of agricultural sector in terms of both employment and GDP has declined to 50% and 14% respectively in 2011-12 (Rangarajan, Seema & Vibeesh, 2014). Increased marginalization of land holding and population pressure on limited land have contributed to falling farm productivity. Marginal land holdings have increased from 39% in 1960–61 to 70% in 2002–03 (Kashyap & Mehta, 2007). Therefore, the expansion of the rural non-farm sector (RNFS) has been prioritized by many developing nations due to its various welfare implications (Jatav & Sen, 2013). Some of these benefits include increased participation of the rural labor force especially women, prevention of exploitation of urban resources due to persistent migration and reduction in livelihood vulnerability of migrant workers in urban regions (Ranjan, 2006; Jatav & Sen, 2013; Chand, Srivastava & Singh, 2017).

The RNFS is defined as constituting all economic activities undertaken in a designated rural region except agriculture, livestock, fishing and hunting (Lanjouw & Lanjouw, 2001; Panda, 2017). It, therefore incorporates activities like manufacturing, mining and quarrying, electricity, gas and water supply, construction, trade, hotel and restaurant, transport and communication and services. Agro-processing which includes milling, storage, packaging and transportation of agricultural products forms an important component of rural non-agricultural activities. The small-scale and labour-intensive nature of activities in this sector facilitates many unskilled or semi-skilled workers to get employment. Even female workers are highly represented in household cottage industries where they can manage their household work as well (Lanjouw & Lanjouw, 2001). A study undertaken by Hossain in 1979-80 in 11 villages in rural Bangladesh found that women mainly dominated activities like rice husking, mat making, coir products and net making (Lanjouw & Lanjouw, 2001).

Although the RNFS was envisioned to wither away with economic growth, this residual sector, in turn, has transformed into an important livelihood strategy with its substantial contribution to employment and income. The share of RNFS employment is 32 percent in Asia, 40 percent in Latin America and 42 percent in Africa (Reardon, 1997) and accounts for 35 to 50 percent of rural household income (Haggblade, Hazell & Reardon, 2010). In case of India, the growth

of RNFS has been increasing at a substantial rate, particularly after the reforms period (Jatav & Sen, 2013). Share of non-farm employment increased by 13.7% between 1993–94 and 2004–05 (Jatav & Sen, 2013). Also, the willingness of the rural population to settle in rural areas has put burden on the RNFS as rural economy has become more non-agricultural than ever before (Chand et al, 2017). Now, rural households can no longer be identified with a single economic activity as they have either started shifting from farm to non-farm activities or have combined more than one economic activity (Dercon & Krishnan, 1996; Start, 2001). This process is widely referred to as rural occupational diversification. As Reardon (1997) points out, rural households now allocate labor to agricultural activities, rural non-agricultural activities or migration activities either to smooth out income levels under conditions of low agricultural productivity, drought or to finance agricultural and other credit requirement activities.

Expansion of RNFS employment is particularly pressing for India where continuous fall in farm productivity, increased marginalization of land holding and the stunted nature of structural transformation has resulted in a decline in labor force absorption capacity by both agriculture and urban manufacturing and services sector (Binswanger-Mkhize, 2013). Poverty and unemployment are, therefore, widespread in rural compared to urban India (Nakajima et al, 2018). As per Tendulkar Committee Report (2009), 41.8 percent of all rural households are poor compared to 25.7 percent in urban India (Ravi & Engler, 2015). Employment generation within the RNFS can not only provide subsistence living to rural households but also act as a vehicle to enhance rural livelihood by reducing rural-urban migration, poverty and food insecurity (Jatav & Sen, 2013; Haggblade et al, 2010). In India, a growing share of RNFS in employment and output has been observed since the mid-1970s (Kumar, Kumar & Singh, 2011). This trend became more prominent after the reforms period when 6 out of every 10 jobs were generated in the RNFS between 1993–94 and 2004–05 and between 2004–05 to 2009–10, about 13 million jobs were generated by the rural non-farm sector (Kumar et al, 2011).

Even though the RNFS is beneficial for rural livelihoods, unlike agriculture, this sector is characterized by heterogeneity in the form of entry barriers, returns to labor and nature of work where some activities are highly lucrative consisting of jobs in formal sector and modern enterprises while menial low-return activities persist at the bottom of it (Start, 2001). As such, entry into this sector is restricted by the presence of several constraints which are broadly classified in the literature as "pull" and "push" factors (Drall & Mandal, 2020; Haggblade et al, 2010; Jatav & Sen, 2013; Aloba Loison, 2015; Nakajima et al, 2018; Panda, 2017; Ranjan, 2009; Unni, 1996). Under a dynamic agricultural situation, favorable production and

consumption linkages expand the growth of lucrative non-farm jobs which acts as a pull factor for diversification. The RNFS also expands because of urbanization, developed transport and communication facilities and well-functioning financial and credit markets. The other side of the picture depicts diversification as a survival strategy undertaken to maintain a subsistence level of living, particularly in regions with stagnant and underdeveloped agricultural sector. Population pressure on limited land holding, uncertain climatic conditions, absence of proper markets are other push factors of diversification. Extant literature points towards the existence of various determinants in the form of demographic, household and locational factors that determine the choice of rural non-farm employment.

Again, rural India suffers from widespread poverty where 80% of the country's poor reside here (Carpena, 2019). Also, 50% of the population is still engaged in agriculture and allied activities which contributes only 14% to the country's GDP (Rangarajan et al, 2014). Despite economic growth, the pace of poverty reduction and improvement in nutritional aspect is slow in India compared to other Asian countries like Vietnam (Karan & Selvaraj, 2008; Imai et al, 2015). Given the small-holding nature of agriculture and increased marginalization of land holdings, this sector cannot be expected to augment household welfare in the long run (Rahman & Mishra, 2020). Although India is self-sufficient in food production, horticultural crops and dairy products and the largest exporter of cotton and rice, yet at the micro level, the country suffers from issues of food insecurity (Dsouza, Mishra & Sonoda, 2020). Also, a gradual fall in the share of cultivators and a rise in agricultural labourers has made the farming community more food insecure (Rahman & Mishra, 2020). As such, one of the solutions lies in the generation of adequate in-situ rural non-farm employment opportunities whose share in rural income has increased from 35 percent to 62 percent between 1980–81 to 2004–05 (GOI, 2010). Diversification also results in the stability of household income (Rahman & Mishra, 2020).

Therefore, the focus has been placed by extant studies on the role of rural non-farm employment in promoting household well-being where well-being is measured in terms of increased consumption expenditure, income level, dietary diversity, and a reduction in poverty, food insecurity and vulnerability. Even though rural individuals also migrate to urban areas, yet it only signifies displacement of poverty rather than reduction of poverty (Janvry, Sadoulet & Zhu, 2005). Due to a lack of employment in the organised sector, these migrants involve in unproductive activities where returns are lower compared to non-migrant households (Chandrasekhar, Das & Sharma, 2015).

Further, we observe that wages form an important indicator of the economic well-being of rural workers where wages can be earned from either agriculture or the RNFS. Except for highly lucrative non-farm jobs, rural wage workers shift from farm to non-farm sector in expectation of receiving higher returns or when the market wage rate is higher than their reservation wage. Focusing on this particular section of wage workers is important as majority of the workforce in India is dependent on wage employment. Out of a total of 172 million rural labor households, 70 million of them are primarily engaged in wage labor (Jose, 2013). Wages, particularly farm wages are considered a proxy for the poverty status of rural households as it represents the lowest level of earnings at which workers are willing to supply their labor (Himanshu & Kundu, 2016; Himanshu, 2018). Wages form an important source of livelihood and a useful policy instrument for poverty alleviation (Acharya, 2017). Therefore, a rise in the real wage rate could significantly enhance the financial status of wage workers which can occur when labourers move from one sector to the other, especially from agriculture to the RNFS resulting in a tightening of the rural labor market. Several studies observed a continuous rise in rural farm wages or a fall in the incidence of poverty (since farm wage is used as a proxy for poverty) between 1999–00 and 2004–05 which was a period of agrarian distress (Himanshu & Kundu, 2016). Incidence of poverty continued to fall after 2004–05 when there was an expansion in construction sector employment, expansion of employment in the non-farm sector and a revival in the agrarian economy (Lanjouw & Murgai, 2009, Himanshu & Kundu, 2016; Himanshu, 2018).

Therefore, some studies point out that this increase in agricultural wages is possible due to the expansion of employment opportunities in the non-agricultural sector particularly after 2004–05 when MGNREGA was implemented. Also, a rise in farm wages at the rate of 12% per annum since 2007–08 (Himanshu & Kundu, 2016) might have played an important role in this respect. However, some studies have placed more emphasis on the role of growth-driven factors like agriculture GDP, construction GDP in augmenting wages rather than solely on MGNREGA (Eswaran, Kotwal, Ramaswami & Wadhwa, 2009; Gulati, Jain & Satija, 2014). Again, Bhalla (1993) pointed out the role of both agricultural productivity and an expansion in non-farm employment as important factors of rural wage growth.

## **1.2. Statement of the problem**

The gradual shift of rural livelihoods from agriculture to the RNFS witnessed in many developing nations is not a transient phenomenon. Rural households have been found to highly

benefit from this diversification process and in India, expansion of this sector became prominent after the reforms period. But unlike agriculture, the RNFS is a heterogeneous sector that comprises both high-return and low-return non-farm activities. The heterogeneous nature of this sector implies the presence of entry barriers and as such an individual's preference for a particular non-farm activity would depend on his demographic, household and locational factors. This heterogeneity is addressed in our study as ignoring this aspect may mask many differences that exist between them and even cause negligence of its role in economic development (Lanjouw & Lanjouw, 2001). Fisher, Mahajan & Singha (1997) and Unni (1998) also pointed out a lack of proper emphasis on this heterogeneity in existing literature. The thesis addresses this through a proper segregation of the RNFS into its several sub-sectors. Additionally, our study also adopts a broader definition of diversification where diversification not only indicates a shift from traditional (agriculture) sector to a modern (non-farm) sector but also implies engaging in multiple economic activities. This is necessitated by the fact that although diversification has become the norm, yet few studies also observe that households are in a better position when they specialize in one economic activity either in agriculture or non-agriculture rather than combining multiple activities. Therefore, we also examine the factors that influence farm workers to either specialize in it or combine farming with non-farm activities. In addition, we also analyze the factors which affects non-farm workers to either specialize in non-farm employment or combine non-farm with farm activities. Although non-farm sector is a better livelihood option than agriculture, its heterogeneous character implies that not all activities have a high return and as such it is crucial to understand the characteristics of non-farm workers diversifying to farm activities. The analysis is done for three-periods i.e. 2004–05, 2009–10 and 2011–12 to understand the changing effect of time on these factors.

Again, this process of occupational diversification is beneficial for rural farm households as they are able to increase their income level, reduce poverty, malnutrition and even food insecurity. But within farm households, the economic status of self-employed farm or cultivator households and casual farm households differ as cultivator households being the producer of food are more food secure and have lower incidence of poverty compared to casual farm households (Dzanku, 2018; Chandrasekhar, Dev & Pandey, 2015; Rahman & Mishra, 2020). For instance, poverty is prevalent among agricultural labor households as they represent 41% of the rural poor while for self-employed farm households, the incidence of poverty has reduced from 32% to 21.6% between 1993–94 and 2004–05 (Chandrasekhar et al, 2015). Hence, the motives and implications behind diversification between these two types of farm households

would also vary (Rahman & Mishra, 2020). Therefore, it is important to segregate farm households into cultivator and casual types which remained ignored in the extant studies. In addition, we also examined whether non-farm households are better off or worse off if they diversify to farm activities. This is necessitated by the fact that although farm households are most likely to benefit from diversification, yet opinions differ regarding the non-farm sector's ability to improve the living standards of the rural poor. Some strand of literature (Lanjouw, 2001; Lanjouw & Shariff, 2004; Dey, 2018; Imai et al 2015) supports the notion that non-farm employment can significantly uplift the rural poor while others (Scharf & Rahut, 2014; Dzanku, 2018) point out the lower returns associated with low-quality non-farm jobs indicating its inability to enhance household income. In other words, not all non-farm employment leads to higher household welfare (Scharf & Rahut, 2014; Dzanku, 2018). Therefore, we also investigate the diversification strategies of non-farm households toward farm sector employment, which will shed light on whether this sector can be pursued as the major income source, or it still plays a supplementary role. Furthermore, our outcome variable comprises of household consumption expenditure classified into food and non-food components. This distinction is important as poverty being a multidimensional concept, cannot only be identified in terms of food expenditure as other aspects such as education and health care services, comprising the non-food component, are also significant contributors to labour productivity leading further to increased income and economic growth (Imai et al., 2015; Maity, 2018; Carpena, 2019). The present study, therefore, segregates the household consumption part into its food and non-food components.

Further, we study the linkages between rural farm and non-farm wages of casual workers. This linkage is studied in the form of how responsive wages in one market are when there is a change in the wage rate in the other market. This might occur when labourers move from one sector to the other in anticipation of a better return. As wages of agricultural labourers also reflect the poverty status of households (Himanshu & Kundu, 2016), any rise in farm wages would improve the economic status of this section of workers. Due to the non-inclusive nature of the growth process and falling farm productivity (Chandrasekhar et al, 2015), emphasis is placed on the role of the non-farm sector in augmenting farm wages. Given that non-farm wages are generally higher than farm wages (Himanshu & Kundu, 2016), a rise in the productivity of non-farm workers should attract workers from the primary sector leading to a tightening of the rural labor market and hence augmenting wages of agricultural laborers. But, on the other hand, if non-farm sectors are established in regions having surplus labor, then their wages may fall

to the level of the existing farm wages due to the availability of cheap labor. Therefore, there might exist a close linkage between farm and non-farm wages and understanding the nature of this linkage would reflect the functioning of the rural labor market. The study of this linkage forms one of the objectives of our thesis.

### **1.3. Objectives of the study**

The study has the following three objectives

1. To examine the determinants of occupational choice of individuals in rural India. To analyse the factors affecting diversification or specialization of economic activities in rural India.
2. To examine the effect of diversification on the magnitude and share of food and non-food consumption expenditure between farm and non-farm households.
3. To determine wage rate of agricultural and non-agricultural wage workers and examine whether wages in the two markets are interlinked or not.

### **1.4. Research Questions**

The research questions for the first objective are the following.

- 1) How do the individual, household and locational factors affect the probability of employment in rural non-farm sub-sectors? Does their effect changes over time?
- 2) Can education be an important pull factor of diversification for female workers compared to male workers?
- 3) Do ST, SC and OBC workers diversify more to non-farm employment compared to upper caste workers?
- 4) How do educated male and female workers differ in their choice of employment when they belong to landowning households compared to landless households?
- 5) Is there any difference in the nature of workers who diversify from farm to non-farm sector and those who diversify from non-farm to farm sector?
- 6) What is the role of education and land ownership size in diversification or specialization of economic activities?

The research questions for the second objective are given below

1. Is there any significant difference in the consumption expenditure between diversified farm and non-farm households?
2. Does the allocation of consumption expenditure share by self-employed farm households differ between those who diversify and those who completely shift to non-farm occupations?

3. Can self-employment in agriculture still be considered a better source of household income compared to self-employment in non-farm activities?
4. Do casual households diversify to enhance their food expenditure share compared to non-food expenditure share?
5. Do casual non-farm households enjoy greater household welfare than casual farm households due to diversification in rural India?

The research questions related to the third objective include the following

1. How wages in the farm and non-farm markets are determined?
2. What is the nature of the linkage between farm and non-farm wages?

## **1.5.Data and Method**

### **1.5.1. Data**

The present study is entirely based on secondary data sources. The required data is obtained from the Employment and Unemployment Survey (EUS) of NSSO which is collected in an interval of every five years. NSSO's EUS data is one of the most reliable sources of data that provides in-depth information on the employment situation in India. It is also a nationally representative data which makes it appropriate for analysing the objectives of this thesis which covers the entire rural India. Furthermore, we have utilized the unit level data of NSSO which gathers information from individuals and households and is thus appropriate for studying the determinants of diversification and its welfare impact at individual and household levels. The study uses this EUS data for three-time periods, i.e, 61<sup>st</sup> (2004–05), 66<sup>th</sup> (2009–11) and 68<sup>th</sup> (2011–12) round. Data from other sources have also been utilised to fulfil the requirements of the third objective. This comes from the Land Use Statistics (LUS) of the Directorate of Economics and Statistics, Government of India. These data are available at the district level and to obtain the estimates at the state-region level, a simple average of the variables was calculated. These values were then aggregated at the state-region level.

The reason for using employment-unemployment survey (EUS) data for the periods 2004-05 (61<sup>st</sup> round), 2009-10 (66<sup>th</sup> round) and 2011-12 (68<sup>th</sup> round) and not incorporating any latest EUS data is that after 2011-12, NSSO stopped collecting quinquennial data of employment situation and instead the annual periodic labor force survey (PLFS) data became available since 2017. Although these data are also employment data several modifications were made in the data set due to which utilisation of it is not found appropriate for the purpose of this thesis. The major difference between NSSO EUS and PLFS data is the availability of information. The

PLFS data lacks information on several crucial variables including the principal activity and occupation of the household, information on land and a lack of detailed information on the household's spending on various food and non-food items (Jajoria & Jatav, 2020) which practically limits its use for our thesis. Due to these limitations, NSSO EUS data and PLFS data are not comparable for the current study.

Another rationale for using data from the 61<sup>st</sup> round (2004-05) is the uniformity of information present since this round. For instance, in previous rounds, information on two subsidiary economic activity statuses was collected but from 61<sup>st</sup> round, details of only one subsidiary activity are provided. Moreover, previous rounds also lacked information on vocational training. Also, it classified caste into ST, SC and others, but now the others category is divided into OBC and others (Mishra & Singh, 2018). Moreover, significant structural changes happened between 2004-05 and 2011-12 which made data of this period suitable to study the time effect. Although occupational diversification from farm to the RNFS has been occurring in India since the 1980s, yet a more significant turning point occurred since 2004-05 when agriculture sector experienced a negative growth in employment whereas all the additional jobs were being created in the rural non-agricultural sector (Himanshu, Lanjouw, Murgai & Stern, 2013; Kumar et al, 2020). This period from 2004-05 to 2009-10 also witnessed a rise in casual employment and a fall in the employment share of agriculture, manufacturing and service sectors (Chowdhury, 2011). Also, the percentage share of self-employment fell to its lowest level since 1993-94 and was more significant for female workers compared to male workers (ibid), thereby depicting a gloomy picture of the Indian employment scenario. But in the next period from 2009-10 to 2011-12, certain developments were observed. There was an increase in the share of regular wage employment and self-employment in both rural and urban regions and for both males and females (Rangarajan et al, 2014). On the other hand, rate of growth of casual employment declined by 4.1% per annum during 2004-05 to 2009-10 to 2.6% during 2009-10 and 2011-12 for rural males and by 7.5% for rural females for the same time period (Rangarajan et al, 2014). Also, during this period, manufacturing and services sector witnessed a rise in employment share (Rangarajan et al, 2014). Therefore, under conditions of changing sectoral composition and activity status of work, it is crucial to identify the characteristics of workers diversifying from farm to rural non-farm sector.

### **1.5.2. Method**

The first objective is estimated using the multinomial logistic regression model as the dependent variable is a categorical variable with six occupational categories including agriculture and allied activities. This method is applied since the occupational categories do not follow any particular ordering. An alternative method for categorical dependent variable is the multinomial probit model but it is suitable to apply only when there are few categories (usually three) as computation gets more complicated with more categories compared to multinomial logit (Demie & Zeray, 2016). Again, to examine the determinants of diversification or specialization, we apply a binary logistic regression model as the dependent variable in this case is a dummy variable taking value zero when the individual specializes in one economic activity and one when he/she diversifies.

The second objective analyzes the effect of diversification on rural household consumption expenditure and for this, we have applied the Propensity Score Matching (PSM) which is used to estimate the effect of the treatment by comparing diversified and non-diversified households based on their observed characteristics. Based on the propensity scores, diversified and non-diversified households are matched and the outcome difference between the two groups constitutes the treatment effect.

To examine the determinants and linkage between farm and non-farm wages, we have applied a panel model using the data for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds. Also, the unit of aggregation of wage rate is at the NSSO state region level. Although it was pointed out that wages in farm and non-farm markets are determined simultaneously (Bardhan, 1973), yet we observe no such simultaneity issue and therefore, we analyze the farm and non-farm wage linkage through the fixed effects model.

Detailed discussions of the above-mentioned methods are provided in the respective chapters.

## Chapter 2

### Literature Review

This chapter delves into the extant literatures that have focused on the various determinants and welfare implications of the rural non-farm sector (RNFS) employment in most of the developing nations including India. Review of literature is also done for the various determinants of rural agricultural and non-agricultural wage rates depicting the functioning of the rural labor markets. Before undertaking any research, extensive knowledge on the topic is a sine-qua-non and as such this chapter is devoted to understanding the nature of the rural non-farm sector, its determinants, welfare effects on households as well as its linkages with the agriculture sector. Considering the growing significance of the RNFS particularly for resource poor households, extant literatures have focused on the functioning of the various determinants that have favoured some and hindered others from adopting a diversified livelihood strategy. Some of the studies have even highlighted the heterogeneity of this sector but adequate attention towards proper classification of this sector into different sub-segments has been lacking. Again, the welfare effect of diversification has been examined through various dimensions of welfare measurement. Furthermore, to assess the determinants and linkage between farm and non-farm wages, various articles have been reviewed. The literatures reviewed have been categorised into four sub-themes which include: 2.1) A theoretical review of literature 2.2) Determinants of rural non-farm employment 2.3) Welfare effect of rural non-farm occupational diversification 2.4) Determinants of agricultural and non-agricultural wages. Section 2.5 sums up the entire discussion of this chapter.

#### 2.1. A theoretical review of literature

The original idea of occupational diversification can be traced back to the models developed by Lewis and Harris-Todaro who primarily focused on factors that determine a labourer's decision to shift from one sector to the other. In Lewis model, this shift happened from the traditional sector (agriculture) to the modern sector (industry) or from rural to urban areas. This shift is possible due to productivity differences between the traditional and the modern sector. Moreover, this theory assumes that there is an unlimited supply of labor in the traditional sector and any movement of labor from traditional to the modern sector would render the farm output unchanged due to zero marginal productivity of labor here. On the other hand, it is also assumed that the capacity of the modern sector to absorb rural labor force depends on the level of capital

investment. Therefore, the basic idea of this model is that as long as productivity differences persist and there is expansion in the modern sector, surplus labor force can easily be shifted from the traditional sector with economic development and the issue of unemployment and disguised unemployment would be eliminated.

Another notable theory on rural-urban migration is the Harris-Todaro model. This model assumes the presence of wage differences between the urban formal sector and the rural agriculture sector and this wage difference encourages workers to migrate from rural to urban areas as formal sector wages are much higher and inflexible compared to rural farm wages. Although this wage difference attracts workers to migrate to urban regions, there is no guarantee of obtaining formal jobs for all those who migrate and hence, they face a situation of uncertainty. They might end up getting work in the informal urban sector or remain unemployed. Therefore, their choice of migrating to urban regions would depend on the expected wage from this sector which depends on the probability of getting work in either urban formal sector or informal sector. Hence, workers would migrate if their expected wage from urban sector is higher than the actual wage from agriculture and this labor movement would continue till the point where expected urban returns are equal to the actual farm wage which is also the equilibrium position.

Both these theories focused on productivity and wage differences between rural and urban sectors which results in migration of workers. But there is a limit to which urban sector can absorb the migrant labour force due to limitations in investment. Again, in rural regions, farm productivity is declining, and land fragmentation is increasing which has resulted in the expansion of an informal economy within the rural regions which is the rural non-farm sector. While in both the Lewis and Harris-Todaro model, the shift of workers was purely based on pull factors, in the case of diversification from farm to the RNFS, the motives can be both pull and push factors.

Buchenrieder and Mollers (2006) observe that this diversification process can also be incorporated within the sustainable livelihood framework (SLF) where livelihood is first defined by Chambers and Conway (1992) as comprising “the capabilities, assets and activities required for a means of living”. The interpretation of diversification within the SLF is defined as an action where individuals try to either augment the assets and capabilities or reduce poverty and vulnerability of a household. This again, depends on whether an individual has access to the five forms of capital which include natural, human, physical, financial and social

assets. These capital assets combine with the structure of the existing economy and its institutions to make available different livelihood opportunities. They also highlight the diversity within the RNFS which includes both high return and low-return activities. Although pull factors are associated with higher income, diversification as a result of push factors also benefits the rural population through an overall rise in household income as well as a fall in vulnerability and greater risk management capacity.

RNF employment diversification is also explained in the literature through a basic welfare model (Buchenrieder & Mollers, 2006). This welfare model states that whether it is distress push or demand pull, diversification would always be beneficial for rural households. The distress diversification takes place as a result of an incomplete agricultural labor market and also due to the existence of high level of unemployment in developing economies. As a result of a shift of workers to distress push non-farm activities, labor productivity as well as wages of those who remain in agriculture increase which would augment the total household income. Welfare gains also occur when workers shift to non-farm activities due to demand-pull factors.

Extant literatures (Demie & Zeray, 2016; Abdulai & Crolerees, 2001; Owusu, Abdulai & Abdul-Rahman, 2011; Musafiri & Sjolander, 2018) point out that labor allocation between farm and non-farm work occurs when the marginal value of farm labor is equal to the non-farm wage rate. In other words, engagement in non-farm work occurs when reservation wage in agriculture is lower than wages in non-farm sector. While allocating labor between agriculture and non-agriculture, the farm household tries to maximize utility which is subject to several constraints that include time constraints, budget constraints and farm production constraints.

Again, household utility depends on consumption and leisure. Here, time is allocated between farm work, non-farm work and leisure. Also, consumption expenditure depends on income from non-farm sources, net farm income and income from other sources. Furthermore, farm production is a function of the quantity of inputs used, farm-specific factors, human capital characteristics and time allocated to farming.

Here, the allocation of time among farm work, different non-farm activities and leisure are determined from utility maximization problem. Therefore, the optimum amount of time allocated to different activities is a function of time endowment of household members, the price vector of consumption goods, prices of farm output, wages of hired labor and non-farm workers, prices of non-labor inputs, income from other sources, household characteristics and

constraints to farm production like credit accessibility and also locational factors and other fixed factors of production (Drall & Mandal, 2020).

## **2.2. Determinants of rural non-farm employment**

Extant literatures have broadly classified the determinants of occupational diversification into “pull” and “push” factors also known as distress-driven or growth-driven diversification (Drall & Mandal, 2020; Haggblade et al, 2010; Jatav & Sen, 2013; Loison, 2015; Nakajima et al, 2018; Panda, 2017; Ranjan, 2009; Unni, 1996; Deininger & Olinto, 2001; Senadza, 2012). A rise in farm productivity not only augments the income of farmers but their demand for farm inputs also increases which needs to be supplied by the non-agricultural sector. Again, higher the income of farm households, more will be their demand for non-food goods and services. These favourable production and consumption linkages between agriculture and rural non-farm sector (RNFS) expand the range of non-farm activities. Growth of the RNFS also occurs because of urbanization, proximity to urban centres, developed transport and communication facilities, well-functioning financial and credit markets and expansion of educational facilities operation of the pull factors.

The other side of the picture depicts diversification as a survival strategy undertaken to maintain a subsistence level of living, particularly in regions with stagnant and underdeveloped agricultural sector. Push factors are negative factors such as drought, ex-ante and ex-post risk related to farm productivity and low returns from agriculture, lack of credit facilities, etc. that drive farm households to find alternative sources of income earning opportunities (Davis et al, 2009). Push factors generally operate in high risk, uncertain agricultural sector where agricultural productivity is stagnant or declining due to negligible application of modern techniques of cultivation coupled with adverse agro-climatic situations such as frequent floods, drought and environmental degradation (Alobo Loison, 2015; Haggblade et al, 2010; Nakajima et al, 2018). Population pressure on limited land holding, geographical isolation, poor quality physical infrastructure and incomplete factor markets are other push factors of diversification (Alobo Loison, 2015; Haggblade et al, 2010; Nakajima et al, 2018; Rearden, 1997, Ranjan,2006). Push factors of diversification generally drive rural households, particularly marginal and landless households to engage in low-return activities like mat making and pottery because these households lack the necessary resources like both physical and human capital and credit facilities to compete for lucrative non-farm jobs (Haggblade et al, 2010; Alobo Loison, 2015). Extant literature points towards the existence of various entry barriers in

the form of demography, household and locational factors that determine the choice of employment. Following are some of the studies undertaken in several developing nations including India that elaborate on the various motives behind occupational diversification.

### **2.2.1. Determinants of rural non-farm employment diversification in other developing countries**

The issue of low farm productivity, income uncertainty, food insecurity and poverty have pushed small farm households in Nigeria, Burkina Faso, Ethiopia and Sudan to resort to non-farm employment opportunities (Fabusoro, 2010; Akaakohol & Aye, 2014; Demie & Zeray, 2016; Gansonre, 2019; Asfaw et al, 2017; Ebaidalla, 2022). They found that in Burkina Faso, diversification to non-farm wage and self-employment increases when there is a negative rainfall shock but falls when there is a positive rainfall shock. Moreover, due to non-availability of high-return non-farm jobs, education is found to have no significant impact on diversification. But access to paved roads that connect nearby cities facilitates farm households to devote time and labor to non-farm occupations. Again, in Ethiopia and Sudan, lack of adequate land pushes farm households to diversify. Here, diversification also varies between males and females. While female-headed households are more likely to join non-farm self-employment, male-headed households prefer wage employment (Demie & Zeray, 2016). Furthermore, the study by Akaakohol and Aye (2014) in rural Nigeria observes that non-farm activities are pursued more by male-headed households compared to female-headed households. Due to the greater involvement of females in household chores, their likelihood to work outside is limited by non-availability of time. Similarly, Chaplin (2007) observes that although the willingness to join RNFS is highest among small farm households in Poland, yet lack of human and physical capital prevents them from diversifying. Diversification is also low for the older age population and those who face credit and other financial constraints.

Even in Vietnam and Ethiopia, importance of agriculture as a principal livelihood source has declined over time and rural households have resorted to multiple employment options (Brunjes & Diez, 2016; Bezu & Holden, 2014). Among other factors, small size of land holding is identified as a key cause for involvement of workers in multiple activities, while those having land and livestock are less likely to move out of agriculture. Land ownership also determines the future occupational choice of rural youths in Ethiopia. Further, the study by Bezu, Barette & Christopher (2010) focuses on the relative role of push and pull factors that affect the choice of high-return and low-return non-farm wage and self-employment in rural Ethiopia. They

found that capacity variables like education, experience and wealth significantly affect the likelihood of joining skilled wage employment and high-investment businesses whereas push factors like rainfall variability, illiteracy and low land ownership size significantly affect participation in low-skilled wage work and low return self-employment activities. Again, self-employed non-farm activities are adversely affected by weather risk as these activities are highly correlated with agriculture.

A few literatures emphasized the significance of education for livelihood diversification in rural Mexico, Ghana and Africa. The study by De Janvry and Sadoulet (2001) and Yunez-Naude and Taylor (2001) demonstrate that years of schooling not only enhances the probability of joining high-remunerative non-farm employment but even expands the employment opportunities for rural females in Mexico. Their likelihood to diversify also increases with easy access to urban regions. Senadza (2012) also found that an additional year of schooling not only raises the share of non-farm income by 0.05 but even the probability of joining a number of non-farm income sources. Furthermore, male-headed households dominate non-farm wage employment whereas female-headed households are concentrated in non-farm self-employed activities. Similarly, Matsumoto et al (2006) also found that an additional year of schooling increases non-farm income by 9.1% in Kenya, 12.1% in Ethiopia and 14.6% in Uganda. Furthermore, the studies by Owusu et al (2011) and Kuwornu et al (2018) in rural Ghana found that apart from education, access to credit and household size also positively affect participation in the non-farm sector. With each additional family member, the likelihood of working in non-farm sector increases by 1.3 %. On the other hand, the roofing quality of the household which is an indicator of economic well-being decreases the probability of participation in non-farm activities.

Again, a few studies demonstrated how individual and demographic factors affect the joint decision of farm operator and spouse to diversify to non-farm activities. Abdulai and Delgado (1999) observe that one more year of schooling not only raises the likelihood of wives joining non-farm employment, but they also earn more returns from it compared to their husbands in Northern Ghana. One more year of schooling increases the likelihood of females to join RNFS by 0.51 while the effect for males is 0.30. Similarly, one year of schooling increases wife's wage by 6.9% while it rises by 4.9% for husbands. Chang and Mishra (2008) also observed a growing significance of off-farm activities among farm operators and spouses in the United States. They found that while the decision to participate in off-farm activities is made jointly by the farm operator and spouse, the choice of non-farm activities depends on individual and

household characteristics. The bivariate probit results suggest that while the decision of farm operator to join off-farm activities is adversely affected by the size of land cultivated and number of years devoted to farming, the reasons behind lower diversification by spouse are larger household size and the presence of children. Unemployment rate also negatively affects the spouse's decision to work off the farm. Similarly, Lin-Applegate et al (2002) found that both tertiary education and vocational training facilitate farm operator and spouse to diversify in rural Australia. Diversification also increases in metropolitan and high population density regions.

Furthermore, Abdulai and Crolerees (2001) demonstrate that although poorer households should diversify more as they are more risk averse, yet it is the wealthier households who have started diversifying towards off-farm activities in Southern Mali. They found that lack of asset endowment and credit facilities adversely affect resource-poor households' ability to engage in cash crop production, livestock and non-farm wage employment where returns are high. Apart from human and physical assets, Xia and Simmons (2004) found the significance of political factors in influencing occupational choice in rural China. By using a multinomial logistic regression, they found that for a party member, the probability of securing off-farm wage employment is 24.31% while it is only 6.78% for non-party member. Also, being a village leader raises the likelihood of wage employment by 1.3%.

Although employment diversification has become a norm in rural regions, Deininger and Olinto (2001) in Colombia observe that individuals who specialize in either farm or non-farm sector, can raise their welfare by 10% to 36%. This strategy of expanding household expenditures through specialization is further enhanced through higher education of the worker. An additional year of education increases income by 3.4% to 12%. The returns are even higher for those having 7 years of education and it ranges between 25% to 70%. However, due to lack of well-functioning land, labor and credit markets, households involve in multiple activities.

### **2.2.2. Determinants of rural non-farm employment diversification in India**

Diversification of households from farm to the RNFS in India started during the 1980s, but the actual expansion of this sector occurred after 2004–05 (Himanshu et al, 2013; Kumar et al, 2020). After a prolonged agrarian distress during 1999–00 to 2004–05, rural India witnessed growth of the non-farm sector especially a rise in casual employment along with a revival of

the agrarian economy. Furthermore, with the implementation of MGNREGA in 2006, the expansion of the RNFS has become even more stark. Although several studies (Lanjouw & Lanjouw, 2001; Jatav & Sen, 2013) consider this sector a boon for rural livelihoods due to its capacity to absorb surplus labor force and provide a way out of poverty and generate income, yet the sudden rise of this sector after a period of agrarian distress raises speculation about the type of activities that is being generated and the factors that affect participation in these sectors. The following studies elaborate on the various push and pull factors that are operational in determining the choice between farm and non-farm employment in rural India.

Jatav and Sen (2013) analysed the relative strength of various “pull” and “push” factors of RNFS diversification with the help of NSSO employment data for 66<sup>th</sup> round (2009–10). By applying an optimum regression equation, they found that at the region level, factors like dependency ratio, landlessness and unemployment rate were significant push factors of diversification. However, at the individual level, education favoured workers to engage in remunerative non-farm activities. But land-owning size adversely affected their participation. This suggests that landless and small land-owning households are more likely to enter the non-farm economy. Again, diversification is also high among SC individuals who are the most marginalised group. They, therefore, demonstrate that both push and pull factors influence diversification.

Lanjouw and Shariff (2004) undertook a comprehensive study on the determinants of occupational choice in rural India. By applying NCAER data for 1993–94, they categorised non-farm activities into casual, regular and self-employment. The findings of the logit model demonstrate that involvement in non-farm occupations is higher among males, whereas females dominate agricultural wage work. Land ownership is found to facilitate households to engage in either cultivation or non-farm activities by acting as collateral. But it negatively affects casual wage employment. Workers are also more likely to diversify to either cultivation or regular salaried jobs with a rise in their education level. But rather than being cultivators or non-farm employees, ST and SC households are concentrated in agricultural wage labor.

Similarly, Kumar et al (2011) analyzed the determinants of rural non-farm employment using 66<sup>th</sup> (2009–10) round of NSSO data. They found that with an increase in age, the likelihood of working in non-farm sector declines by 0.13 percent. Again, being male increases non-farm employment choice by 20%. Unlike the findings by Lanjouw and Sharif (2004), the study observed a negative impact of landholding size on non-farm participation indicating a distress

diversification phenomenon. However, Kumar et al (2011) did not disaggregate the occupations within the RNFS and instead offered an aggregate picture of the effects of various determinants on non-farm employment probability.

Using a panel probit technique, Zeeshan, Mohapatra, and Giri (2018) investigated the factors of farm households diversifying to non-farm enterprise employment in rural India and across different agro-ecological zones between 2005 and 2012. They found diversification to be high among small and marginal land-owning households while it is lower for large households. Again, because of the easy availability of labor, non-farm enterprise employment is carried out by households with a greater number of adult working members. Diversification is also high among farm households residing in regions with greater road density which minimises travel cost and time to work in the non-farm sector. Furthermore, farmers residing in semi-arid and arid regions diversify less compared to those residing in humid regions.

Drall and Mandal (2020) focused on the determinants and intensity of non-farm employment diversification in the semi-arid tropical and eastern states of India in their two separate studies during 2020 and 2021 using a panel data set for the period 2010 to 2014. By applying a fractional multinomial logit model and a fractional response model, they observed that both education and vocational training favorably affect diversification towards non-farm wage and self-employment as well as raise the intensity of diversification. Diversification is also found to be higher among female-headed households compared to male-headed households. Social capital and access to credit help in establishing non-farm enterprises. But income from agriculture, on the contrary, lowers their probability of diversification. Also, diversification is high among eastern states that suffer from low farm income and land holding size compared to states of semi-arid regions.

Some studies focused on specific states to examine the livelihood patterns prevailing in those regions. Unni (1996) studied the nature and processes of employment diversification or specialization in rural Gujarat. Results indicate that individuals are more likely to remain unemployed and less likely to participate in economic activities with an increase in age. But younger males are more likely to diversify rather than specialize in agriculture or not work. Education significantly impacts specialization in non-farm activities and reduces participation in agriculture regardless of gender. Again, the effect of land and other assets on non-farm participation differs across gender. While high value of land encourages males to specialize in

non-agriculture, for females' specialization in non-farm occurs with a rise in the value of non-land assets. Distance to towns also favors workers to get involved in multiple activities.

Mishra (2014) emphasizes the relevance of RNFS employment in Maharashtra which is not only the most urbanized state but also records the highest incidence of farmer suicides. Also, the pace of employment diversification increased from 14.3% to 20.6% between 1983 and 2009–10 while at the national level, the increase is between 19% to 32% during the same time. Findings from the binary logit model indicate that males are shifting more towards non-farm employment while females are concentrated in agriculture and allied activities. The probability of diversification is also high among ST and SC workers which indicates a distress diversification process as they not only suffer from landlessness but also have low education qualification. Unlike the findings from Unni (1996) where land ownership facilitates specialization in non-farm, the findings for Maharashtra show a negative and significant impact.

Panda (2017) looked into the significance of rural non-farm occupational choice in India's North-East region (NER) where increased mechanization in agriculture and issue of insurgency have led to a fall in employment generation in agriculture and low private-sector investment. Also, the share of RNFS employment is 34.9% which is higher than the all-India average of 32.1%. The findings from the primary survey of 1000 households from Assam and Meghalaya indicate a strong consumption linkage between agriculture growth and non-farm diversification as income from agriculture facilitates expansion of trade and commerce activities which have little direct impact on the economy's productive capacity but improves the consumption status of the households. Access to credit and education are other pull factors of diversification. Diversification is also high among households that are below the poverty line. Their study points towards the operation of both push and pull factors of diversification.

Ranjan (2009) and Mishra and Singh (2018) studied the pattern and determinants of non-farm employment in rural Uttar Pradesh where considerable regional differences in terms of employment distribution across gender, caste and land ownership exist. Diversification towards the non-farm sector is sharper for rural males while females are mostly engaged in cultivation and manufacturing employment. Later, the increase in construction employment primarily created jobs for men. Both studies observed a higher share of educated workers in the non-farm sector. Mishra and Singh (2018), through regression estimates, also found that graduates are 42% more likely to be in non-farm regular employment compared to the illiterate group. But

in comparison to males, the likelihood of females joining agriculture increased from 19% in 1993-94 to 34% in 2011-12. Participation is also high among OBC, SC and ST individuals particularly in casual non-farm employment. Most of them also belong to landless households as cultivation is undertaken by “other category” workers. With a rise in 1 hectare of land ownership, there is 68% fall in non-farm employment during 1993–94 and by 10% during 2011–12. Therefore, these studies point towards a distress-induced diversification in rural Uttar Pradesh.

Another recent study on occupational diversification was conducted by Nakajima et al (2018) in the semi-arid regions of India which comprise Bihar, Odisha, West Bengal and Uttar Pradesh. Expansion of RNFS in these states is crucial for the farming community due to increased population pressure and falling farm productivity. Similar to earlier studies, they found that diversification is higher for males compared to females whether it is in construction, factory or migration activities. However, the impact of education varies for different non-farm activities. It positively affects non-farm self-employment and service activities without having any significant impact on employment in factory work. This implies that disadvantaged groups are concentrated more in factory jobs. Again, landless and marginal farmers seek agricultural wage work as well as industry jobs. Individuals from SC and ST have a greater likelihood of agriculture wages and construction work. Furthermore, while SCs also prefer factory jobs, it is less preferred by STs due to inadequate transportation facilities. The paper highlights the importance of factory jobs for low-caste individuals which do not require high skilled workers yet the returns are higher than casual non-farm jobs.

Srivastava and Srivastava (2010) also pointed out that occupational diversification is increasingly becoming popular among males while majority of females are still confined to agriculture and allied activities. Unlike males, whose labour market participation is determined by economic factors, female participation is affected by various socioeconomic, religious and cultural factors. This study observes that non-farm wage and self-employment are preferred by young and unmarried women while regular activity is undertaken by widowed, separated and elderly women. Education solely favours employment in non-farm regular and self-employed activities and does not exhibit any impact for wage work. Diversification is also high among Muslim women and women from SC, ST and OBC households while it is lower among ST women. Economic factors like land ownership and monthly per capita consumption expenditure also adversely affect a female’s opportunities to work outside agriculture. Therefore, they conclude that although education favours women in becoming economically

independent, yet the influence of sociocultural norms becomes stronger with wealth and social status that affects their participation.

### **2.3. Welfare effect of rural non-farm occupational diversification**

#### **2.3.1. Extant literature on the benefits of diversification in other developing nations**

The focus on non-farm employment diversification in developing and transition economies has revolved around its potential role in reducing the perennial issues like poverty, malnutrition, hunger and its ability to uplift household well-being, especially by rural farm households. Limitations in the expansion of land for operational holding and ever-escalating rural population have led to a fall in farm productivity. This resulted in a shift of workers to either RNFS or migration. But the hazards associated with migrant work outweigh its benefits and therefore, expansion of work within the rural region and in sectors outside agriculture is highly desirable. The following literatures explore the myriad ways in which non-farm diversification can benefit rural households.

Owusu et al (2011), Kuwornu et al (2018) and Zereyesus et al (2017) studied the impact of non-farm employment in reducing poverty, and food insecurity and enhancing household income in Northern Ghana. With the application of propensity score matching method, they found that diversified households could earn 138.9 GHS (Ghanaian Sedi) more than non-diversified households. They are also less likely to experience food shortages during critical periods and more likely to consume an amount of calories that is higher than the minimum daily recommended. Zereyesus et al (2017) further found that food poverty is only 44.7 percent for participating households compared to 87.1 percent for non-participating households. Similarly, Shehu and Sidique (2013) demonstrated the importance of rural non-farm enterprise employment on household consumption expenditure and food security status. They found that working in enterprise employment increases consumption expenditure by \$524.

A few studies examined the poverty reducing and income augmenting effects of non-farm self-employment activities in rural Vietnam. Van de Walle and Cratty (2004) found that a household head's education not only increases the likelihood of enterprise employment but also contributes significantly to poverty reduction. But an additional household member although increases the impetus to work in non-farm enterprises, lowers the household's welfare. They further demonstrate that although land-owning households are better off through diversification, but time constraint prevents them from dividing labor between farm and non-farm sector. Similarly, Hoang et al (2014) found that with a rise in the number of non-farm workers in a household, poverty declined by 12.1%, 9.5% and 7% in 2004, 2006 and 2008

respectively. Again, Janvry, Sadoulet and Zhu (2005) observed that in rural China, not only income inequality has declined as measured by the Gini index but both incidence and depth of poverty have reduced considerably with an expansion in non-farm employment.

Chang and Mishra (2008) and Seng (2015) both evaluated how non-farm employment affects farm households' expenditure on food in the U.S. and Cambodia respectively. Chang and Mishra (2008) observed that although the decision to participate in off-farm employment is jointly determined by both farm operator and spouse, yet their participation has different impact on consumption expenditure. While the farm operator spends income from off-farm employment on household food consumption, the spouse spends more on non-food items like education, recreation, transportation etc. Again, in rural Cambodia, farm households could spend 725.26 riels more on food if they diversify to non-farm occupations compared to non-diversified farm households.

The study by Hossain and Abdullah Al-Amin (2019) in rural Bangladesh and Akaakohol and Aye (2014) in Nigeria examined the various factors that affect both the likelihood of non-farm employment as well as on household consumption expenditure. Both studies found that households earning either non-farm income or participating in it could spend significantly more on consumption expenditure compared to non-participating households. Age of the household head, education and availability of credit are additional factors that enhances the level of household welfare. Similarly, Adjognon et al (2017) demonstrated the role of non-farm wage and self-employment in reducing household poverty in rural Malawi. They found a relatively higher poverty reducing impact of non-farm self-employment compared to non-farm wage employment. Non-farm self-employment reduces poverty by 8.5 percent whereas non-farm wage employment reduces it by 7 percent.

Again, Dzanku (2019) using a panel data for six African countries examined the effect of diversification on food availability across gender and regions. Although off-farm income increases food availability thereby reducing food insecurity, its benefits are greater for female-headed households compared to male-headed households. Also, diversification effects on food security become more important for people residing in agro-ecologically backward regions than advanced regions. Apart from household consumption expenditure, Ruben and van den Berg (2001) and Babatunde and Qaim (2010) have drawn particular attention to the nutritional and food security status of diversified farm households in Honduras and Nigeria. Babatunde and Qaim (2010) observed that for every 1000-naira increase in yearly off-farm income, calorie

consumption rises by 22 kcal per day. But the increased consumption of calories also occurs with a rise in the level of farm income. In addition, there is also a shift towards consumption of high-value crops like vegetables, fruits and animal products and greater intake of micronutrients like iron and vitamin A when they are employed in either farm or off-farm activities. As both farm and non-farm income contribute to an improvement in these households' food security status, they suggest that the level of income is more crucial for these households to be more food secure than the source of income. However, in case of child nutritional status, only off-farm income is found to have a positive significant impact. Ruben and van den Berg (2001), on the other hand, demonstrate that not all households in rural Honduras benefit from non-farm employment and also the importance of this sector is not uniform across household types. They observed that for poorer households, nutritional adequacy is achieved through engaging in farm activities while for middle and affluent households, food consumption is enhanced through working in non-farm wage and self-employment respectively. Results indicate that a 10 percent rise in farm and non-farm income augment nutritional adequacy by 0.8% and 0.2% respectively

### **2.3.2. Literature on the welfare implications of diversification in India**

Among the available literature in India, the work of Imai, Gaiha and Thapa (2015) and Dey (2018) focuses on non-farm employment's role on rural household welfare. Farm households, particularly, landless, marginal and small have started combining non-farm activities in order to supplement household income. Therefore, both studies examine the contribution of different non-farm occupations in reducing ex-ante and ex-post poverty of rural households. While emphasis of the former study is on farm households, the latter paper focused only on small and marginal land-holding households which constitute the economically vulnerable section. Imai et al (2015) found that non-farm diversification reduced poverty by 10.2 percent in 1993–94 and by 10.4 percent in 2004–05. Vulnerability is also significantly reduced by 3.8 percent and 7.1 percent during the same period. Dey (2018) further observed that households with human capital have the greatest poverty and vulnerability reducing impact as 1 percent rise in educational level reduces poverty by 26.5 percent whereas a 1 percent rise in the share of non-farm workers reduces poverty by 5 percent. Further division of non-farm occupations shows that poverty and vulnerability are the least among farm households engaged in skilled non-farm activities like managerial, clerical, professional, machine work and sales related activities. On the other hand, small holder households specializing in craft and elementary non-farm

occupations could not significantly reduce poverty and vulnerability compared to those engaged in only agriculture activities.

In yet another study by Imai (2011) in rural India, focus has been placed exclusively on the impact of rural public works and food for work programs on household's poverty, vulnerability and undernutrition. They found that a household is more susceptible to experience poverty, vulnerability and undernutrition if they are burdened with higher dependent members and belong to SC, ST households. But their participation in rural public works significantly reduces their chance of being poor or suffer from undernutrition.

Scharf and Rahut (2014) examined the role of high and low-skilled non-farm occupations on rural household's consumption expenditure in the hilly regions of Sikkim and Darjeeling. They observed that although low-skilled non-farm employment did not significantly impact household welfare, yet their expansion has led to a fall in income inequality. On the contrary, high-skilled non-farm work significantly improves consumption expenditure of these households. They conclude that while skilled non-farm occupations increase household welfare, growth of low-return non-farm activities lowers income inequality.

Rahman and Mishra (2020) investigated the role of non-farm income on household's nutritional status and dietary diversity. In the presence of income disparities, studying the impact of non-farm income on nutritional status becomes crucial. They applied Shannon and Simpson index of diversification to quantify dietary diversity. The results show that not only dietary diversity but the pattern of consumption has shifted to non-cereal and protein-based items with an increase in non-farm income. Cereal consumption and dietary diversity are also high among households with higher levels of education. The paper also observes a positive impact of remittances on household food security indicators.

Kumar et al (2020) studied the impact of non-farm employment diversification on rural household's consumption expenditure in the 7 eastern Indian states of Assam, Bihar, Chhattisgarh, Eastern Uttar Pradesh, Jharkhand, Odisha and West Bengal which are characterized by rapid population growth, small size of land holding, high incidence of poverty and poor rural infrastructure. With the help of NSSO employment data for 50<sup>th</sup>, 61<sup>st</sup> and 68<sup>th</sup> rounds and making use of an instrumental variable approach, they found that rural non-farm employment as a whole has a positive impact on household consumption expenditure. But among the various non-farm occupations, diversifying to regular non-farm employment results in the highest benefits as these households could spend 50 percent more on household expenses compared to farm employment. Similarly, consumption expenditure increases by 20 percent

and 16 percent for engaging in overall and self-employed non-farm vocations respectively. Therefore, both regular and self-employed non-farm activities can uplift rural households but because of the vulnerable nature of casual non-farm workers, it plays no role in raising household expenditure.

Dsouza et al (2020) made a similar attempt to assess the role of off-farm employment on food security status of smallholder households in rural India. However, they further segregated non-farm occupations into casual and regular categories as different occupations may affect food security differently. They further analyzed the results separately for farm operator and spouse, and applied panel data estimation for 2005 and 2012 using IHDS data set. According to the findings, food insecurity increases for those engaged in farm activities while for households with off-farm income, food insecurity decreases by 0.8 to 1.7 percent. Differential impact on food insecurity is also found when farm operator and spouse engage in casual and regular non-farm activities. Food insecurity declines when farm operator participates in permanent off-farm employment but in case of spouses, engagement in only casual off-farm activities leads to a rise in food security of the household.

Apart from the direct effect of employment diversification, Lanjouw and Shariff (2004) estimated its indirect impact on poverty through agricultural wages. The OLS regression result shows that a 1 percent rise in construction employment results in an increase in wages by rupees 3 and rupees 5 for sowing and harvesting respectively. Chandrasekhar et al (2015) focused on rural households' dietary diversity measured using the Shannon index of diversification and tried to analyze whether dietary diversity varies across different household types and skill level. They found that dietary diversity is higher for self-employed households whether in farm or non-farm sector and it is lower for rural labour households. Dietary diversity is also high among households where greater share of workers is engaged in cultivation while household members engaged in elementary occupations have a low dietary diversity due to their lower skill level which leads to low earnings. Compared to STs, dietary diversity is high for SC, OBC and upper caste households.

The study by Zeesan, Mohapatra & Giri (2018) estimated the impact of non-farm enterprise diversification on income and consumption expenditure of farm households. The estimates from the propensity score method showed that diversified farm households could earn rupees 12736.90 more from agriculture and can spend an additional amount of rupees 15517.77 on household consumption expenditure compared to non-diversified households. In their

subsequent study, Zeeshan et al (2022) further estimated the implications of non-farm enterprise income on different indicators of household consumption expenditure and its role in farm investment. By applying a generalized two stage least squares regression for a panel data of two periods 2004–05 and 2011–12, they found that a 1 percent rise in non-farm enterprise income increases spending on food by 0.22 percent, on dietary diversity by 0.05 percent and on non-veg food items by 0.41 percent. However, as non-farm enterprise income increases, the share of food expenditure declines. Apart from food expenditure, non-farm income also raises spending on household assets and also enables them to invest in agricultural activities.

#### **2.4.Determinants of agricultural and non-agricultural wages.**

Several studies have been conducted in India to examine the trends and determinants of agricultural wages. Bardhan (1973) investigated the factors responsible for interstate variation in wage rates between 1956–57 and 1970–71. The author suggests that a complex interplay of several factors affect wages of casual farm workers that include factors not only related to farm productivity but also the presence of wages prevalent in the non-agricultural sector. Regression estimates show that the reason for inter-state wage differences accounts for differences in irrigation intensity, cropping intensity, variation in agricultural productivity and the proportionate size of agricultural laborers. While the first two factors raise casual wages, the increased uncertainty about farm productivity and presence of surplus labor force have a dampening effect on wage rates. In addition, the presence of casual non-agricultural labor and full-time industrial workers also pushes up the farm wage rates. Similar findings for farm wage determinants were obtained at the village level. Again, Papola and Mishra (1980) also investigated the causes of inter-district wage variations among rural male and female farm workers in Uttar Pradesh during 1970–71. The study finds the relative significance of supply side determinants like availability of surplus labor and employment opportunities in the non-farm sector in explaining inter-district variations in wages whereas demand-driven factors such as per hectare yield, cropping and irrigation intensity have a marginal impact. These supply side factors consistently have a negative impact on wages. Concentration of land holding in the hands of few farmers also has a dampening impact on wages due to lower or negligible bargaining power of the existing landless laborers. Mechanization, on the other hand, has a pull effect on farm wages of male workers.

Bhalla (1993) studied the factors affecting real farm wages in 13 major states of India and examined whether these factors can explain the inter-state variations in wages for the period

between 1971–72 to 1983–84. The author observes that one of the most important reasons behind state-level variation in farm wages is due to differences in labor productivity. However, time series regression for each state shows that it is the availability of non-farm employment opportunities that pushes up the farm wage whereas, labor productivity came out to be an insignificant determinant. Cost of living, on the other hand, negatively impacts real farm wages. Jose (2013) also analyzed the presence of inter-state variations in rural wages from 1999–00 to 2009–10 and found that factors like land and labor productivity, magnitude of domestic production and linkages with the global economy can highly affect rural wages. Rural wage growth is also positively influenced by migration and worker's educational level. However, after 2007–08, states that shared a closer link with the global economy experienced a fall in the wage rate growth whereas states with low income did not exhibit any decline in wages. In an attempt to analyze the role of economic liberalization on Indian economy, particularly rural economy, Srivastava and Singh (2006) examined the implications of liberalization on rural farm wages. They found that the reform process has a positive impact on wages and employment only in the developed states like Kerala, Haryana, Gujarat and Rajasthan while in low-income states of West Bengal, Assam, Bihar, Uttar Pradesh and Odisha, the trend of faster growth of farm and non-farm wages has weakened in the post-reform era. Panel regression estimates from 1983 to 1999–00, show a significant positive impact of non-farm employment expansion on farm wages. A 1% increase in rural nonfarm workers raises real farm wages by 1.2%, while a 1% increase in farm income per worker raises real manual farm wages by 0.33%. However, a 1% rise in the share of farm laborers, on the contrary, reduces wages by 1.2%. In yet another study, the author noted that factors such as urbanization, public spending, and the expansion of non-farm employment were responsible for an increase in farm wages in the post-liberalization period. However, revival in the agrarian economy after 2004–05 also resulted in farm wage increase. Again, growth of construction sector was effective in raising farm wages of male workers compared to female workers through labor market tightening.

Similarly, Reddy (2015) also observed that economic reforms have a favorable impact on developed states like Kerala, Punjab, Haryana, Himachal Pradesh, and Tamil Nadu where not only wage gaps between farm and non-farm sector is low but wage rates are also higher compared to other states. The paper also demonstrates that while non-farm sector plays an important role in raising wages in high wage rate states, it is the agricultural productivity that enhances rural wages in low wage rate states. Moreover, inter-state variations in the magnitude and growth of wages are also attributed to factors like initial levels of urbanization, share of

non-agricultural sector in income and employment, higher per capita income and less divergence between rural and urban areas. Himanshu and Kundu (2016) evaluated the trends and determinants of farm and non-farm wages in rural India from 1999–00 to 2011–12. They found a steady decline in the rate of growth of wages after 1993–94 which further decelerated during 1999 to 2005. However, this trend reversed after 2007–08 when both farm and non-farm wages increased at a higher rate of 12% and 8.4% per annum respectively. The cross-section regression of real farm and non-farm wages show that, while agricultural productivity has a significant and positive impact on farm wages for all three time periods, its magnitude is declining, indicating a reduction in its impact over time. On the other hand, the effect of farm productivity was significant in explaining non-farm wages only during 2007–2008. However, in panel regression, its impact became insignificant. Literacy rate, expansion of MGNREGA and construction sector GSDP are other factors that raise farm wages. Therefore, they established that in addition to enhancing farm productivity, growth of construction sector employment and work in MGNREGA can play a crucial role in augmenting rural wages.

Pandey (1973) focused on how supply and demand factors affect rural farm wages in the predominantly wheat growing regions of Punjab, Haryana, Madhya Pradesh, Uttar Pradesh and Rajasthan. Results indicate the positive and significant impact of demand side variables like cropping intensity, irrigation intensity and size of cultivated land holdings in determining farm wages. But factors like the proportion of agricultural laborers and man-land ratio exhibit a negative impact on wages. A one percent fall in the proportion of farm labor and a rise in cropping intensity and size of cultivated holding increases farm wages by 0.24, 3.32 and 0.63 percent respectively. Among these factors, the impact of cropping intensity was the highest. Similarly, Sidhu (1988) also found that in the agriculturally developed states of Punjab and Haryana, demographic pressure on land and labor market segmentation, as represented by the proportion of unreserved category workers, tend to depress wage rates, whereas land productivity and unequal distribution of land tend to raise wage rates. It implies that, while productivity raises wage rates, it is the pressure of population on land that dampens the effect of a rise in wages. Therefore, there should be growth of non-agricultural activities that would absorb the surplus rural labor force.

Ahmed (1981) also looked into the determinants of real wages of casual farm laborers in rural Bangladesh between 1975–76 and found that despite a high overall unemployment rate, wages of casual farm workers did not fall. The reason being a low unemployment rate among farm laborers (7.9%) compared to an overall high unemployment rate (42.5%). Also, factors such as

labor demand and rice prices have pushed wages higher. Regression estimates show that wage rate responded positively to the degree of inequality of land per acre, price of paddy and cropping intensity while it negatively responded to the proportion of landless and near landless workers. As such, both demand and supply factors were for change in farm wages. Hossain (1990) also attempted to analyze the determination of real wage rate in Bangladesh agriculture. The paper found that real farm wage increases less than proportionately to a rise in fertilizer. Rainfall has a positive effect on wages whereas abnormal weather conditions have a negative effect.

Some recent studies have primarily focused on the role of the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA), which was initiated by the government of India in 2005 and which comes within the broad spectrum of RNFS. The implementation of MGNREGA has had an impact on not only the demand and supply of agricultural workers but also on rural wages. Narayanamoorthy and Bhattarai (2013) observed a higher growth rate of farm wages after 2006–07 compared to pre-MGNREGA period. Real wages of male agricultural laborers increased at the rate of 2.42% per annum after 2006–07 compared to only 0.31% per annum in the pre-MGNREGA period. Moreover, growth of farm wages was witnessed in all four operations, namely- ploughing, transplanting, sowing and harvesting. Regression results show a rise in farm wages of both male and female workers due to an increase in the average days of employment in MGNREGA. Food grain productivity and improved road connectivity also contributed to farm wage growth. Also, states with fewer irrigation facilities registered a high growth of farm wages after 2006–07. Similarly, Kumar et al (2020) observed that not only wage rates increased but there was also a narrowing of the wage gap between farm and non-farm sector after 2008–09. Their fixed effects regression results for 1995–96 show that non-farm wages and employment in MGNREGS both have a positive influence on average real farm wage rates at the all-India level. Other factors that increased real farm wages are irrigation and rural literacy. Gulati, Jain and Satija (2014) on the other hand pointed out that the rise in agricultural wages after 2007–08 is not only due to a rise in employment in MGNREGA but due to other pull factors like GDP in the construction and agriculture sector which have a larger impact on wages. The study by Nagaraj et al (2016) also pointed out that the rise in both farm and non-farm wages are also due to urbanization and employment growth in the non-farm sector in six villages of Telangana and Maharashtra apart from MGNREGA. This is because the growth rate of farm and non-farm wages was 3% whereas the growth of wages in MGNREGA was only 1.71% in Telangana post MGNREGA.

Wages are also high in mining and construction sector which resulted in a shift of workers, particularly males towards non-farm sector employment. However, they also found that in villages where irrigation facilities are developed and easily accessible, farm wage is found to be higher than MGNREGA wages. Berg et al (2012) examined the effect of MGNREGA on rural agricultural wage growth at the district level. By applying a difference-in-difference (DID) method, they found a positive and significant result. After controlling for district, rainfall, and time-fixed effects, the findings reveal that an additional per capita person-day of MGNREGA work in a district raises the real daily agricultural wage rate by 1.6% and by 5.3% annually. The study also found that the implementation of MGNREGA has enhanced real wages of unskilled work rather than that of skilled work.

A few other studies focused on the role of the linkage between agriculture and non-agriculture sector in reducing rural poverty and unemployment. Vyas and Mathai (1978) pointed out that although income from agriculture increased at a higher rate between 1951 to 1971, yet there was no corresponding improvement in poverty reduction. This was attributed to a rise in marginalization of land holdings and increased population pressure along with a weak linkage between farm and the organized industrial sector which resulted in a lower purchasing power of majority of rural households. This reduced the demand for non-farm goods thereby affecting the expansion of industries. The author, therefore, states that the expansion of the rural non-farm sector can only enhance income of the rural poor and thereby reduce poverty. Lanjouw and Murgai (2009) studied the effect of an expansion of non-farm employment on rural poverty through its impact on farm wages. Persistence of rural poverty is also pointed out by them where poverty declined by less than 10% between 1993–94 to 2004–05. However, during the second half of the decade, there was a fall in poverty despite reduction of farm wage growth which is possible due to the expansion of non-farm employment. Regression analysis also demonstrates the greater role of agricultural productivity, urban per capita expenditure, land abundance and non-farm employment in reducing poverty. However, the study by Eswaran et al. (2009) found a limited role of the non-farm sector in reducing rural poverty as its increasing share of GDP had no significant impact on farm wages between 1999 to 2005. Therefore, the study demonstrates that majority of workers who are engaged in agriculture can come out of poverty only through a rise in agricultural productivity.

## 2.5. Summing up

The growing importance of rural non-farm sector as an additional source of income generation has driven researchers to dive deep into its nature, pattern and determinants in emerging economies. Although it was considered a residual sector, in recent times many rural households have shifted towards this livelihood option either as a principal or as a supplementary source of income. However, unlike agriculture, the RNFS is characterised by heterogeneity and hence, several factors determine an individual or household's decision to diversify which are broadly classified into "pull" and "push" factors. The major reason behind diversification as pointed out by numerous studies are factors related to poor performance of agriculture like small land holding sizes, weather variability and prevalence of traditional practices that increase the riskiness of farm productivity and compel farm households to engage in non-farm pursuits. However, some literature also observes that diversification is not solely undertaken for maintaining subsistence but is also carried out for accumulating purposes. This growth-led diversification is determined by pull factors like human capital variables which enable employment in high-return non-farm activities. Education not only facilitates males to compete for non-farm jobs but also opens up avenues for females as well. Proximity to markets and urban centres also facilitate households to diversify. In the Indian context, literatures point out that this diversification trend is more pronounced for males compared to females. Apart from education, diversification is also high among low-caste workers who are not only asset-poor but are less qualified and as such their diversification has been termed as a distress induced phenomenon. The heterogeneous nature of the non-farm sector is also addressed by a few studies by classifying it into different activity statuses yet proper sectoral classification of it is missing. Again, studies have also attempted to classify states into different agroecological zones, yet the overall pattern and determinants have remained similar.

Literatures that have focused on the welfare dimension of occupational diversification by farm households have constructed various indicators like consumption expenditure, income, level of poverty and vulnerability and food security to measure welfare. The studies pointed out that not only developing nations but even developed countries have witnessed this diversification trend and found evidence of its beneficial effects. Many of the literatures have observed that diversified households are better off not only in terms of higher household spending but also are able to escape poverty and food insecurity. Even consumption pattern of these households have shifted towards high value foods thereby improving their nutritional status. On the

contrary, some studies pointed out that rather than diversification, households are better off when they specialize in one economic activity whether in the farm or the RNFS. Furthermore, it is also observed that not all non-farm occupations can augment income or expenditure. Some studies have found that only regular and self-employed non-farm activities can accrue higher returns while no significant rise in expenditure is observed for casual non-farm employment. These different implications of diversification on welfare are region-specific and is greatly influenced by the presence of the type of non-farm activities available and the characteristics of households engaged in it.

Literatures on wages have mostly focused on the reasons behind inter-state and inter-district variations in wage rates of rural casual farm workers whereas scant studies were undertaken for non-farm wage determination in rural India. Most of the studies in the pre-reform period focused on the demand and supply framework in determining agricultural wages and explaining wage variations. Some of these studies observed that supply factors like availability of wage workers and concentration of land in the hands of few land owners tend to depress wages in spite of controlling for demand factors. However, on the contrary, some studies point out that differences in farm productivity explain the major variations in wage rates. Again, studies after the mid-1970s have shifted their focus from the demand-supply framework to factors outside of agriculture which includes availability of opportunities in non-farm employment. Also, in the post-reform era, it is claimed that wage variations depend on the extent to which state economy is linked to the global market and the role of economic reforms. In addition to this, urbanization, public spending and non-farm sector growth also played a crucial role in augmenting wages. But the significance of non-farm employment in increasing rural wages was witnessed in developed states while in low-wage rate states, farm productivity is found to play a dominant role. Focusing on the mid-2000s, literatures have further shifted their attention to the role of the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) on rural labor markets. The effect of MGNREGA on farm wages is found to be ambiguous. Some studies have found positive feedback of this initiative in increasing the earnings of casual workers but some have pointed out a negligible impact of this scheme and rather emphasized the role of growth driven factors like construction and agriculture GDP for rural household welfare.

## Chapter 3

### Determinants of non-farm employment choice in rural India

From the previous chapter, it is clear that non-farm employment has transitioned from a residual to a dominant livelihood option in rural India. The sector has diverse welfare implications ranging from availability of in-situ employment opportunities, especially for rural females. Expansion of RNFS also reduces rural-to-urban migration thereby lessening urban congestion and has even contributed to rural household welfare. However, the heterogeneous nature of this sector indicates that certain sectors are high-return whereas others are low-return and as such, several factors act as constraints in choosing different non-farm sectors. This chapter examines the role of various individual, household and regional factors in explaining the choice of different non-farm occupations compared to agriculture activities. It adds to the body of existing literature by examining the gender dimension of occupational diversification and focuses on the role of education, caste and land ownership in explaining employment probabilities across gender. The present chapter is divided into the following four sections. Section 3.1 discusses the data source and method applied for the analysis. Section 3.2 consists of descriptive statistics and section 3.3 discusses the findings of our study. Section 3.4 sums up the entire discussion of this chapter.

#### 3.1. Methodology

##### 3.1.1. Data source

The analysis in this chapter is carried out with the help of employment and unemployment survey (EUS) data of NSSO for 61<sup>st</sup> (2004–05), 66<sup>th</sup> (2009–10) and 68<sup>th</sup> (2011–12) rounds. The 61<sup>st</sup> round consists of 79, 306 households and 3,98,025 individuals while the 66<sup>th</sup> and 68<sup>th</sup> rounds have a sample size of 59,120 and 59,700 households and 2,81,327 and 2,80,763 individuals respectively in rural India. Among them, information on the employment of about 3,95,210 individuals is present combining all three survey rounds which are utilized for our empirical purposes.

The employment status of workers in NSSO is divided into principal and subsidiary status when the reference period is 365 days. An individual is considered to be working in the principal status when he/she spends at least 180 days in one economic activity and the same person can also engage in a secondary source of employment when he/she devotes at least 30 days. The most popular employment status is the usual principal and subsidiary status (UPSS)

which includes every individual who has worked in either principal status (PS), subsidiary status (SS), or both. Only the industrial classification associated with the principal status of a worker is considered for those who are engaged in both principal and subsidiary status. By applying this concept of UPSS, we obtain information regarding the industry in which each individual is employed. We apply this concept of employment status and classify the 5-digit non-farm industry as per the National Industrial Classification (NIC) criteria into five broad sectors in addition to agriculture and allied activities. These sectors are provided below.

- 1) agriculture and allied activities (base category), 2) mining, quarrying, electricity, gas, and water supply, 3) manufacturing, 4) construction, 5) trade, transport and communication, hotel and restaurant and 6) service activities.

### **3.1.1.1. The covariates used in the analysis are explained below**

**Age:** The age of a worker reflects the demographic situation. It can also be regarded as a proxy for experience that is acquired in any field of work (Demeke & Zeller, 2012). With age, the knowledge and experience gathered in a particular work may adversely affect the worker's decision to shift to a new activity. Therefore, we hypothesize that with an increase in age, the likelihood of working outside agriculture will also decline.

**Gender** - "Gender is also a factor in the ability to access income-earning opportunities and the impact of development interventions" (Niehof, 2004). Traditionally, cultural norms, societal issues and other restrictions are more stringent for females compared to males. They are also responsible for household duties and looking after the family (Srivastava & Srivastava, 2010; Serumaga-Zake & Naude, 2003). Lack of adequate educational qualification and absence of any ownership rights over assets like land are some other constraints faced by females that might adversely affect their ability to engage in profitable ventures (Gansonre, 2019; Niehof, 2004). Therefore, we hypothesize that female's participation in non-farm employment will be lesser compared to males.

**Education:** The level of education is an important capacity variable which is important for enhancing human capital. It has significant implications on the type of work that an individual chooses. It not only enables individuals to learn new skills that would open up avenues for high-return jobs but also helps them to be aware of any new employment opportunities available (Yunez-Naude & Taylor, 2001; Senadza, 2012). Educated individuals also prefer to get employed than remain unemployed (Naude & Serumaga-Zake, 2001, Serumaga-Zake &

Naude, 2003). Therefore, education can be hypothesized to have a positive effect on non-farm sector employment.

**Vocational training:** Vocational training facilitates an individual to get work in the labor market. Therefore, vocational training is expected to have a positive impact on non-farm employment participation.

**Marital status:** It is observed that married individuals have more family responsibilities and as such, they cannot afford to remain unemployed. However, it is also claimed that married individuals are employed in agriculture more than any other activities (Xia & Simmons, 2006). So, we hypothesize that individuals currently married are less likely to work in low-return non-farm activities.

**Caste:** The segregation of society based on caste is a prominent feature in India and it is closely associated with occupational choice, particularly in rural India (Nakajima et al, 2018). Traditionally, individuals of lower caste like ST and SC are confined to manual low-return activities like pottery making, weaving, barbering etc. while cultivation is undertaken by upper caste households (Gang et al, 2017; Mishra & Singh, 2018). But it has also been pointed out that the effect of caste on employment choice has reduced to a certain extent after the reforms period (ibid). Therefore, it is hypothesized that while upper-caste individuals are more likely to do cultivation, other caste workers will engage in different non-farm activities.

**Religion:** Given that Hindus make up to 80% of the country's population, there may exist some biasedness in their favor in terms of occupations in rural India. For instance, it is observed that Muslims have a higher share in casual employment than members of other religious groups in rural Uttar Pradesh (Mishra & Singh, 2018). Therefore, workers from the Hindu religion can be hypothesized to be involved more in cultivation compared to people of other religions.

**Size of land ownership:** Land is an important income-earning asset which is a household-level capacity variable that also influences occupational choice in rural India (Bezu & Holden, 2014). However, there are mixed responses regarding the role of land as it might either be used as collateral to establish any non-farm businesses (Fritsch, 2012) or might be utilized fully for cultivation purposes (Demek & Zeller, 2012; Gansonre, 2019). But in the absence of a proper land market, we hypothesize that land ownership would exhibit a negative impact on diversification.

**Household size:** Household size represents the demographic composition of the household. A larger household size represents the existence of more manpower and can easily divide their work into farm and non-farm sectors (Demeke & Zeller, 2012). Therefore, a larger household size can increase the probability of an individual joining the RNFS. Hence, a positive relationship can be expected between household size and non-farm employment.

**Dependency ratio:** Dependency ratio is defined as the ratio of the number of dependents in a household to the number of adult working members. This variable has important implications for employment diversification (Niehof, 2004). More dependents in a household means more requirement of resources to feed them and this might influence the working members to choose non-farm employment where returns are normally higher than in agriculture (Demeke & Zeller, 2012). Therefore, dependency ratio is assumed to have a positive impact on diversification.

**Urbanization:** This variable is defined as the percentage of urban population to total population in a region which is used as a proxy for urbanization. This variable is hypothesized to have a favorable effect on generating non-farm employment opportunities in rural regions through sub-contracting or urban demand for certain indigenous rural goods and services (Jatav & Sen, 2013; Visaria, 1995). Therefore, a higher level of urbanization will increase the choice of rural non-farm employment.

**Average distance of a rural region from its cities:** Villages that have easy access to nearby urban areas may act as an incentive for rural individuals to work in urban centers and this can be possible if the transportation cost is lower. It also reflects communication links with urban regions which might help in expanding the non-farm sector through channels like sub-contracting (Xia & Simmons, 2004; Demeke & Zeller, 2012; Jatav & Sen, 2013). For empirical analysis, the average distance of the district from urban centers within a state is calculated and these urban centers are the tier 1 and tier 2 cities which are taken from the source "Maps of India".

**Unemployment rate in a region:** This variable is used as an indicator of the employment opportunities available in rural areas. When the unemployment rate is low, then economic activities taking place in a region are generating sufficient jobs for a given demand for jobs and if the unemployment rate is high given a similar demand for jobs, then it implies that economic activities are not generating sufficient employment opportunities. This in turn indicates the labor absorption capacity in that region. Therefore, the unemployment rate is an important indicator of the nature of activities taking place in that region. Since we are focusing on

individual choices, the aggregate level of unemployment rate in a region is determined by these individual choices and these individual choices are constrained by the availability of jobs. So in a way, there is a problem of reverse causality but at the aggregate level. This variable is used as a push indicator for employment diversification.

**Gender and education:** Some existing literature (de Janvry & Sadoulet, 2001; Yunez-Naude & Taylor, 2001) have pointed out that although males, in general, have a higher probability of employment in non-farm activities yet in comparison to educated males, it is found that educated females have a higher likelihood of joining the labor force (ibid). This means that exposure of females to education may enhance their ability to participate in employment other than in farming. Therefore, to verify this finding in rural India, we use an interaction term between gender and education.

**Gender and caste:** Although low-caste workers diversify more towards non-farm occupations (Jatav & Sen, 2013; Mishra & Singh, 2018), yet their participation may vary between males and females. This is because low-caste females are not constrained by social rules and regulations and so they participate more in economic activities compared to upper-caste females (Srivastava & Srivastava, 2010). Similarly, upper-caste males having ownership rights over land may abstain from working outside agriculture.

Table 3.1 below provides the mean and standard deviations of the above-mentioned covariates

**Table 3. 1Description of explanatory variables**

Variable name	Variable description	Mean	S. D
<b>Continuous variables</b>			
<b>Age</b>	Age of working members (in years)	27.43	19.21
<b>HH size</b>	Household size	6.01	2.91
<b>Dependency ratio</b>	The ratio of dependents to working-age members in a household	0.84	0.75
<b>Unemployment rate</b>	The ratio of unemployed people to total labor force in state-region <sup>1</sup> .	32.69	30.61
<b>Urbanization</b>	Percentage of urban population in a state region	33.67	12.08

<sup>1</sup> State-region concept of NSSO represents a cluster of districts having similar geographical and population characteristics.

<b>Average dis</b>	The average distance of rural region from the urban centres (in kilometres)	306.58	214.76
<b>Categorical variables</b>		<b>Percentage share</b>	
<b>Gender</b>	male=1 female=0	51.102	
<b>Education (illiterate= base category)</b>			
<b>Edu1</b>	below primary and primary level education	33.310	
<b>Edu2</b>	middle and secondary level education	23.435	
<b>Edu3</b>	higher secondary and diploma	5.902	
<b>Edu4</b>	Graduate and above	3.546	
<b>Vocation</b>	Receiving/received vocational training =1, not received=0	8.784	
<b>Married</b>	currently married=1, 0 otherwise	47.143	
<b>Household level factors</b>			
<b>Caste (unreserved category= base category)</b>			
<b>ST</b>	Schedule Tribe	16.150	
<b>SC</b>	Schedule Caste	16.979	
<b>OBC</b>	Other Backward Classes	38.973	
<b>Religion (other religion= base category)</b>			
<b>Hindu</b>	Hindu	75.432	
<b>Muslim</b>	Muslim	12.329	
<b>Size of land ownership (landless= base category)</b>			
<b>Marginal</b>	Land size< 1 hectare	66.359	
<b>Small</b>	1<land size<2 hectare	13.234	
<b>Medium</b>	2<land size<10 hectare	9.441	
<b>Large</b>	Land size>10 hectares	1.419	

### 3.1.2. Empirical Method

The choice of occupation by an individual is made in such a way that maximizes his or her utility by maintaining a certain level of consumption and time for leisure. Utility being a subjective concept is not directly observable. Therefore, it can be assumed that among the various employment alternatives available to an individual, he will choose that occupation from where he can obtain the maximum satisfaction. We have also classified the non-farm sector

into its different sub-categories to focus on its heterogeneous nature. Ignoring this heterogeneity may “mask many differences between them” (Lanjouw & Lanjouw, 2001; Demeke & Zeller, 2012). Here, an individual has six different employment alternatives available to him and to estimate the effect of determinants on these occupational choices, we have applied the multinomial logit model.

Multinomial logit model requires a base category against which the findings of all other alternatives are compared and, in our case, agriculture and allied activities are considered as the base category. Therefore, the probability of choice of an occupation is compared with the base group. The multinomial logit model is explained below-

Let us assume that the decision of an individual to choose a particular occupation depends on certain explanatory variables represented by  $X_i$ . Let us take an indicator variable  $Y_{ij}$  where  $Y_{ij}=1$  if individual ‘i’ chooses occupation ‘j’ over the base outcome and it takes value 0, otherwise.

Further, let  $\pi_{ij} = \Pr(Y_{ij} = 1)$ , Where, Pr denotes the probability of choosing ‘j’.

Therefore, the probability of an individual “i” that chooses employment “j” given the explanatory variables can be written as-  $\pi_{ij} = \Pr(Y_{ij} = j/x) = \frac{\exp(x\beta_j)}{\sum \exp(x\beta_j)}$  (Demeke & Zeller, 2012). In case of the base category,  $\beta_j = 0$ , and therefore the probability for the base category

$$\text{is- } \pi_{i1} = \frac{1}{\sum_{j=1} \exp(x\beta_j)}.$$

To estimate the logit model, we need to obtain the log of the odds ratio, which is given as-  $\ln\left(\frac{\pi_{ij}}{\pi_{i1}}\right) = \beta_j x$  where  $j=2,3..6$ . Therefore, an individual can choose any one of the available non-farm activities as there is no meaningful ordering among them. Data for all three rounds are combined and a pooled multinomial logistic regression model is applied. The model is explained below as-

$$\Pr(Y_i = j) = \frac{\exp(X_i\gamma_i + X_h\gamma_h + X_l\gamma_l)}{\sum_{j=0..5} \exp(X_i\gamma_i + X_h\gamma_h + X_l\gamma_l)}, j = 0 \dots \dots 5. \text{ (Nakajima et al, 2018)}$$

Where  $\Pr(Y_i = j)$  indicates the probability of choosing outcome  $j$  by individual  $i$  of household  $h$ . The six categories of activities denoted by ‘j’ are agriculture and allied activities (0), mining, quarrying, electricity, gas and water supply (1), manufacturing (2), construction (3), trade,

transport, hotel and restaurant (4) and services (5). For comparison of employment probabilities, agriculture and allied activities (0) are considered as the base category.

The explanatory variables are denoted by  $X_i$ ,  $X_h$  and  $X_l$ . The individual variables represented by the vector  $X_i$  include age, gender, educational level, vocational training and marital status. Caste, religion, land ownership size, dependency ratio and household size which forms the household characteristics are denoted by  $X_h$ . Locational factors represented by the vector  $X_l$  comprises the unemployment rate, rate of urbanization and average distance of a district to the urban centre.  $\gamma_i$ ,  $\gamma_h$  and  $\gamma_l$  represents the vector of coefficients to be estimated.

Our analysis further supports the multinomial logit model's applicability by satisfying the assumption of independence of irrelevant alternatives (IIA). This presumption indicates that the choice of one alternative is not affected by the presence of other alternatives (Demeke & Zeller, 2012). The result of Small-Hsiao test is presented in Appendix 3A, table 3A.1 which shows that the IIA assumption is satisfied.

### 3.2. Descriptive statistics

This section provides a brief idea about the sectoral composition of rural non-farm employment for 2004–05, 2009–10 and 2011–12. Here, we will also describe the characteristics of rural non-farm workers and the relation between various covariates in explaining employment probabilities.

**Table 3. 2Trend in the percentage share of rural workers in agricultural and non-agricultural sector for the period from 2004–05 to 2011-12**

Sector	2004–05	2009–10	2011–12
<b>Rural persons</b>			
Agriculture & allied activities	72.7	67.95	64.10
Rural non-farm	27.3	32.05	35.9
<b>Rural male</b>			
Agriculture & allied activities	66.50	62.81	59.36
Rural non-farm	33.5	37.19	40.64
<b>Rural female</b>			
Agriculture & allied activities	83.34	79.35	74.94
Rural non-farm	16.66	20.65	25.06

Source: Author's computation from NSSO EUS data for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> round.

Table 3.2 shows a clear decline in the share of workers in agriculture and allied activities whereas the share of male and female employment in the RNFS witnessed a gradual rise. Shaw (2013) also pointed out that more and more people are joining secondary and tertiary activities. However, the share of males in rural non-farm employment is higher compared to females. Males are always in an advantageous position in terms of shifting towards non-farm occupations compared to females (Srivastava & Srivastava, 2010; Jatav & Sen, 2013; Ebaidalla, 2022). For instance, the share of male employment in RNFS has risen from 33.5% in 2004–05 to 40.64% in 2011–12 while for females, their share in rural non-farm employment increased from 16.66% to 25.06% during the same period. Given the presence of different rural non-farm sub-sectors, it is important to examine the sectoral composition and change in it over time to understand its significance for rural livelihood. Table 3.3 below shows the industrial classification of rural male and female workers.

**Table 3.3 Percentage share of rural workers in different non-farm sub-sectors**

Sector	2004–05	2009–10	2011–12	2021–22 <sup>2</sup>
<b>Rural male</b>				
Agriculture & allied activities	66.50	62.79	59.36	51.02
Mining & quarrying	0.64	0.82	0.54	0.41
Manufacturing	7.92	7.02	8.13	7.87
Electricity, gas & water supply	0.24	0.20	0.31	0.47
Construction	6.84	11.28	13.01	16.64
Trade, hotel & restaurant	8.27	8.12	8.03	10.58
Transport & communication	3.80	4.15	4.23	5.56
Other services	5.80	5.62	6.40	7.45
<b>Rural female</b>				
Agriculture & allied activities	83.34	79.35	74.94	75.90
Mining & quarrying	0.29	0.26	0.29	0.13
Manufacturing	8.36	7.53	9.79	7.85
Electricity, gas & water supply	0.01	0.03	0.07	0.08
Construction	1.45	5.20	6.59	5.31
Trade, hotel & restaurant	2.50	2.77	2.95	3.67

<sup>2</sup> Information on sectoral composition for the year 2021–22 has been taken from PLFS data to have an idea about the pattern of industrial classification in recent times. However, this data set is not used exclusively for empirical purposes due to non-compatibility with NSSO data.

<b>Transport &amp; communication</b>	0.16	0.21	0.16	0.30
<b>Other services</b>	3.90	4.66	5.20	6.76
<b>Rural persons</b>				
<b>Agriculture &amp; allied activities</b>	72.65	67.94	64.10	59.01
<b>Mining &amp; quarrying</b>	0.51	0.64	0.47	0.32
<b>Manufacturing</b>	8.08	7.18	8.64	7.86
<b>Electricity, gas &amp; water supply</b>	0.15	0.15	0.23	0.34
<b>Construction</b>	4.87	9.39	11.05	13
<b>Trade, hotel &amp; restaurant</b>	6.16	6.45	6.48	8.36
<b>Transport &amp; communication</b>	2.47	2.92	2.99	3.87
<b>Other services</b>	5.10	5.32	6.04	7.23

*Source: Author's computation from NSSO EUS data for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> round and PLFS round for 2021–22.*

Employment share of the rural labor force in various rural non-farm sub-sectors from the period 2004–05 to 2021–22 is shown in table 3.3. Clearly, males are moving away from agriculture at a more rapid pace than females (Abraham, 2009) as 75.90 % of females are still involved in agriculture and allied activities either in principal status or subsidiary status compared to only 51.02 % for male farm workers in 2021–22. Among the secondary sectors, manufacturing is one of the important employment-generating sectors whose share in rural employment for males was 7.92% in 2004–05. For rural females, manufacturing remained the highest employment-generating sector throughout. However, by 2021–22, construction sector accounted for the major employment generation for rural males where it generated 16.64% of total rural employment. But for rural females, share of employment in both manufacturing and construction declined in the year 2021–22. Again, among the tertiary sector, highest employment for males is generated in trade, hotel and restaurant activities, while for females, services generated most of the tertiary sector jobs followed by trade, hotel and restaurant. The employment shares of mining, quarrying, electricity, gas and water supply remained negligible. Therefore, among all the non-farm sub-sectors, construction has generated the maximum jobs for males while manufacturing provided the highest share of employment for rural females.

### **3.2.1. Transformation in the status of rural employment**

Another important aspect to examine is the change in the status of rural employment. The NSSO employment-unemployment data divides the activity status into three groups- self-

employment, regular and casual work. Taking the one-digit industrial classification along with the activity status, we get the following six categories- self-employed in agriculture, regular work in agriculture and casual work in agriculture, self-employed in non-farm sector, regular in non-farm and casual in non-farm.

**Table 3. 4**Percentage share of rural farm and non-farm workers by their activity status

Years	Farm sector			Non- farm sector		
	Self-employed	Regular	Casual	Self-employed	Regular	Casual
<b>Males</b>						
<b>2004-05</b>	42.41	0.89	23.20	15.73	8.09	9.68
<b>2009-10</b>	38.15	0.64	24.01	15.31	7.90	13.98
<b>2011-12</b>	38.95	0.47	19.94	15.52	9.58	15.55
<b>Females</b>						
<b>2004-05</b>	53.75	0.41	29.18	9.92	3.30	3.44
<b>2009-10</b>	46.62	0.33	32.40	9.01	4.08	7.56
<b>2011-12</b>	48.12	0.44	26.37	11.13	5.17	8.76
<b>Persons</b>						
<b>2004-04</b>	46.55	0.71	25.38	13.61	6.34	7.40
<b>2009-10</b>	40.78	0.55	26.62	13.36	6.71	11.99
<b>2011-12</b>	41.74	0.46	21.90	14.18	8.24	13.48

Source: Author's computation from NSSO EUS data for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds.

Significant transformation in the activity status of rural workforce can be seen in table 3.4. Between 2004–05 and 2009–10, the percentage share of self-employment decreased in both farm and non-farm sectors for male and female workers while in the next period, i.e. between 2009–10 and 2011–12, their share increased irrespective of gender and sector. For example, percentage of male self-employed farm workers declined from 42.41% to 38.15% and then in the next period it increased marginally to 38.95%. Similarly, in case of non-farm employment, male self-employed worker's share declined from 15.73% to 15.31% between 2004–05 and 2009–10 but again increased to 15.52% in 2011-12. The share of regular male workers in the non-farm sector experienced a fall from 8.09% to 7.90% between 2004–05 and 2009–10 but between 2009–10 and 2011–12, it accelerated to 9.58%. However, their share in regular farm work is not only negligible but is also on a declining trend. In case of female non-farm workers, their share in both regular and casual non-farm employment is on an increasing trend. Similarly, for male workers, casual employment increased in non-farm sector while it

decreased in the farm sector. Although casual employment in non-farm sector is on an increasing trend, but between 2009–10 and 2011–12, it has been accompanied by an increase in regular and self-employed non-farm activities (Rangarajan et al, 2014). Jatav and Sen (2013) also points to a rise in casualization of non-farm activities and a greater share of this rise is found between 2004–05 and 2009–10. This increase in casual employment is attributed to the implementation of MGNREGA scheme.

### 3.2.2. Change in the principal and subsidiary status of workers in farm and rural non-farm sector

**Table 3. 5**Percentage share of principal status (PS) and subsidiary status (SS) workers in farm and non- farm sector.

Year	Farm sector		Non – farm sector	
	PS	SS	PS	SS
<b>2004-05</b>	70.82	84.11	29.18	15.89
<b>2009-10</b>	66.82	69.81	33.18	30.19
<b>2011-12</b>	62.82	62.24	37.18	37.76

Source: Author's computation from NSSO EUS data for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> round.

The percentage of workers in agriculture and allied activities in both principal and subsidiary status indicates a declining trend where its share decreases from 70.82% to 62.82% for principal status workers and from 84.11% to 62.24% for subsidiary status workers between 2004–05 and 2011–12. For non-farm sector, the percentage of principal and subsidiary status workers increased from 29.18% to 37.18% and from 15.89% to 37.76% respectively between 2004–05 and 2011–12. This points towards a gradual increase in the acceptance of non-farm work as a primary income-earning source.

Another important aspect is to understand the nature of workers who diversify to occupations outside agriculture. The following table and its corresponding figure show the age composition of rural non-farm workers for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds.

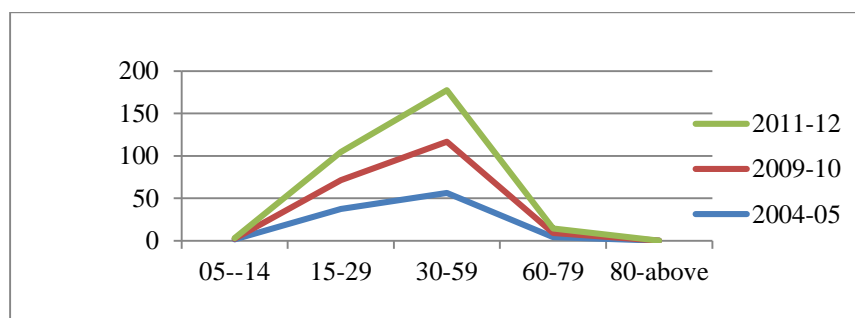
**Table 3. 6**Age distribution of rural non-farm workers (in percentages)

Age distribution	2004-05	2009-10	2011-12
<b>5-14</b>	1.62	0.82	0.68
<b>15-29</b>	37.54	33.98	33.13
<b>30-59</b>	56.53	60.20	60.71

<b>60-79</b>	4.24	4.93	5.37
<b>80-above</b>	0.07	0.08	0.12

Source: Author's computation from NSSO EUS data for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> round.

**Figure 3. 1 Graphical representation of age distribution of non-farm workers**



It is observed that majority of non-farm workers belong to the 30–59 age group and beyond that age, their participation falls. This shows that younger people are more likely to join this sector. Existing literatures (Mishra & Singh, 2018; Basant & Kumar, 1989; Pal & Kynch, 2010; Lanjouw & Shariff, 2004; Nakajima et al, 2018) have pointed out the significance of factors like size of land ownership, religion, caste and educational qualification that play a significant role in non-farm occupational choice. The following tables compare the share of farm and non-farm workers based on their education, land ownership size and caste status.

Education has been found to play an important role in expanding the range of employment opportunities outside agriculture (De Janvry & Sadoulet, 2001; Jatav & Sen, 2013; Lanjouw & Shariff, 2004). In addition to enhancing the capacity of workers to compete for high-return jobs, human capital also enhances the managerial capacity and decision-making power. Individuals with adequate educational qualification can grab employment opportunities whenever they are available. Table 3.7 shows the share of educated individuals in both sectors.

**Table 3. 7 Distribution of rural farm and non-farm workers according to their educational level for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds**

Educational level	2004-05		2009-10		2011-12	
	Farm	Non-farm	Farm	Non-farm	Farm	Non-farm
<b>Males</b>						
Illiterate	38.83	24.06	31.67	21.77	32.17	21.58
Below primary	30.16	28.78	29.29	27.07	28.52	26.67
Middle & secondary	24.71	31.94	30.50	34.94	30.05	34.26

HS & diploma	4.10	8.36	6.15	8.65	6.38	9.56
Graduate & above	2.19	6.85	2.39	7.58	2.89	7.93
<b>Females</b>						
Illiterate	69.35	49.27	60.80	44.39	60.59	42.88
Below primary	18.34	22.60	22.88	24.34	21.78	23.43
Middle & secondary	10.97	18.37	14.19	20.35	15.09	21.16
HS & diploma	1.11	5.68	1.62	5.37	1.98	6.17
Graduate & above	0.24	4.07	0.52	5.54	0.55	6.36
<b>Persons</b>						
Illiterate	51.63	29.67	42.24	26.30	42.28	26.10
Below primary	25.20	27.41	26.96	26.52	26.12	25.98
Middle & secondary	18.95	28.92	24.58	32.01	24.73	31.48
HS & diploma	2.85	7.77	4.50	7.99	4.82	8.84
Graduate & above	1.37	6.23	1.71	7.17	2.06	7.60

Source: Author's computation from NSSO EUS data for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> round.

A comparison of the educational qualifications of farm and non-farm workers exhibit different patterns for males and females. In case of agriculture sector, most of the male workers are illiterate but for non-farm sector, majority of them have an education of middle and secondary level. The share of illiterate worker is lower and that of educated worker is higher in non-farm sectors. On the other hand, female workers are mostly illiterate whether in the farm or non-farm sector, but among the educated group, female participation in non-farm employment is highest for those having education below primary and primary, middle and secondary. Therefore, education can augment the capacity of workers to engage in high-return non-farm activities.

The second important factor that affects occupational choice is the size of rural household's land ownership. Land being a crucial income-earning asset may be utilized either for cultivation or investing it in non-farm activities.

**Table 3. 8Distribution of workers by the size of their land ownership**

Land holding size	2004-05		2009-10		2011-12	
	Farm	Non-farm	Farm	Non-farm	Farm	Non-farm
<b>Landless (&lt;0.002 hectare)</b>	3.89	6.57	4.28	7.89	3.30	5.94
<b>Marginal (0.003&lt; 1 hectare)</b>	60.05	80.54	62.35	81.46	62.38	84.31
<b>Small (1-2 hectare)</b>	17.15	7.03	15.74	6.01	17.94	5.54
<b>Semi-medium (2-4 hectare)</b>	12.01	3.81	11.76	3.07	11.22	2.89

<b>Medium (4-10 hectare)</b>	5.98	1.78	5.12	1.34	4.46	1.16
<b>Large (10 &amp; above hectare)</b>	0.93	0.26	0.75	0.24	0.69	0.16

Source: Author's computation from NSSO EUS data for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> round.

Table 3.8 shows that lack of adequate amount of land may have driven rural workers to join the non-farm sector as more than 80% of non-farm workers belong to marginal land holding size and the percentage of marginal land holders who diversify has also increased over the three time periods. The share of non-farm workers from medium and large land-holding households is negligible. Agriculture is mostly pursued by those having land between marginal to semi-medium. Therefore, it is seen that marginal land-holding households are the ones who engage in both farm and non-farm activities. Several studies focusing on other developing countries (Bezu and Holden, 2014; Bezu, Barette and Holden, 2014; Demeke and Zeller, 2012; Demie and Zeray, 2016; Fabusoro et al, 2010; Matsumoto et al, 2006) also point towards an adverse relation between land ownership size and the probability of engaging in non-farm activities

**Table 3.9 Percentage share of rural workers belonging to different social group**

Social group	ST		SC		OBC		OTHERS	
	Farm	Nonfarm	Farm	Nonfarm	Farm	Nonfarm	Farm	Nonfarm
<b>2004-05</b>	83.99	16.01	71.75	28.25	72.18	27.82	68.61	31.39
<b>2009-10</b>	79.72	20.28	64.27	35.73	67.90	32.10	65.27	34.73
<b>2011-12</b>	76.19	23.81	59.56	40.44	64.81	35.19	60.14	39.86

Source: Author's computation from NSSO EUS data for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> round

Table 3.9 depicts the distribution of workers between farm and non-farm sector based on caste categories. It is seen that among these caste groups, the share of STs is highest in farm sector followed by OBC, SC and others. But there is a gradual fall in farm sector employment for all category workers. By 2011–12, the share of SC workers is highest in non-farm sector followed by upper caste category and their share has also increased over this period of time. This shows that STs are highly concentrated in agriculture compared to other caste whereas, SCs have started diversifying to non-farm activities. Geographical isolation and lack of information about non-farm occupations might result in a low representation of STs in this sector (Nakajima et al, 2018). Moreover, land distribution is also unequally distributed which might have pushed SCs to work in non-farm (Lanjouw & Shariff, 2004; Mishra, 2014; Mishra & Singh, 2018;

Nakajima et al, 2018; Gang et al, 2017). Implementation of MGNREGA also facilitated low caste workers to join the RNFS (Mishra & Singh, 2018).

### 3.2.3. Caste, education and land ownership of rural non-farm workers

Here, we examine the educational level and economic status (represented through land ownership size) of rural non-farm workers belonging to different social groups. Caste being an important stratifying agent in rural India, not only determines occupation but also educational attainment. Low-caste ST and SC individuals have a higher share in the illiterate group while it is low among upper-caste people (Deshpande, 2001). Also, upper caste households have historically been the owners of land and are also better endowed with physical assets compared to ST/SC households (Srivastava & Srivastava, 2010). Tables 3.10 and 3.11 below depict the share of non-farm workers of different social groups according to land ownership and educational level for the 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds.

**Table 3. 10 Caste-wise distribution of educational qualification of rural non-farm workers**

<b>Educational level</b>	<b>ST</b>	<b>SC</b>	<b>OBC</b>	<b>Others</b>
<b>61<sup>st</sup> round</b>				
<b>Illiterate</b>	48.41	37.88	28.71	19.81
<b>Below primary &amp; primary</b>	25.26	28.10	27.94	26.56
<b>Middle &amp; secondary</b>	17.95	25.16	30.52	32.23
<b>HS &amp; diploma</b>	4.71	5.48	7.66	10.55
<b>Graduate &amp; above</b>	3.67	3.38	5.18	10.85
<b>66<sup>th</sup> round</b>				
<b>Illiterate</b>	35.99	34.23	25.13	17.42
<b>Below primary &amp; primary</b>	24.82	28.28	27.00	24.48
<b>Middle &amp; secondary</b>	27.02	28.22	33.45	34.90
<b>HS &amp; diploma</b>	7.20	5.12	7.84	11.36
<b>Graduate &amp; above</b>	4.97	4.15	6.58	11.84
<b>68<sup>th</sup> round</b>				
<b>Illiterate</b>	40.37	33.43	24.79	16.65
<b>Below primary &amp; primary</b>	26.05	28.56	25.78	23.87
<b>Middle &amp; secondary</b>	22.88	28.26	33.81	33.37
<b>HS &amp; diploma</b>	5.87	5.84	8.99	12.44

**Graduate & above**                      4.84                      3.92                      6.64                      13.68

*Source: Author's computation from NSSO EUS data for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> round*

We found that illiteracy is high among SC and ST non-farm workers although its share has declined over time. But for STs, the share of illiterate workers increased between 2009–10 and 2011–12. On the other hand, the share of OBC and upper caste non-farm workers having an educational level of higher secondary, graduate and above is more compared to ST and SC workers. Among, the educated non-farm workers, most of the OBC and upper caste have an education of middle and secondary level while SC and ST workers are mostly below primary and primary educated. However, a positive change is the increasing share of workers in higher secondary and graduate level irrespective of the caste category.

Studies (Pal and Kynch, 2010; Mishra and Singh, 2018) have pointed out that the relation between caste and occupation is also influenced by the presence of land ownership. Upper caste being the land owners enjoy greater economic stability while the low caste SC and ST people are mostly engaged in menial low-return jobs (Lanjouw and Shariff, 2004; Mishra, 2014; Mishra and Singh, 2018; Nakajima et al, 2018; Gang et al, 2017). For instance, ST, SC and OBC households in rural Uttar Pradesh and West Bengal mostly work as casual labor while cultivation is done by upper-caste households.

**Table 3. 11Percentage share of non-farm workers across different caste and size of land ownership.**

<b>61<sup>st</sup> round (2004–05)</b>				
<b>Land ownership</b>	ST	SC	OBC	Upper Caste
<b>Landless</b>	4.94	5.71	9.36	6.31
<b>Marginal</b>	77.07	77.29	83.63	81.64
<b>Small</b>	9.03	10.55	4.25	6.64
<b>Semi-medium</b>	5.47	4.13	1.96	3.67
<b>Medium</b>	3.01	2.25	0.71	1.49
<b>Large</b>	0.48	0.07	0.08	0.25
<b>66<sup>th</sup> round (2009–10)</b>				
<b>Landless</b>	6.51	7.02	10.90	7.10
<b>Marginal</b>	80.18	77.11	84.01	81.48
<b>Small</b>	7.24	10.87	3.20	6.05

<b>Semi-medium</b>	3.99	4.02	1.33	3.38
<b>Medium</b>	1.82	0.79	0.52	1.64
<b>Large</b>	0.27	0.20	0.04	0.35
<b>68<sup>th</sup> round (2011–12)</b>				
<b>Landless</b>	4.77	6.05	7.70	5.61
<b>Marginal</b>	82.00	82.02	86.75	84.72
<b>Small</b>	7.07	7.15	3.79	5.33
<b>Semi-medium</b>	4.04	3.81	1.25	2.97
<b>Medium</b>	1.74	0.89	0.51	1.24
<b>Large</b>	0.38	0.08	0.00	0.14

*Source: Author's computation from NSSO EUS data for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> round*

Table 3.11 depicts that share in non-farm activities is highest for individuals belonging to marginal land-holding households irrespective of the caste category. Also, over the period from 2004–05 to 2011–12, there has been a rise in the share of non-farm workers belonging to marginal land-owning households. As the size of land holdings increases, their participation in non-farm activities declines and a very small fraction of medium and large land owners are involved in it, depicting an inverse relationship between land and rural non-farm diversification for different caste categories. But amongst the medium and large landholder households, the participation is high for ST and upper caste households.

The choice of employment may also be determined by the religion of the worker. In rural regions, it is found that Muslims have a higher percentage of workers in non-farm activities while Sikhs and other religious people are more in cultivation (Gang et al, 2017; Mishra & Singh, 2018). To look at the distribution of non-farm rural workers across different religious groups, we have the following table.

**Table 3. 12 Percentage share of farm and non-farm workers across different religious groups.**

<b>2004-05</b>					
<b>Industry</b>	Hindu	Islam	Christian	Sikh	Others
<b>Farm</b>	74.29	56.75	66.69	75.16	80.17
<b>Non-farm</b>	25.71	43.25	33.31	24.84	19.83

### 2009-10

Industry	Hindu	Islam	Christian	Sikh	Others
Farm	69.76	52.39	60.76	69.95	73.49
Non-farm	30.24	47.61	39.24	30.05	26.51

### 2011-12

Industry	Hindu	Islam	Christian	Sikh	Others
Farm	66.30	46.57	56.32	62.50	74.37
Non-farm	33.70	53.43	43.68	37.50	25.63

Source: Author's computation from NSSO EUS data for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> round

The share of different religious groups from table 3.12 shows that Muslims in all the three time periods have the highest share in non-farm rural employment compared to other religious group. It has also been noted that there is a gradual shift of rural employment from agriculture and allied activities to RNFS for all religious group but Hindus, Sikhs and Others still have a higher proportion employed in the primary sector. The dominance of Hindus in agriculture can be due to the distribution of land ownership in their favor.

The above descriptive statistics show that employment in the RNFS is determined by several factors like education, land ownership, caste, religion and other demographic and socio-economic indicators. Given the heterogeneity associated with RNFS, there will be differences on the extent to which these variables influence employment choice. The effects of the various constraints have been empirically analyzed in the following section.

### 3.3. Determinants of rural occupational choice

First, we estimate the determinants of occupational choice by applying a multinomial logistic regression model for the pooled data of 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> NSSO round. Table 3.13 below provides the nature and characteristics of workers diversifying to non-farm occupations.

**Table 3. 13** Determinants of rural non-farm employment in India for 2004–05, 2009–10 and 2011–12.

Variables	Mining & quarrying	Manufacturing	Construction	Transport	Services
	<b>Coefficient Values</b>				
Age	0.021* (0.003)	-0.007* (0.001)	-0.013* (0.001)	0.007* (0.001)	0.042* (0.001)
Gender	1.875*	0.285*	1.456*	1.617*	0.327*

	(0.070)	(0.018)	(0.018)	(0.020)	(0.019)
<b>Education (illiterate = base category)</b>					
<b>Edu1</b>	0.272*	0.409*	0.035***	0.568*	0.625*
	(0.068)	(0.022)	(0.02)	(0.022)	(0.031)
<b>Edu2</b>	0.440*	0.545*	-0.119*	1.064*	1.583*
	(0.068)	(0.022)	(0.02)	(0.021)	(0.03)
<b>Edu3</b>	1.037*	0.618*	-0.354*	1.406*	3.049*
	(0.087)	(0.034)	(0.036)	(0.028)	(0.033)
<b>Edu4</b>	1.520*	0.814*	-0.359*	1.637*	4.362*
	(0.098)	(0.046)	(0.053)	(0.035)	(0.035)
<b>Vocation (yes=1, 0= no)</b>	0.638*	1.517*	0.241*	0.513*	0.556*
	(0.061)	(0.02)	(0.024)	(0.02)	(0.023)
<b>Married</b>	0.101	-0.079*	-0.004	0.101*	-0.104*
	(0.064)	(0.020)	(0.020)	(0.019)	(0.022)
<b>Caste (other caste = base category)</b>					
<b>ST</b>	0.130	-0.322*	0.325*	-0.527*	0.027
	(0.08)	(0.033)	(0.028)	(0.027)	(0.03)
<b>SC</b>	0.349*	0.092*	0.732*	-0.295*	0.298*
	(0.071)	(0.025)	(0.023)	(0.022)	(0.026)
<b>OBC</b>	-0.072	0.215*	0.253*	-0.100*	0.171*
	(0.063)	(0.022)	(0.022)	(0.018)	(0.021)
<b>Religion (other religion = base category)</b>					
<b>Hindu</b>	0.467*	0.171*	0.282*	0.072**	0.081**
	(0.095)	(0.042)	(0.037)	(0.033)	(0.034)
<b>Muslim</b>	0.476*	0.770*	0.725*	0.578*	0.452*
	(0.133)	(0.047)	(0.044)	(0.039)	(0.044)
<b>Land ownership (landless= base category)</b>					
<b>Marginal</b>	-0.487*	-0.525*	-0.468*	-0.424*	-0.583*
	(0.105)	(0.036)	(0.034)	(0.034)	(0.042)
<b>Small</b>	-1.551*	-1.899*	-2.019*	-1.627*	-1.691*
	(0.124)	(0.045)	(0.043)	(0.039)	(0.047)
<b>Semi-medium</b>	-1.936*	-2.414*	-2.535*	-2.104*	-2.064*
	(0.137)	(0.052)	(0.053)	(0.044)	(0.05)
<b>Medium</b>	-2.653*	-2.907*	-3.084*	-2.636*	-2.399*
	(0.182)	(0.067)	(0.073)	(0.053)	(0.056)
<b>Large</b>	-2.098*	-3.549*	-3.141*	-2.925*	-2.732*
	(0.251)	(0.151)	(0.142)	(0.094)	(0.093)
<b>HH size</b>	-0.041*	0.005	-0.047*	-0.015*	-0.045*
	(0.01)	(0.003)	(0.003)	(0.003)	(0.004)
<b>Dependency ratio</b>	0.132*	0.063*	0.170*	0.149*	0.178*
	(0.043)	(0.015)	(0.013)	(0.013)	(0.015)
<b>Unemployment rate</b>	0.005*	0.0004	0.002*	0.003*	0.003*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)

<b>Urbanization</b>	0.007** (0.003)	0.005* (0.001)	-0.003* (0.001)	-0.004* (0.001)	0.000 (0.001)
<b>Average dis</b>	0.0001*** (0.000)	0.0001* (0.000)	0.0001** (0.000)	0.00005 (0.000)	0.000 (0.000)
<b>Year (2004= base year)</b>					
<b>2009</b>	0.347* (0.073)	0.210* (0.023)	0.996* (0.024)	0.246* (0.02)	0.145* (0.026)
<b>2011</b>	0.317* (0.074)	0.217* (0.023)	1.206* (0.024)	0.212* (0.021)	0.315* (0.027)
<b>State code</b>	Yes	Yes	Yes	Yes	Yes
<b>Constant</b>	-6.363* (0.253)	-1.711* (0.092)	-1.867* (0.087)	-2.656* (0.079)	-4.098* (0.091)

**Number of observations: 248,634**

**Wald chi2(125): 79109.05**

**Prob>chi2: 0.0000**

**Pseudo R2:0.1603**

**Log pseudolikelihood: -280881.47**

*Notes: Figures in parenthesis are robust Standard Errors. \*, \*\* & \*\*\* indicates significance at 1%, 5% and 10% level of significance.*

Here, we observe from table 3.13 that with an increase in age, individuals are more likely to join mining and quarrying, trade, transport and service activities but less likely to join manufacturing and construction implying a lesser probability to engage in physically demanding activities as people become older. Diversification to any of the non-farm occupations is high among males whereas females are more likely to engage in agriculture and allied activities. This is consistent with the findings by Jatav and Sen (2013) and Mishra and Singh (2018).

Again, with a rise in education and vocational training, the probability of diversification also increases except for construction where workers with an education of below primary and primary level are mostly employed. Married people are less likely to choose manufacturing and services and more likely to engage in trade and transport activities. Among the household-level determinants, caste significantly affects diversification. Individuals from ST, SC and OBC households tend to diversify to construction employment and are less likely to work in trade and transport sector. SC and OBC workers are also more likely to join manufacturing and services. Non-farm employment is also preferred by Hindus and Muslims compared to other religion group. Land ownership and household size have a significant negative impact on diversification. With a rise in household size, working members are more likely to focus on agriculture but as the number of dependents increases, diversification towards non-farm also

increases. This shows that as the dependency ratio increases, working members tend to diversify more in order to cope with the rising expenses. Similarly, land being an important income-earning asset exhibits an adverse impact on diversification for rural workers.

Furthermore, among the state-region and district-level determinants, unemployment rate has a positive impact on diversification towards mining, construction, trade and services. As people are diversifying more towards non-farm occupations with a rise in unemployment rate, it may imply the limitations of agriculture to absorb workers which increases the tendency of workers to join the non-farm sector. Jatav and Sen (2013) also demonstrate the tendency of rural households to enter easy-entry non-farm jobs like construction and manufacturing with a rise in rural unemployment rate. But with the inclusion of unemployment rate, the issue of reverse causality may arise because not all individuals who are looking for jobs will get one. Moreover, we cannot say whether the actual non-farm occupation in which the individual is engaged also matches his/her preference for that particular occupation. But it is definitely based on the availability of jobs. However, at the NSSO state-region level, we do not have any information on job availability which in turn also determines the unemployment rate. Therefore, the choice of an individual for a particular non-farm occupation does not have any direct effect on the unemployment rate but may affect through the availability of jobs and aggregation of individual preferences over different occupations.

Urbanization rate has a favorable impact on diversification towards mining and manufacturing while it negatively impacts diversification in construction and trade activities. This might indicate that regions that are characterized by a greater degree of urbanization, rural workers might migrate to urban areas for non-farm employment rather than working in rural non-farm sectors. Average distance to urban centers also favorably impacts diversification towards mining, manufacturing and construction employment although the coefficient value is very small. One reason can be the implementation of MGNREGA in the most backward districts at the first phase of its inception. While other can be the initiation of programs like Pradhan Mantri Gram Sadak Yojana (PMGSY) which has improved connectivity of rural regions that might have facilitated them to do trade-related activities. Isgut (2004) observes that better rural road infrastructure enables households in Honduras to earn higher returns from non-farm wage employment. Year dummies imply that occupational diversification among rural individuals has increased over time.

Now, table 3.14 to table 3.17 demonstrate whether the effect of gender, education, caste and land ownership on the choice of different non-farm occupations change over time. We specifically focus on these factors because our objective emphasizes the significance of these determinants and their effect on occupational choice which might change over time. Further, in rural India, occupations significantly vary between males and females where females remain confined to farm activities (Srivastava & Srivastava, 2010). However, with the rise in educational attainment and fall in fertility rate, it is likely that their participation would increase in sectors outside agriculture which is shown below by interacting gender with year dummies. Similarly, caste is one of the crucial factors affecting occupational choice. Caste system is one of the prime sources of stratification in Indian society where households are classified into upper caste, Other Backward Castes (OBC), Schedule Caste (SC) and Schedule Tribes (ST). Among them, STs and SCs lie at the bottom of the caste hierarchy whereas, upper-caste households comprise the superior group (Gang et al, 2017). One of the most distinctive features of this caste system is its close associations with occupations as well as economic status and well-being (Gang et al, 2017). Upper caste being the land owners enjoy greater economic stability while the low caste SC and ST people are mostly engaged in menial low-return activities (Lanjouw and Shariff, 2004; Mishra, 2014; Mishra and Singh, 2019; Nakajima et al, 2018; Gang et al, 2017). Furthermore, land ownership represents not only a household's source of income and economic status but also influences the occupational choice of individuals (Bezu & Holden, 2014). However, with increased marginalization of land holdings, even land-owning households have started looking for work outside agriculture. Therefore, to capture the effect of land ownership size on occupational choice over time, we have interacted land with year dummies.

**Table 3. 14 Effect of gender on occupational choice over time.**

Variables	Mining & quarrying	Manufacturing	Construction	Transport	Services
<b>Coefficient Values</b>					
<b>Age</b>	0.022* (0.003)	-0.007* (0.001)	-0.013* (0.001)	0.006* (0.001)	0.043* (0.001)
<b>Gender</b>	1.265* (0.145)	0.036 (0.033)	2.249* (0.065)	1.818* (0.045)	0.170* (0.044)
<b>Gender_09</b>	0.640* (0.179)	0.321* (0.042)	-0.910* (0.070)	-0.334* (0.053)	0.113** (0.051)
<b>Gender_11</b>	0.878* (0.185)	0.344* (0.042)	-0.838* (0.069)	-0.152* (0.054)	0.247* (0.05)
<b>Education (illiterate = base category)</b>					
<b>Edu1</b>	0.272* (0.042)	0.408* (0.042)	0.033*** (0.009)	0.569* (0.054)	0.623* (0.05)

	(0.068)	(0.022)	(0.019)	(0.022)	(0.031)
<b>Edu2</b>	0.439*	0.542*	-0.118*	1.065*	1.581*
	(0.068)	(0.023)	(0.020)	(0.021)	(0.029)
<b>Edu3</b>	1.035*	0.613*	-0.349*	1.408*	3.047*
	(0.087)	(0.034)	(0.036)	(0.028)	(0.033)
<b>Edu4</b>	1.516*	0.808*	-0.353*	1.639*	4.359*
	(0.098)	(0.046)	(0.053)	(0.035)	(0.035)
<b>Vocation</b> (yes=1, 0= no)	0.634*	1.512*	0.244*	0.513*	0.554*
	(0.061)	(0.02)	(0.024)	(0.020)	(0.023)
<b>Married</b>	0.083	-0.093*	0.011	0.106*	-0.109*
	(0.065)	(0.02)	(0.019)	(0.019)	(0.022)
<b>Caste (other caste = base category)</b>					
<b>ST</b>	0.129	-0.324*	0.326*	-0.527*	0.027
	(0.080)	(0.033)	(0.028)	(0.027)	(0.029)
<b>SC</b>	0.350*	0.092*	0.731*	-0.295*	0.299*
	(0.071)	(0.025)	(0.023)	(0.022)	(0.026)
<b>OBC</b>	-0.071	0.215*	0.252*	-0.100*	0.172*
	(0.063)	(0.022)	(0.022)	(0.018)	(0.021)
<b>Religion (other religion = base category)</b>					
<b>Hindu</b>	0.467*	0.171*	0.281*	0.072**	0.081**
	(0.095)	(0.042)	(0.037)	(0.033)	(0.034)
<b>Muslim</b>	0.477*	0.769*	0.724*	0.578*	0.452*
	(0.133)	(0.047)	(0.044)	(0.039)	(0.044)
<b>Land ownership (landless= base category)</b>					
<b>Marginal</b>	-0.485*	-0.524*	-0.467*	-0.422*	-0.581*
	(0.105)	(0.036)	(0.034)	(0.034)	(0.042)
<b>Small</b>	-1.549*	-1.897*	-2.019*	-1.626*	-1.689*
	(0.124)	(0.045)	(0.043)	(0.039)	(0.047)
<b>Semi-medium</b>	-1.935*	-2.412*	-2.534*	-2.103*	-2.062*
	(0.137)	(0.052)	(0.053)	(0.044)	(0.050)
<b>Medium</b>	-2.652*	-2.905*	-3.082*	-2.634*	-2.396*
	(0.182)	(0.067)	(0.073)	(0.053)	(0.056)
<b>Large</b>	-2.097*	-3.547*	-3.139*	-2.923*	-2.731*
	(0.251)	(0.151)	(0.142)	(0.094)	(0.093)
<b>HH size</b>	-0.040*	0.005	-0.047*	-0.015*	-0.045*
	(0.009)	(0.003)	(0.003)	(0.003)	(0.004)
<b>Dependency ratio</b>	0.127*	0.059*	0.173*	0.151*	0.177*
	(0.043)	(0.015)	(0.013)	(0.013)	(0.015)
<b>Unemployment rate</b>	0.005*	0.001	0.002*	0.003*	0.003*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
<b>Urbanization</b>	0.007**	0.005*	-0.003*	-0.004*	-0.000
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
<b>Average dis</b>	0.0001***	-0.0002*	0.0001**	0.0001	-0.0001
	(0.0001)	(0.0001)	(0.000)	(0.000)	(0.0001)
<b>State</b>	Yes	Yes	Yes	Yes	Yes
<b>Year (2004–05= base year)</b>					
<b>2009</b>	-0.199	-0.003	1.776*	0.539*	0.065
	(0.165)	(0.035)	(0.066)	(0.05)	(0.043)
<b>2011</b>	-0.429**	-0.007	1.934*	0.354*	0.139*
	(0.172)	(0.035)	(0.066)	(0.051)	(0.043)

<b>Constant</b>	-5.847*	-1.552*	-2.549*	-2.839*	-3.983*
	(0.269)	(0.093)	(0.104)	(0.087)	(0.095)

**Number of observations: 248,634**

**Wald chi2 (305): 118248.39**

**Prob>chi2: 0.0000**

**Pseudo R2: 0.1784**

**Log pseudo likelihood: -274810.62**

*Notes: Figures in parenthesis are robust Standard Errors. \*, \*\* & \*\*\* indicates significance at 1%, 5% and 10% level of significance.*

**Table 3. 15 Effect of education on occupational choice over time.**

<b>Variables</b>	<b>Mining &amp; quarrying</b>	<b>Manufacturing</b>	<b>Construction</b>	<b>Transport</b>	<b>Services</b>
<b>Coefficient Values</b>					
<b>Age</b>	0.024*	-0.007*	-0.014*	0.006*	0.043*
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
<b>Gender</b>	1.868*	0.285*	1.458*	1.619*	0.323*
	(0.070)	(0.018)	(0.018)	(0.019)	(0.019)
<b>Education (illiterate = base category)</b>					
<b>Edu1</b>	-0.384*	0.384*	0.117**	0.556*	0.279*
	(0.139)	(0.044)	(0.051)	(0.050)	(0.073)
<b>Edu2</b>	-0.665*	0.536*	0.106**	1.179*	0.919*
	(0.152)	(0.043)	(0.051)	(0.047)	(0.067)
<b>Edu3</b>	-0.739**	0.649*	-0.057	1.665*	2.607*
	(0.307)	(0.070)	(0.101)	(0.062)	(0.074)
<b>Edu4</b>	0.203	0.827*	-0.232	1.865*	3.791*
	(0.338)	(0.104)	(0.183)	(0.084)	(0.081)
<b>Education (illiterate= base category)</b>					
<b>Edu1_09</b>	0.787*	-0.009	-0.142**	-0.001	0.376*
	(0.172)	(0.055)	(0.058)	(0.059)	(0.088)
<b>Edu2_09</b>	1.308*	0.001	-0.288*	-0.177*	0.839*
	(0.179)	(0.054)	(0.058)	(0.055)	(0.079)
<b>Edu3_09</b>	1.965*	-0.104	-0.329*	-0.350*	0.606*
	(0.331)	(0.088)	(0.114)	(0.074)	(0.087)
<b>Edu4_09</b>	1.538*	-0.038	-0.024	-0.272*	0.826*
	(0.366)	(0.126)	(0.199)	(0.098)	(0.094)
<b>Education (illiterate= base category)</b>					
<b>Edu1_11</b>	0.860*	0.077	-0.038	0.045	0.425*
	(0.176)	(0.055)	(0.058)	(0.060)	(0.085)
<b>Edu2_11</b>	1.377*	0.023	-0.225*	-0.101***	0.716*
	(0.183)	(0.054)	(0.057)	(0.056)	(0.077)
<b>Edu3_11</b>	2.125*	0.017	-0.349*	-0.283*	0.434*
	(0.332)	(0.086)	(0.112)	(0.075)	(0.085)
<b>Edu4_11</b>	1.565*	0.0002	-0.244	-0.261*	0.526*
	(0.366)	(0.123)	(0.198)	(0.098)	(0.092)
<b>Vocation (yes=1, 0= no)</b>	0.649*	1.517*	0.239*	0.509*	0.557*
	(0.061)	(0.02)	(0.024)	(0.020)	(0.023)
<b>Married</b>	0.046	-0.079*	0.002	0.104*	-0.124*
	(0.064)	(0.02)	(0.019)	(0.019)	(0.022)

<b>Caste (other caste = base category)</b>					
<b>ST</b>	0.124 (0.080)	-0.322* (0.033)	0.324* (0.028)	-0.528* (0.027)	0.029 (0.029)
<b>SC</b>	0.361* (0.071)	0.092* (0.025)	0.731* (0.023)	-0.296* (0.022)	0.302* (0.026)
<b>OBC</b>	-0.064 (0.063)	0.215* (0.022)	0.253* (0.022)	-0.101* (0.018)	0.175* (0.021)
<b>Religion (other religion = base category)</b>					
<b>Hindu</b>	0.466* (0.095)	0.170* (0.041)	0.281* (0.037)	0.071** (0.033)	0.081** (0.034)
<b>Muslim</b>	0.481* (0.133)	0.769* (0.047)	0.723* (0.044)	0.577* (0.039)	0.453* (0.044)
<b>Land ownership (landless= base category)</b>					
<b>Marginal</b>	-0.479* (0.106)	-0.525* (0.036)	-0.469* (0.034)	-0.424* (0.034)	-0.582* (0.042)
<b>Small</b>	-1.540* (0.124)	-1.899* (0.045)	-2.021* (0.043)	-1.628* (0.039)	-1.691* (0.047)
<b>Semi-medium</b>	-1.921* (0.137)	-2.414* (0.052)	-2.537* (0.053)	-2.105* (0.044)	-2.062* (0.050)
<b>Medium</b>	-2.642* (0.182)	-2.907* (0.067)	-3.086* (0.073)	-2.638* (0.053)	-2.398* (0.056)
<b>Large</b>	-2.089* (0.252)	-3.549* (0.151)	-3.144* (0.142)	-2.927* (0.094)	-2.735* (0.093)
<b>HH size</b>	-0.039* (0.009)	0.005 (0.003)	-0.047* (0.003)	-0.015* (0.003)	-0.045* (0.004)
<b>Dependency ratio</b>	0.125* (0.043)	0.063* (0.015)	0.169* (0.013)	0.149* (0.013)	0.174* (0.015)
<b>Unemployment rate</b>	0.006* (0.002)	0.0004 (0.001)	0.002* (0.001)	0.003* (0.001)	0.004* (0.001)
<b>Urbanization</b>	0.007** (0.003)	0.005* (0.001)	-0.003* (0.001)	-0.004* (0.001)	-0.0001 (0.001)
<b>Average dis</b>	0.0002*** (0.0001)	-0.0002* (0.0001)	0.0001** (0.000)	0.0001 (0.000)	-0.0001 (0.000)
<b>State</b>	Yes	Yes	Yes	Yes	Yes
<b>Year (2004–05= base year)</b>					
<b>2009</b>	-0.549* (0.133)	0.219* (0.044)	1.153* (0.044)	0.382* (0.049)	-0.505* (0.069)
<b>2011</b>	-0.655* (0.139)	0.185* (0.044)	1.320* (0.044)	0.295* (0.050)	-0.209* (0.067)
<b>Constant</b>	-5.772* (0.249)	-1.703* (0.094)	-1.958* (0.091)	-2.732* (0.084)	-3.639* (0.099)

**Number of observations: 248,634**

**Wald chi2 (335): 115860.25**

**Prob>chi2: 0.0000**

**Pseudo R2: 0.1784**

**Log pseudo likelihood: -274825.52**

*Notes: Figures in parenthesis are robust Standard Errors. \*, \*\* & \*\*\* indicates significance at 1%, 5% and 10% level of significance.*

**Table 3. 16 Effect of caste on occupational choice over time.**

<b>Variables</b>	<b>Mining &amp; quarrying</b>	<b>Manufacturing</b>	<b>Construction</b>	<b>Transport</b>	<b>Services</b>
<b>Coefficient Values</b>					
<b>Age</b>	0.022* (0.003)	-0.007* (0.001)	-0.013* (0.001)	0.007* (0.001)	0.043* (0.001)
<b>Gender</b>	1.873* (0.070)	0.286* (0.018)	1.458* (0.018)	1.619* (0.019)	0.328* (0.019)
<b>Education (illiterate = base category)</b>					
<b>Edu1</b>	0.271* (0.068)	0.408* (0.022)	0.034*** (0.019)	0.568* (0.022)	0.625* (0.031)
<b>Edu2</b>	0.439* (0.068)	0.542* (0.023)	-0.119* (0.020)	1.062* (0.021)	1.581* (0.029)
<b>Edu3</b>	1.038* (0.087)	0.613* (0.034)	-0.356* (0.036)	1.403* (0.028)	3.047* (0.033)
<b>Edu4</b>	1.516* (0.098)	0.811* (0.046)	-0.359* (0.053)	1.637* (0.035)	4.362* (0.035)
<b>Vocation (yes=1, 0= no)</b>	0.645* (0.062)	1.519* (0.019)	0.242* (0.024)	0.514* (0.020)	0.556* (0.023)
<b>Married</b>	0.089 (0.064)	-0.079* (0.019)	-0.002 (0.019)	0.103* (0.019)	-0.103* (0.022)
<b>Caste (other caste = base category)</b>					
<b>ST</b>	0.927* (0.215)	-0.666* (0.065)	0.061 (0.069)	-1.016* (0.056)	-0.221* (0.068)
<b>SC</b>	1.152* (0.207)	0.016 (0.049)	0.625* (0.058)	-0.578* (0.046)	0.209* (0.062)
<b>OBC</b>	0.805* (0.198)	0.267* (0.041)	0.159* (0.057)	-0.201* (0.036)	0.145* (0.051)
<b>Caste (other caste = base category)</b>					
<b>ST_09</b>	-0.807* (0.228)	0.446* (0.077)	0.351* (0.076)	0.574* (0.062)	0.317* (0.073)
<b>SC_09</b>	-0.793* (0.227)	0.116*** (0.061)	0.158** (0.067)	0.374* (0.055)	0.109 (0.072)
<b>OBC_09</b>	-0.924* (0.216)	-0.019 (0.050)	0.179* (0.065)	0.139* (0.043)	-0.024 (0.059)
<b>Caste (other caste = base category)</b>					
<b>ST_11</b>	-0.936* (0.229)	0.439* (0.076)	0.292* (0.075)	0.632* (0.063)	0.296* (0.073)
<b>SC_11</b>	-0.991* (0.229)	0.084 (0.061)	0.110*** (0.066)	0.337* (0.057)	0.116 (0.071)
<b>OBC_11</b>	-1.037* (0.216)	-0.116** (0.049)	0.045 (0.064)	0.113* (0.043)	0.079 (0.058)
<b>Religion (other religion = base category)</b>					
<b>Hindu</b>	0.461* (0.095)	0.166* (0.041)	0.282* (0.037)	0.076** (0.033)	0.084** (0.034)
<b>Muslim</b>	0.477* (0.133)	0.765* (0.047)	0.722* (0.044)	0.577* (0.039)	0.449* (0.044)
<b>Land ownership (landless= base category)</b>					
<b>Marginal</b>	-0.484* (0.133)	-0.525* (0.047)	-0.469* (0.044)	-0.424* (0.039)	-0.581* (0.044)

	(0.106)	(0.036)	(0.034)	(0.034)	(0.042)
<b>Small</b>	-1.544*	-1.900*	-2.022*	-1.630*	-1.692*
	(0.124)	(0.045)	(0.043)	(0.039)	(0.047)
<b>Semi-medium</b>	-1.929*	-2.416*	-2.538*	-2.105*	-2.062*
	(0.137)	(0.052)	(0.053)	(0.044)	(0.050)
<b>Medium</b>	-2.646*	-2.911*	-3.087*	-2.640*	-2.397*
	(0.182)	(0.067)	(0.073)	(0.053)	(0.056)
<b>Large</b>	-2.095*	-3.555*	-3.144*	-2.928*	-2.729*
	(0.251)	(0.151)	(0.142)	(0.094)	(0.093)
<b>HH size</b>	-0.040*	0.005	-0.047*	-0.016*	-0.046*
	(0.009)	(0.003)	(0.003)	(0.003)	(0.004)
<b>Dependency ratio</b>	0.133*	0.063*	0.169*	0.149*	0.178*
	(0.043)	(0.015)	(0.013)	(0.013)	(0.015)
<b>Unemployment rate</b>	0.005*	-0.0001	0.002**	0.003*	0.003*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
<b>Urbanization</b>	0.007**	0.005*	-0.003*	-0.004*	-0.0001
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
<b>Average dis</b>	0.0001**	-0.0002*	0.0001**	0.000	-0.0001
	(0.0001)	(0.0001)	(0.000)	(0.000)	(0.000)
<b>State</b>	Yes	Yes	Yes	Yes	Yes
<b>Year (2004–05= base year)</b>					
<b>2009</b>	1.074*	0.139*	0.829*	0.050	0.076***
	(0.188)	(0.042)	(0.053)	(0.034)	(0.045)
<b>2011</b>	1.150*	0.196*	1.112*	0.026	0.212*
	(0.188)	(0.041)	(0.053)	(0.034)	(0.045)
<b>Constant</b>	-7.093*	-1.621*	-1.723*	-2.447*	-4.001*
	(0.302)	(0.096)	(0.096)	(0.082)	(0.097)

**Number of observations: 248,634**

**Wald chi2 (325): 117484.97**

**Prob>chi2:0.0000**

**Pseudo R2:0.1782**

**Log pseudolikelihood: -274872.95**

*Notes: Figures in parenthesis are robust Standard Errors. \*, \*\* & \*\*\* indicates significance at 1%, 5% and 10% level of significance.*

**Table 3. 17 Effect of land ownership on occupational choice over time.**

<b>Variables</b>	<b>Mining &amp; quarrying</b>	<b>Manufacturing</b>	<b>Construction</b>	<b>Transport</b>	<b>Services</b>
<b>Coefficient Values</b>					
<b>Age</b>	0.021*	-0.007*	-0.013*	0.006*	0.042*
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
<b>Gender</b>	1.878*	0.286*	1.458*	1.619*	0.329*
	(0.070)	(0.018)	(0.018)	(0.019)	(0.019)
<b>Education (illiterate = base category)</b>					
<b>Edu1</b>	0.274*	0.410*	0.036***	0.570*	0.627*
	(0.068)	(0.022)	(0.019)	(0.022)	(0.031)
<b>Edu2</b>	0.441*	0.544*	-0.117*	1.064*	1.584*
	(0.068)	(0.022)	(0.020)	(0.021)	(0.029)
<b>Edu3</b>	1.039*	0.619*	-0.351*	1.408*	3.052*

	(0.087)	(0.034)	(0.036)	(0.028)	(0.033)
<b>Edu4</b>	1.523*	0.819*	-0.352*	1.643*	4.366*
	(0.098)	(0.046)	(0.053)	(0.035)	(0.035)
<b>Vocation</b>	0.637*	1.518*	0.243*	0.512*	0.558*
<b>(yes=1, 0= no)</b>	(0.061)	(0.019)	(0.024)	(0.020)	(0.023)
<b>Married</b>	0.103	-0.075*	-0.003	0.101*	-0.103*
	(0.064)	(0.019)	(0.019)	(0.019)	(0.022)
<b>Caste (other caste = base category)</b>					
<b>ST</b>	0.220*	0.414*	0.409*	0.232*	0.273*
	(0.081)	(0.033)	(0.026)	(0.029)	(0.031)
<b>SC</b>	-0.201*	0.536*	-0.071*	0.426*	0.144*
	(0.075)	(0.030)	(0.025)	(0.026)	(0.028)
<b>OBC</b>	-0.130	0.319*	-0.326*	0.524*	-0.028
	(0.079)	(0.033)	(0.028)	(0.027)	(0.029)
<b>Religion (other religion = base category)</b>					
<b>Hindu</b>	0.466*	0.169*	0.281*	0.072**	0.078**
	(0.095)	(0.041)	(0.037)	(0.033)	(0.034)
<b>Muslim</b>	0.476*	0.769*	0.726*	0.579*	0.451*
	(0.133)	(0.047)	(0.044)	(0.039)	(0.044)
<b>Land ownership (landless households = base category)</b>					
<b>Marginal</b>	-0.402	-0.376*	-0.575*	-0.428*	-0.529*
	(0.264)	(0.074)	(0.079)	(0.071)	(0.102)
<b>Small</b>	-1.305*	-1.515*	-1.834*	-1.404*	-1.566*
	(0.309)	(0.087)	(0.103)	(0.080)	(0.115)
<b>Semi-medium</b>	-1.495*	-2.003*	-2.258*	-1.749*	-1.764*
	(0.331)	(0.099)	(0.126)	(0.087)	(0.119)
<b>Medium</b>	-3.018*	-2.435*	-3.011*	-2.185*	-2.023*
	(0.563)	(0.122)	(0.186)	(0.101)	(0.132)
<b>Large</b>	-1.394*	-3.389*	-3.700*	-2.244*	-2.303*
	(0.528)	(0.302)	(0.512)	(0.165)	(0.228)
<b>Land ownership (landless households = base category)</b>					
<b>Marginal_09</b>	-0.179	-0.117	0.149	0.062	-0.053
	(0.298)	(0.090)	(0.092)	(0.086)	(0.118)
<b>Small_09</b>	-0.286	-0.339*	-0.082	-0.210	-0.087
	(0.350)	(0.110)	(0.120)	(0.099)	(0.133)
<b>Semi-medium_09</b>	-0.541	-0.512*	-0.260***	-0.469*	-0.245***
	(0.379)	(0.129)	(0.148)	(0.108)	(0.139)
<b>Medium_09</b>	0.066	-0.618*	0.055	-0.626*	-0.341**
	(0.627)	(0.165)	(0.213)	(0.129)	(0.154)
<b>Large_09</b>	-0.482	0.052	-0.929***	-0.938*	-0.408
	(0.609)	(0.375)	(0.544)	(0.230)	(0.267)
<b>Land ownership (landless households = base category)</b>					
<b>Marginal_11</b>	0.017	-0.314*	0.062	-0.092	-0.106
	(0.325)	(0.095)	(0.096)	(0.093)	(0.124)
<b>Small_11</b>	-0.280	-0.734*	-0.406*	-0.405*	-0.261***
	(0.375)	(0.115)	(0.124)	(0.105)	(0.138)
<b>Semi-medium_11</b>	-0.503	-0.638*	-0.443*	-0.487*	-0.512*
	(0.405)	(0.132)	(0.151)	(0.113)	(0.144)
<b>Medium_11</b>	0.717	-0.719*	-0.299	-0.603*	-0.603*
	(0.624)	(0.165)	(0.219)	(0.134)	(0.159)

<b>Large_11</b>	-1.710** (0.802)	-0.536 (0.403)	0.179 (0.565)	-0.938* (0.229)	-0.657** (0.268)
<b>HH size</b>	-0.042* (0.009)	0.004 (0.003)	-0.048* (0.003)	-0.016* (0.003)	-0.046* (0.004)
<b>Dependency ratio</b>	0.132* (0.043)	0.063* (0.015)	0.169* (0.013)	0.149* (0.013)	0.178* (0.015)
<b>Unemployment rate</b>	0.005* (0.002)	0.001 (0.001)	0.002* (0.001)	0.004* (0.001)	0.004* (0.001)
<b>Urbanization</b>	0.007** (0.003)	0.005* (0.001)	-0.003* (0.001)	-0.004* (0.001)	-0.0001 (0.001)
<b>Average dis</b>	0.0001*** (0.0001)	-0.0002* (0.000)	0.0001** (0.000)	0.0001 (0.000)	-0.0001 (0.000)
<b>State</b>	Yes	Yes	Yes	Yes	Yes
<b>Year (2004–05= base year)</b>					
<b>2009</b>	0.573*** (0.292)	0.385* (0.088)	0.909* (0.089)	0.289* (0.084)	0.249** (0.115)
<b>2011</b>	0.391 (0.319)	0.599* (0.093)	1.230* (0.094)	0.403* (0.091)	0.513* (0.121)
<b>Constant</b>	-6.397* (0.341)	-2.243* (0.109)	-1.516* (0.107)	-3.282* (0.097)	-4.208* (0.126)

**Number of observations: 248,634**

**Wald chi2 (345): 119756.24**

**Prob>chi2: 0.0000**

**Pseudo R2:0.1783**

**Log pseudolikelihood: -274860.15**

*Notes: Figures in parenthesis are robust Standard Errors. \*, \*\* & \*\*\* indicates significance at 1%, 5% and 10% level of significance.*

From the interaction terms, we observe that although the extent of diversification is high for males as they can easily shift to almost every non-farm occupation, over time the pattern of occupational choice has changed between males and females. Females have now started diversifying toward construction, trade and transport-related activities while male's participation has remained high in mining, manufacturing and services. One major reason for females to participate in construction during 2009–10 and 2011–12 is the implementation of MGNREGA after 2005 which mostly focused on construction-related activities (Jatav & Sen, 2013; Reddy et al, 2014). Moreover, Lahoti and Swaminathan (2013) and Swaminathan (2020) observe that work under MGNREGA is one of the major sources of non-farm employment for rural females.

Again, human capital variables like education which is regarded as a 'pull' factor of diversification exhibit a positive likelihood of joining manufacturing, trade and services while it has a negative impact on employment in mining activities during the base period. For employment in construction sector, individuals are more likely to join if they are educated till

middle and secondary level. However, the interaction effect demonstrates that by 2009–10 and 2011–12, educated individuals are more likely to join mining, quarrying, electricity and service activities and less likely to engage in construction and trade-related work. Several studies (Bhaumik, 2007; Fabusoro, 2010; Demeke & Zeller, 2012; Senadza, 2012; Nakajima et al, 2018; Mishra and Singh, 2018) have also found that education and any other skill increase the probability of an individual to join high return non-farm activities compared to the illiterate group. This suggests that education is a significant barrier to lucrative non-farm jobs (Kumar et al, 2011; Lahoti and Swaminathan, 2013).

Furthermore, we observe that compared to upper caste, SC and OBCs are more likely to engage in mining and quarrying, construction and services and less likely to join trade. Again, STs are more likely to engage in mining and quarrying activities and less likely to join manufacturing, trade and services during 2004–05. By 2009–10 and 2011–12, the choice of employment in mining and quarrying declined among all caste workers while the likelihood of working in trade and services increased. ST workers are now more likely to engage in manufacturing and construction employment while for OBCs, participation in manufacturing has declined over time. The findings reveal the gradual shift of caste-based workers towards non-agricultural employment which might be due to greater inheritance of land by upper caste households which favours them to engage in farm-related activities while the lower caste households diversify (Gang et al, 2017). As pointed out by Srivastava and Srivastava (2010), lesser social taboos and material deprivation also push them to join the non-farm labor market.

Again, land ownership is an important income-earning asset in rural India, and our findings demonstrate its adverse impact on occupational diversification. This exemplifies land-owning households' preference for agricultural activities. The negative impact of land ownership on employment diversification is also found by Srivastava and Srivastava (2010), Nakajima et al (2018), Demie and Zeray (2016), Jatav and Sen (2013) and Kumar et al (2011). However, in rural Bangladesh, it is found that land is used as collateral by households to invest in non-agricultural livelihoods (Rahman & Akter, 2014). Therefore, it might reflect that land in rural India is used exclusively for cultivation. Further, in the absence of proper credit facilities, the household's ability to utilize land for other purposes becomes limited. We also found that as the number of dependents increases, individuals are more likely to diversify although their likelihood falls with an increase in household size. This might reflect a distress-induced process where diversification is undertaken to financially support the dependent members (Jatav & Sen,

2013). Ebaidalla (2022) also observes that households with more dependents diversify to non-farm activities in rural Sudan to meet the household income requirements.

**Table 3. 18 Effect of interaction between gender and education on choice of rural non-farm employment.**

<b>Variables</b>	<b>Mining</b>	<b>Manufacturing</b>	<b>Construction</b>	<b>Trade</b>	<b>Services</b>
<b>Coefficient Values</b>					
<b>Age</b>	0.023* (0.002)	-0.008* (0.001)	-0.015* (0.001)	0.004* (0.000)	0.044* (0.001)
<b>Gender (male=1, female=0)</b>	1.211* (0.200)	-0.074 (0.068)	1.848* (0.088)	2.032* (0.102)	0.870* (0.111)
<b>Education (illiterate= base category)</b>					
<b>Edu1</b>	-0.617** (0.303)	0.324* (0.061)	-0.615* (0.154)	0.757* (0.120)	0.041 (0.135)
<b>Edu2</b>	-2.374* (0.726)	0.483* (0.062)	-1.102* (0.202)	1.336* (0.112)	1.155* (0.110)
<b>Edu3</b>	-0.327 (0.603)	0.697* (0.105)	-0.635*** (0.379)	1.764* (0.160)	3.774* (0.106)
<b>Vocation (yes=1, 0= no)</b>	0.629* (0.061)	1.492* (0.019)	0.221* (0.024)	0.485* (0.019)	0.485* (0.023)
<b>Married</b>	0.050 (0.064)	-0.094* (0.019)	0.021 (0.019)	0.114* (0.018)	-0.121* (0.021)
<b>Caste (other caste = base category)</b>					
<b>ST</b>	0.146*** (0.080)	-0.285* (0.032)	0.364* (0.027)	-0.497* (0.026)	0.013 (0.029)
<b>SC</b>	0.461* (0.070)	0.221* (0.025)	0.859* (0.023)	-0.173* (0.022)	0.378* (0.025)
<b>OBC</b>	-0.034 (0.063)	0.265* (0.021)	0.297* (0.021)	-0.057* (0.017)	0.176* (0.020)
<b>Religion (other religion = base category)</b>					
<b>Hindu</b>	0.490* (0.094)	0.199* (0.041)	0.316* (0.036)	0.102* (0.032)	0.140* (0.034)
<b>Muslim</b>	0.559* (0.133)	0.860* (0.046)	0.826* (0.043)	0.666* (0.038)	0.553* (0.043)
<b>Land ownership (landless= base category)</b>					
<b>Marginal/small</b>	-0.653* (0.105)	-0.710* (0.035)	-0.663* (0.033)	-0.606* (0.034)	-0.760* (0.041)
<b>Medium/large</b>	-1.994* (0.126)	-2.482* (0.047)	-2.582* (0.047)	-2.175* (0.040)	-1.984* (0.046)
<b>HH size</b>	-0.058* (0.009)	-0.020* (0.003)	-0.073* (0.003)	-0.038* (0.002)	-0.065* (0.003)
<b>Dependency ratio</b>	0.145** (0.042)	0.090* (0.014)	0.202* (0.012)	0.179* (0.012)	0.201* (0.014)
<b>Unemployment rate</b>	0.005* (0.001)	0.000 (0.000)	0.001* (0.0002)	0.001* (0.000)	0.0003 (0.0002)
<b>Urbanization</b>	0.006** (0.002)	0.005* (0.000)	-0.002* (0.001)	-0.003* (0.0007)	0.001 (0.0008)
<b>Average dis</b>	0.0001	-0.0002	0.000	0.0001	-0.0001*

	(0.000)	(0.000) *	(0.000)	(0.000)	(0.000)
<b>Year (2004= base year)</b>					
<b>2009</b>	-0.864*	-0.067	1.528*	0.728*	-0.435*
	(0.223)	(0.063)	(0.083)	(0.106)	(0.103)
<b>2011</b>	-0.933*	-0.080	1.581*	0.646*	0.182***
	(0.229)	(0.063)	(0.083)	(0.107)	(0.100)
<b>Interaction terms (gender &amp; education, where female= base category, illiterate= base group)</b>					
<b>A*X</b>	0.366	0.180**	0.699*	-0.289**	0.141
	(0.343)	(0.088)	(0.164)	(0.132)	(0.161)
<b>A*Y</b>	1.882**	0.081	1.086*	-0.322*	-0.562*
	(0.744)	(0.087)	(0.210)	(0.123)	(0.137)
<b>A*Z</b>	-0.139	-0.059	0.275	-0.315***	-1.286*
	(0.655)	(0.132)	(0.379)	(0.171)	(0.133)
<b>Interaction terms (gender, education &amp; time dummies where female= base category, illiterate= base group &amp; 2004–05= base year)</b>					
<b>A*X*09</b>	-0.016	-0.364	-0.851*	0.022	-0.130
	(0.445)	(0.113)	(0.175)	(0.153)	(0.193)
<b>A*X*11</b>	0.144	-0.410**	-0.990*	0.228	-0.053
	(0.456)	(0.112)	(0.175)	(0.157)	(0.187)
<b>A*Y*09</b>	-1.680**	-0.482**	-0.797*	0.250***	0.220
	(0.796)	(0.110)	(0.223)	(0.145)	(0.164)
<b>A*Y*11</b>	-0.965	-0.391***	-1.387*	0.291***	0.210
	(0.818)	(0.110)	(0.220)	(0.147)	(0.159)
<b>A*Z*09</b>	0.208	-0.140	-0.041	0.040	0.415**
	(0.753)	(0.174)	(0.413)	(0.202)	(0.161)
<b>A*Z*11</b>	0.525	-0.091	-0.743***	0.360***	0.530*
	(0.755)	(0.166)	(0.398)	(0.205)	(0.156)
<b>State code</b>	Yes	Yes	Yes	Yes	Yes
<b>Constant</b>	-5.082*	-1.234*	-2.265*	-2.833*	-3.601*
	(0.273)	(0.107)	(0.121)	(0.124)	(0.128)

**Number of observations: 248,634.**

**Wald chi2 (525) = 114161.28**

**Probability > chi2 = 0.0000**

**Pseudo R2 = 0.1629**

**Log pseudo likelihood = -279991.01**

*Notes- Figures in parenthesis are robust standard errors, \*, \*\* & \*\*\* indicates significant at 1 %, 5% and 10% level. A= 1 if male and 0 if female. X= below primary and primary, Y= middle and secondary, Z= HS & above and illiterate= base category.*

It is well recognised that education has a greater beneficial impact on rural female's capacity to uplift their economic status. Therefore, in case of rural India, we try to examine whether education can have any significant favourable impact on females to diversify to non-farm activities. Interacting education dummy with gender, we found that during 2004–05, educated females are more likely to engage in trade, transport and service activities as their education level increases. Males diversify to mining, manufacturing and construction if they are primary,

middle and secondary educated. Examining the effect of time on their employment probabilities, we observed that between 2009–10 and 2011–12, males with a higher secondary and above education favoured services employment. They are also more likely to join trade related activities if they have education above middle and secondary level. While for females, participation increased in manufacturing and construction for those having education of below primary and primary and middle and secondary level. Deshpande and Singh (2021) also found a decline in female employment by 25% in education sector where they have a comparative advantage.

We further observe that educated females have diversified more towards construction and manufacturing sectors during 2009–10 and 2011–12 which might reflect the absence of better remunerative jobs in rural India, forcing them to join these low-return and easy-entry jobs. This is also evident in the findings of table 3.19 given below, where gender and education interact with the land ownership variable. Although educated females from land-owning households preferred manufacturing, trade and service sector employment, their likelihood of diversifying into construction also increased in later years which indicates a lack of suitable employment opportunities for educated rural women. Again, it is observed that women belonging to affluent households are employed in high-return activities like services. But service sector jobs being less labor intensive and skill-based indicate that women can access service sector jobs only when they are not only educated but also belong to medium and large land-owning households. Here land might act as an important asset for establishing their enterprises. Lahoti and Swaminathan (2013) observed that service sector jobs are suitable for women compared to men.

**Table 3. 19 Effect of education and land ownership on choice of rural non-farm employment across gender.**

Variables	Mining & quarrying	Manufacturing	Construction	Transport	Services
<b>Coefficient Values</b>					
Age	0.029* (0.003)	-0.006* (0.001)	-0.016* (0.001)	0.007* (0.001)	0.047* (0.001)
Gender	1.913* (0.472)	0.477* (0.093)	1.682* (0.122)	1.882* (0.121)	0.558* (0.107)
<b>Education (illiterate = base category)</b>					
Edu2	0.129** (0.059)	0.074* (0.019)	-0.211* (0.019)	0.447* (0.017)	0.941* (0.024)
Edu3	0.839* (0.069)	0.137* (0.028)	-0.499* (0.030)	0.804* (0.022)	2.952* (0.026)

<b>Vocation</b> (yes=1, 0= no)	0.740* (0.066)	1.522* (0.022)	0.299* (0.028)	0.544* (0.021)	0.509* (0.025)
<b>Married</b>	0.143*** (0.074)	-0.076* (0.023)	0.058** (0.024)	0.135* (0.020)	-0.058** (0.023)
<b>Caste (other caste = base category)</b>					
<b>ST</b>	0.150*** (0.091)	-0.313* (0.039)	0.342* (0.034)	-0.496* (0.029)	0.102* (0.031)
<b>SC</b>	0.467* (0.078)	0.202* (0.029)	0.970* (0.027)	-0.179* (0.025)	0.412* (0.027)
<b>OBC</b>	-0.021 (0.069)	0.279* (0.024)	0.337* (0.025)	-0.058* (0.019)	0.144* (0.022)
<b>Religion (other religion = base category)</b>					
<b>Hindu</b>	0.415* (0.100)	0.219* (0.045)	0.253* (0.041)	0.104* (0.034)	0.155* (0.036)
<b>Muslim</b>	0.398* (0.146)	0.772* (0.052)	0.762* (0.049)	0.655* (0.041)	0.588* (0.046)
<b>Land ownership (landless= base category)</b>					
<b>Marginal/small</b>	-0.804*** (0.465)	-0.651* (0.079)	-0.642* (0.115)	-0.428* (0.115)	-0.629* (0.094)
<b>Medium/large</b>	-2.798* (0.674)	-2.405* (0.105)	-2.032* (0.150)	-1.807* (0.136)	-1.428* (0.102)
<b>HH size</b>	-0.055* (0.011)	-0.013* (0.004)	-0.069* (0.004)	-0.034* (0.003)	-0.064* (0.004)
<b>Dependency ratio</b>	0.093*** (0.049)	0.071* (0.018)	0.193* (0.016)	0.162* (0.014)	0.168* (0.016)
<b>Unemployment rate</b>	0.006* (0.002)	0.001** (0.001)	0.004* (0.001)	0.004* (0.001)	0.005* (0.001)
<b>Urbanization</b>	0.006*** (0.003)	0.005* (0.001)	-0.003* (0.001)	-0.005* (0.001)	-0.001 (0.001)
<b>Average dis</b>	0.0002* (0.0001)	-0.0002* (0.0001)	0.0001 (0.000)	0.0002 (0.000)	-0.0001** (0.000)
<b>State</b>	Yes	Yes	Yes	Yes	Yes
<b>Year (2004= base year)</b>					
<b>2009</b>	0.385*** (0.213)	0.095** (0.041)	1.613* (0.074)	0.423* (0.049)	0.156* (0.045)
<b>2011</b>	0.035 (0.229)	0.127* (0.040)	1.932* (0.073)	0.273* (0.051)	0.198* (0.044)
<b>Interaction term (educated male (educated female= base category) and size of land ownership (land less group= base category)</b>					
<b>M*LAND2</b>	-0.162 (0.531)	-0.394* (0.099)	0.489* (0.142)	-0.214*** (0.129)	-0.419* (0.117)
<b>M*LAND3</b>	0.589 (0.754)	-0.154 (0.137)	0.098 (0.199)	-0.046 (0.155)	-0.652* (0.134)
<b>M*LAND2*09</b>	0.218 (0.229)	0.234* (0.049)	-0.712* (0.079)	-0.141* (0.054)	0.099*** (0.055)
<b>M*LAND2*11</b>	0.577** (0.243)	0.221* (0.049)	-0.819* (0.078)	-0.004 (0.055)	0.284* (0.054)
<b>M*LAND3*09</b>	-0.009 (0.335)	-0.228** (0.103)	-1.137* (0.145)	-0.754* (0.077)	-0.198** (0.082)
<b>M*LAND3*11</b>	0.385	-0.127	-1.192*	-0.443*	-0.187**

	(0.344)	(0.100)	(0.142)	(0.077)	(0.082)
<b>Constant</b>	-6.212*	-1.176*	-2.370*	-2.258*	-3.674*
	(0.519)	(0.121)	(0.156)	(0.138)	(0.124)

**Number of observations: 186,203**

**Wald chi2(285): 122757.91**

**Prob>chi2:0.0000**

**Pseudo R2: 0.1522**

**Log pseudolikelihood: -221868.42**

*Notes- Figures in parenthesis are standard errors, \*, \*\* & \*\*\* indicates significant at 1 %, 5% and 10% level. M= educated male=1, 0= educated female, LAND2= workers belonging to marginal and small land-owning households and LAND3= workers belonging to medium and large landed households.*

Although previous studies (Abraham, 2011; Jatav and Sen, 2013; Mishra and Singh, 2018) have established that low-caste households diversify more to non-farm activities, yet these studies have failed to show whether caste has a different impact on diversification strategy across gender. This is analysed in table 3.20 below.

**Table 3. 20 Effect of interaction between gender and caste on choice of rural non-farm employment over time.**

<b>Variables</b>	<b>Mining &amp; quarrying</b>	<b>Manufacturing</b>	<b>Construction</b>	<b>Transport</b>	<b>Services</b>
<b>Coefficient Values</b>					
<b>Age</b>	0.020*	-0.008*	-0.015*	0.005*	0.043*
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
<b>Gender</b>	2.020*	-0.305*	2.589*	1.893*	-0.013
	(0.606)	(0.064)	(0.197)	(0.086)	(0.077)
<b>Education (illiterate = base category)</b>					
<b>Edu1</b>	0.251*	0.373*	-0.001	0.536*	0.608*
	(0.068)	(0.022)	(0.019)	(0.022)	(0.031)
<b>Edu2</b>	0.377*	0.449*	-0.209*	0.978*	1.521*
	(0.068)	(0.022)	(0.020)	(0.021)	(0.03)
<b>Edu3</b>	1.082*	0.517*	-0.516*	1.326*	3.509*
	(0.077)	(0.030)	(0.031)	(0.025)	(0.031)
<b>Vocation (yes=1, 0= no)</b>	0.624*	1.495*	0.223*	0.494*	0.502*
	(0.061)	(0.019)	(0.024)	(0.019)	(0.023)
<b>Married</b>	0.085	-0.094*	0.024	0.118*	-0.098*
	(0.064)	(0.019)	(0.019)	(0.019)	(0.021)
<b>Caste (other caste = base category)</b>					
<b>ST</b>	1.679*	-0.844*	1.086*	-0.314**	-0.415*
	(0.625)	(0.092)	(0.219)	(0.122)	(0.107)
<b>SC</b>	1.989*	-0.177**	0.805*	-0.667*	0.221**
	(0.628)	(0.076)	(0.229)	(0.149)	(0.104)
<b>OBC</b>	1.572**	0.067	0.533**	-0.072	0.023
	(0.617)	(0.062)	(0.220)	(0.104)	(0.087)
<b>Religion (other religion = base category)</b>					

<b>Hindu</b>	0.487*	0.183*	0.316*	0.101*	0.122*
	(0.095)	(0.041)	(0.036)	(0.032)	(0.034)
<b>Muslim</b>	0.557*	0.850*	0.818*	0.658*	0.539*
	(0.133)	(0.047)	(0.044)	(0.038)	(0.043)
<b>Land ownership (landless= base category)</b>					
<b>Marginal/small</b>	-0.658*	-0.714*	-0.673*	-0.614*	-0.761*
	(0.105)	(0.036)	(0.034)	(0.034)	(0.042)
<b>Medium/large</b>	-2.003*	-2.486*	-2.584*	-2.181*	-1.991*
	(0.127)	(0.048)	(0.047)	(0.041)	(0.046)
<b>HH size</b>	-0.059*	-0.021*	-0.074*	-0.039*	-0.066*
	(0.009)	(0.003)	(0.003)	(0.003)	(0.003)
<b>Dependency ratio</b>	0.153*	0.091*	0.208*	0.183*	0.198*
	(0.043)	(0.014)	(0.013)	(0.012)	(0.015)
<b>Unemployment rate</b>	0.005*	0.001	0.002*	0.003*	0.004*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
<b>Urbanization</b>	0.007**	0.005*	-0.003*	-0.004*	-0.000
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
<b>Average dis</b>	0.0001***	-0.0002*	0.0005	0.0000	-0.0001*
	(0.0001)	(0.0001)	(0.000)	(0.000)	(0.0001)
<b>State</b>	Yes	Yes	Yes	Yes	Yes
<b>Year (2004= base year)</b>					
<b>2009</b>	1.018	-0.149**	1.724*	0.235**	0.072
	(0.630)	(0.067)	(0.204)	(0.099)	(0.076)
<b>2011</b>	0.459	-0.095	1.699*	0.161	0.024
	(0.660)	(0.064)	(0.203)	(0.100)	(0.076)
<b>Interaction terms (gender and caste, where female= base category, others caste= base category)</b>					
<b>A*P</b>	-0.847	0.329*	-1.047*	-0.758*	0.336**
	(0.659)	(0.121)	(0.229)	(0.134)	(0.129)
<b>A*Q</b>	-0.785	0.530*	0.030	0.301***	0.153
	(0.665)	(0.097)	(0.237)	(0.157)	(0.127)
<b>A*R</b>	-0.810	0.406*	-0.297	-0.053	0.213**
	(0.651)	(0.079)	(0.228)	(0.110)	(0.105)
<b>Interaction terms (gender, caste and time, where female= base category, others caste= base category, year 2004-05= base year)</b>					
<b>A*P*09</b>	0.574	-0.388**	0.044	-0.189	0.113
	(0.740)	(0.153)	(0.247)	(0.159)	(0.151)
<b>A*P*11</b>	-0.091	0.0002	-0.214	0.053	-0.073
	(0.764)	(0.151)	(0.246)	(0.161)	(0.149)
<b>A*Q*09</b>	0.609	-0.296**	0.205	0.075	0.025
	(0.746)	(0.126)	(0.254)	(0.189)	(0.150)
<b>A*Q*11</b>	-0.025	-0.201	-0.201	0.114	-0.086
	(0.777)	(0.125)	(0.253)	(0.194)	(0.149)
<b>A*R*09</b>	0.467	-0.117	-0.098	-0.213	0.012
	(0.725)	(0.103)	(0.243)	(0.134)	(0.124)
<b>A*R*11</b>	0.015	-0.266*	-0.480**	-0.099	-0.173
	(0.755)	(0.101)	(0.243)	(0.136)	(0.122)
<b>Constant</b>	-7.052*	-1.003*	-2.513*	-2.489*	-3.650*
	(0.633)	(0.102)	(0.209)	(0.112)	(0.108)
<b>Number of observations: 248,634</b>					

**Wald chi2(360): 112628.35**  
**Prob>chi2:0.0000**  
**Pseudo R2:0.1635**  
**Log pseudolikelihood: -279798.52**

*Notes- Figures in parenthesis are standard errors, \*, \*\* & \*\*\* indicates significant at 1 %, 5% and 10% level. Where, A= 1 if male, 0 if female, P=ST, Q=SC, R=OBC, unreserved category= base group.*

Our analysis from table 3.20 reveals significant differences in non-farm employment choice across gender and caste. While ST females are more likely to engage in construction and trade, ST males prefer manufacturing and services. Manufacturing is also more likely to be joined by SC and OBC males. SC males further diversify to trade sector employment while services are preferred by male workers of OBC households. To analyse any changes in their occupational choice over time, we have interacted year dummies with gender and caste variable. We observe that by 2009–10, ST and SC females are more likely to join manufacturing and by 2011–12, the likelihood to join construction and manufacturing increased among OBC females compared to males. Female participation in construction activities can be explained in part by the implementation of MGNREGA after 2005, which primarily includes construction-related activities, and this scheme has played a key role in absorbing rural female workers (Lahoti & Swaminathan, 2013).

### **3.3.1. Robustness of regression results:**

To check the robustness of the findings presented in table 3.13, we use long-term deviation of rainfall at the state region level of NSSO. To arrive at the deviation of rainfall for each survey round from its long-term mean, we first estimated the weighted average rainfall for ten years preceding the survey rounds and calculated the deviation of rainfall by subtracting the long run (past 10 years) average rainfall from the average rainfall of each survey rounds. We incorporated this long-term rainfall deviation data with and without interacting with year dummies to observe whether the inclusion of such a variable has any significant impact on the effects of the existing determinants. Several studies (Demeke & Zeller, 2012; Rose, 2001; Mathenge, 2008; Rosenzweig & Stark, 1989; Lamb, 2003) have demonstrated the significance of weather conditions in determining their allocation of labour to different income-earning options. These studies found that households tend to diversify more towards non-farm activities when they face volatility in farm production due to adverse weather conditions. Since rainfall is directly associated with farm production, therefore, any rainfall shock would adversely affect agricultural income and this is likely to affect the demand for other non-farm goods. Therefore,

rainfall deviation may also act as a shock for non-farm sector in terms of demand and supply of labour. These studies incorporated deviation of annual rainfall from its long-run mean values to represent weather variability. Therefore, we include this crucial variable in our model and observe whether the inclusion of such a variable significantly alters the effect of existing factors. The rainfall data is obtained from India Meteorological Department (IMD).

We observe that the sign and significance of most of the determinants have remained unchanged except for a few changes in case of some of the factors. Most of the changes that have occurred is related to the significance level of the determinants. For instance, the positive effect of unemployment rate for manufacturing became significant and the effect of average distance for trade sector employment became significant after inclusion of rainfall deviation data. The impact of most of the crucial variables has remained unchanged. This demonstrates that our analysis does not suffer from any omitted variable bias related to income shock as inclusion of rainfall deviation variable did not significantly alter the findings of the determinants. The robustness results are provided in appendix of this chapter in tables 3A.2 and 3A.3. In table 3A.2, we have included the rainfall variable while in table 3A.3, we have also interacted rainfall with year dummies.

### **3.3.2 Limitation of the present analysis:**

Our study tried to identify the impact of various factors that are operational in explaining occupational choices in rural India. However, in estimating the determinants, we cannot rule out the possibility of reverse causality, omitted variable bias, measurement error and simultaneity that leads to the issue of endogeneity as several unobserved factors might also be related to some of the observed determinants due to which it is not possible to consider the effects of the explanatory factors as causal effect. For instance, an individual's innate ability might affect the choice of a particular non-farm activity, but we are unable to capture this variable with the given data set. Even though we have included education and vocational training as explanatory variables, yet they cannot be regarded as appropriate proxies for innate ability as an individual's personality, mental capacity and motivation are also influenced by family circumstances (Hansen et al, 1970). Further, an individual's choice of a particular occupation is also likely to be influenced by the occupations chosen by his/her peer group, friends and relatives. However, our data set does not have any information that can represent the network effect of occupational choice. Also, there may be issue of reverse causality due to inclusion of variables like unemployment rate but since its coefficient value is small, therefore, its overall impact on occupational choice is itself very low despite being significant. Therefore,

a lack of adequate information on these variables may make some of the determinants endogenous due to which we can only state that the findings are mostly correlational.

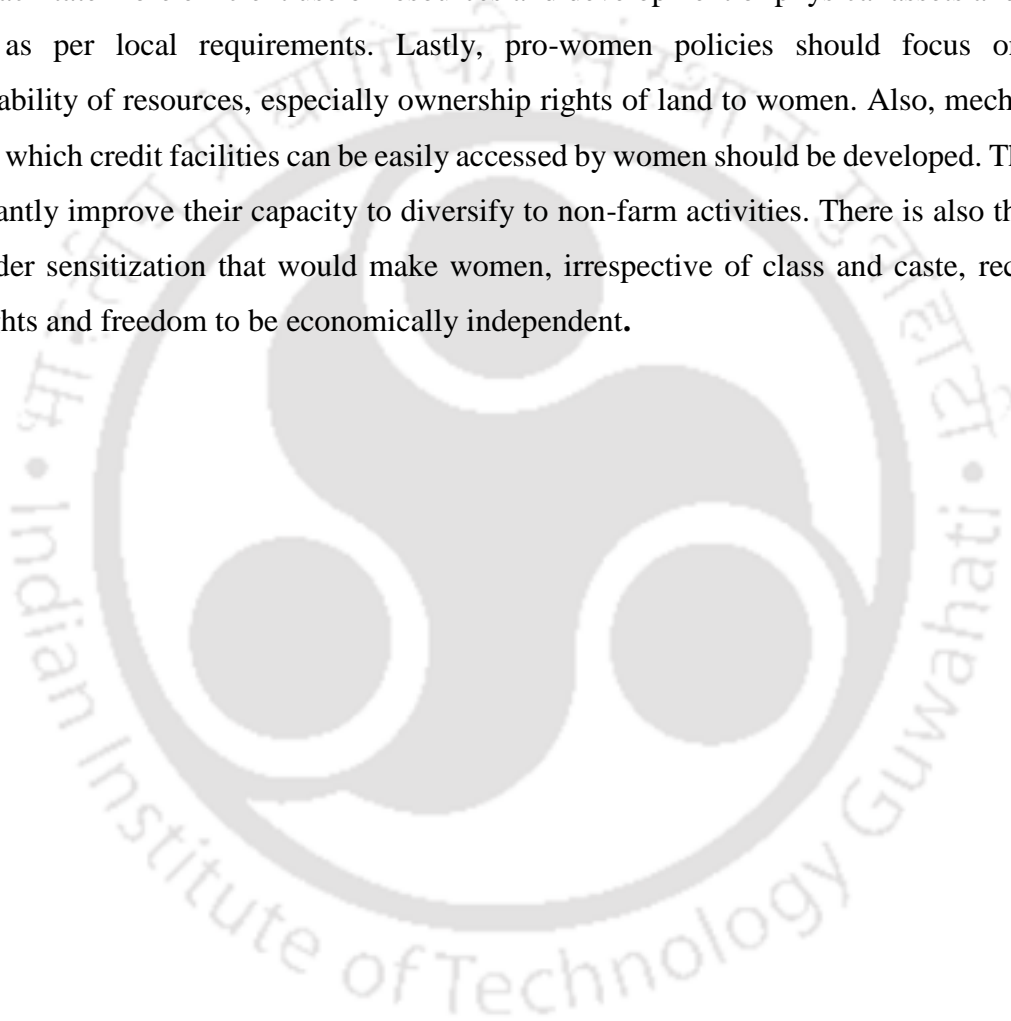
### **3.4. Summing up**

This chapter delves into a thorough assessment of the factors influencing rural employment diversification in India. Despite the numerous benefits of rural non-farm expansion, including increased employment opportunities for females, lessening of poverty, vulnerability and unemployment, several factors determine employment in different non-farm sub-sectors. Our findings from table 3.13 demonstrate that males are more likely to diversify to non-farm employment compared to females. Also, education and vocational training facilitate rural workers to join non-farm activities except for construction sector employment, where diversification is high for those who have below primary and primary education. We further observe that with an increase in household size, individuals are less likely to engage in non-farm occupations but with a rise in dependency ratio, their likelihood to join non-farm sector increases. This shows that as the dependency ratio increases, working members tend to diversify more in order to cope with the rising expenses. This demonstrates the operation of push factors of diversification where the probability of RNFS employment increases with a rise in dependent members and declines with an increase in land ownership size.

Occupational choice also varies across gender and over time. While females are found to join construction and trade, males diversify towards mining and quarrying, manufacturing and services during 2009–10 and 2011–12. Again, the interaction between education and gender show that while education can provide opportunities for females to diversify outside of agriculture, their participation in manufacturing and construction may indicate either a distress-induced diversification or a lack of suitable employment opportunities. Again, educated females belonging to land-owning households also join trade and service-related activities. Further, low-caste females diversify more towards construction and manufacturing.

The findings suggest that in the absence of suitable non-farm employment opportunities, even educated females will be confined to low-return sectors like manufacturing and construction. Because the services sector has a lower absorption capacity, only females with a graduate degree and belonging to economically well-off households can work there. As such, policies should not only focus on enhancing the ability of workers through education and vocational training but should even facilitate greater accessibility to high-remunerative non-farm jobs (Desai et al, 2018). Therefore, the first policy suggestion would be to facilitate workers in

achieving education and vocational training facilities. Provision of skill training programs for rural workers, particularly women would help them to compete for various employment opportunities. Secondly, expansion of infrastructure facilities like all-weather roads, electricity, and telecommunications and even a well-functioning financial market would better serve the diverse employment requirements of the people. Thirdly, to address the heterogeneous nature of the RNFS, policies should be formulated keeping in mind the local requirements through a decentralized process to enable people to actively participate in the decision-making. This would facilitate more efficient use of resources and development of physical assets and social capital as per local requirements. Lastly, pro-women policies should focus on easy transferability of resources, especially ownership rights of land to women. Also, mechanisms through which credit facilities can be easily accessed by women should be developed. This will significantly improve their capacity to diversify to non-farm activities. There is also the need for gender sensitization that would make women, irrespective of class and caste, recognize their rights and freedom to be economically independent.



### Appendix 3A

**Table 3A. 1 Small-Hsiao test for the IIA assumption (N= 234864)**

Ho: Odds (Outcome-J vs Outcome-K) are independent of independent of other alternatives

Omitted	InL(full)	InL (Omit)	Chi2	df	P>chi2	Evidence
1	-1.35e+05	-1.35e+05	83.26	104	0.933	For Ho
2	-1.07e+05	-1.07e+05	107.77	104	0.380	For Ho
3	-1.03e+05	-1.03e+05	97.04	104	0.672	For Ho
4	-9.60e+04	-9.60e+04	105.33	104	0.445	For Ho
5	-1.07e+05	-1.07e+05	105.18	104	0.532	For Ho

**Table 3A. 2 Determinants of rural occupational choice with rainfall data**

Variables	Mining & quarrying	Manufacturing	Construction	Transport	Services
<b>Coefficient Values</b>					
Age	0.021* (0.003)	-0.007* (0.001)	-0.013* (0.001)	0.007* (0.001)	0.042* (0.001)
Gender	1.875* (0.07)	0.283* (0.018)	1.455* (0.018)	1.617* (0.019)	0.327* (0.019)
<b>Education (illiterate = base category)</b>					
Edu1	0.272* (0.068)	0.412* (0.022)	0.035*** (0.019)	0.569* (0.022)	0.625* (0.031)
Edu2	0.439* (0.068)	0.546* (0.023)	-0.119* (0.020)	1.064* (0.021)	1.583* (0.029)
Edu3	1.037* (0.087)	0.618* (0.034)	-0.354* (0.036)	1.406* (0.028)	3.049* (0.033)
Edu4	1.519* (0.098)	0.814* (0.046)	-0.359* (0.053)	1.638* (0.035)	4.362* (0.035)
Vocation (yes=1, 0= no)	0.638* (0.061)	1.524* (0.019)	0.242* (0.024)	0.517* (0.020)	0.559* (0.023)
Married	0.101 (0.064)	-0.082* (0.019)	-0.004 (0.019)	0.099* (0.019)	-0.106* (0.022)
<b>Caste (other caste = base category)</b>					
ST	0.129 (0.08)	-0.321* (0.033)	0.324* (0.028)	-0.527* (0.027)	0.027 (0.03)
SC	0.348* (0.071)	0.090* (0.025)	0.732* (0.023)	-0.295* (0.022)	0.297* (0.026)
OBC	-0.072 (0.063)	0.215* (0.022)	0.252* (0.022)	-0.099* (0.018)	0.172* (0.021)
<b>Religion (other religion = base category)</b>					
Hindu	0.468* (0.095)	0.172* (0.042)	0.282* (0.037)	0.073** (0.033)	0.083** (0.034)
Muslim	0.476* (0.133)	0.768* (0.047)	0.723* (0.044)	0.577* (0.039)	0.453* (0.044)

<b>Land ownership (landless households = base category)</b>					
<b>Marginal</b>	-0.487*	-0.523*	-0.468*	-0.423*	-0.581*
	(0.105)	(0.036)	(0.034)	(0.034)	(0.042)
<b>Small</b>	-1.551*	-1.897*	-2.018*	-1.627*	-1.691*
	(0.124)	(0.045)	(0.043)	(0.039)	(0.047)
<b>Semi-medium</b>	-1.936*	-2.415*	-2.535*	-2.104*	-2.064*
	(0.137)	(0.052)	(0.053)	(0.044)	(0.050)
<b>Medium</b>	-2.654*	-2.909*	-3.084*	-2.637*	-2.399*
	(0.182)	(0.067)	(0.073)	(0.053)	(0.056)
<b>Large</b>	-2.099*	-3.555*	-3.140*	-2.927*	-2.734*
	(0.251)	(0.151)	(0.142)	(0.094)	(0.093)
<b>HH size</b>	-0.041*	0.005	-0.047*	-0.015*	-0.045*
	(0.01)	(0.003)	(0.003)	(0.003)	(0.004)
<b>Dependency ratio</b>	0.132*	0.063*	0.169*	0.149*	0.178*
	(0.043)	(0.015)	(0.013)	(0.013)	(0.015)
<b>Unemployment rate</b>	0.004*	0.001***	0.002*	0.003*	0.003*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
<b>Urbanization</b>	0.007**	0.005*	-0.003*	-0.004*	-0.000
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
<b>Average dis</b>	0.0001***	-0.0001*	0.0001**	0.0001***	-0.0001
	(0.0001)	(0.0001)	(0.000)	(0.000)	(0.000)
<b>Rainfall_deviation</b>	-0.0000	-0.0003*	-0.000	-0.0001*	-
	(0.0001)	(0.0003)	(0.000)	(0.000)	0.0001*
					(0.000)
<b>State</b>	Yes	Yes	Yes	Yes	Yes
<b>Year (2004= base year)</b>					
<b>2009</b>	0.342*	0.192*	0.995*	0.244*	0.143*
	(0.073)	(0.023)	(0.024)	(0.020)	(0.026)
<b>2011</b>	0.316*	0.197*	1.203*	0.203*	0.305*
	(0.074)	(0.023)	(0.024)	(0.021)	(0.027)
<b>Constant</b>	-6.360*	-1.781*	-1.862*	-2.667*	-4.108*
	(0.253)	(0.092)	(0.087)	(0.079)	(0.091)
<b>Number of observations: 248,634</b>					
<b>Wald chi2(300): 119440.85</b>					
<b>Prob&gt; chi2: 0.0000</b>					
<b>Pseudo R2: 0.1780</b>					
<b>Log pseudo likelihood: -274954.44</b>					

Notes: Figures in parenthesis are robust Standard Errors. \*, \*\* & \*\*\* indicates significance at 1%, 5% and 10% level of significance.

**Table 3A. 3 Determinants of rural occupational choice with rainfall data and its interaction with year dummies**

<b>Variables</b>	<b>Mining &amp; quarrying</b>	<b>Manufacturing</b>	<b>Construction</b>	<b>Transport</b>	<b>Services</b>
<b>Coefficient Values</b>					
<b>Age</b>	0.021*	-0.007*	-0.013*	0.007*	0.042*
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
<b>Gender</b>	1.875*	0.283*	1.455*	1.617*	0.326*

	(0.070)	(0.018)	(0.018)	(0.019)	(0.019)
<b>Education (illiterate = base category)</b>					
<b>Edu1</b>	0.272*	0.412*	0.035***	0.570*	0.625*
	(0.068)	(0.022)	(0.019)	(0.022)	(0.031)
<b>Edu2</b>	0.439*	0.546*	-0.119*	1.064*	1.583*
	(0.068)	(0.023)	(0.020)	(0.021)	(0.03)
<b>Edu3</b>	1.036*	0.617*	-0.354*	1.407*	3.049*
	(0.087)	(0.034)	(0.036)	(0.028)	(0.033)
<b>Edu4</b>	1.519*	0.814*	-0.359*	1.638*	4.363*
	(0.098)	(0.046)	(0.053)	(0.035)	(0.035)
<b>Vocation (yes=1, 0=no)</b>	0.638*	1.524*	0.243*	0.518*	0.559*
	(0.061)	(0.02)	(0.024)	(0.020)	(0.023)
<b>Married</b>	0.101	-0.082*	-0.005	0.099*	-0.106*
	(0.064)	(0.02)	(0.019)	(0.019)	(0.022)
<b>Caste (other caste = base category)</b>					
<b>ST</b>	0.127	-0.321*	0.324*	-0.527*	0.026
	(0.080)	(0.033)	(0.028)	(0.027)	(0.03)
<b>SC</b>	0.348*	0.090*	0.731*	-0.296*	0.297*
	(0.071)	(0.025)	(0.023)	(0.022)	(0.026)
<b>OBC</b>	-0.073	0.215*	0.252*	-0.099*	0.170*
	(0.063)	(0.022)	(0.022)	(0.018)	(0.021)
<b>Religion (other religion = base category)</b>					
<b>Hindu</b>	0.466*	0.169*	0.281*	0.075**	0.082**
	(0.095)	(0.041)	(0.037)	(0.033)	(0.034)
<b>Muslim</b>	0.475*	0.765*	0.721*	0.580*	0.449*
	(0.133)	(0.047)	(0.044)	(0.039)	(0.044)
<b>Land ownership (landless households = base category)</b>					
<b>Marginal</b>	-0.489*	-0.524*	-0.468*	-0.422*	-0.583*
	(0.105)	(0.036)	(0.034)	(0.034)	(0.042)
<b>Small</b>	-1.553*	-1.899*	-2.019*	-1.626*	-1.693*
	(0.124)	(0.045)	(0.043)	(0.039)	(0.047)
<b>Semi-medium</b>	-1.939*	-2.416*	-2.535*	-2.103*	-2.066*
	(0.137)	(0.052)	(0.053)	(0.044)	(0.05)
<b>Medium</b>	-2.656*	-2.912*	-3.085*	-2.636*	-2.402*
	(0.181)	(0.067)	(0.073)	(0.053)	(0.056)
<b>Large</b>	-2.100*	-3.556*	-3.141*	-2.927*	-2.736*
	(0.251)	(0.151)	(0.142)	(0.094)	(0.093)
<b>HH size</b>	-0.041*	0.005	-0.047*	-0.015*	-0.045*
	(0.01)	(0.003)	(0.003)	(0.003)	(0.004)
<b>Dependency ratio</b>	0.132*	0.063*	0.169*	0.149*	0.178*
	(0.043)	(0.015)	(0.013)	(0.013)	(0.015)
<b>Unemployment rate</b>	0.004*	0.001***	0.002*	0.003*	0.003*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
<b>Urbanization</b>	0.007**	0.005*	-0.003*	-0.004*	-0.0001
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
<b>Average dis</b>	0.0001**	-0.0001*	0.0001**	0.0001**	-0.0001
	*	(0.000)	(0.000)	*	(0.000)
	(0.0001)			(0.000)	
<b>Rainfall_deviation</b>	0.000	-0.0004*	-0.0001	-0.0001**	-0.0002*
	(0.0002)	(0.000)	(0.0001)	(0.000)	(0.0001)

<b>Rainfall_deviation0</b>	-0.0001	-0.000	0.0001	0.0001	0.0001
<b>9</b>	(0.000)	(0.000)	(0.0001)	(0.0001)	(0.0001)
<b>Rainfall_deviation</b>	0.000	0.0001**	0.0001	-0.000	0.0002*
<b>11</b>	(0.000)	(0.000)	(0.0001)	(0.0001)	*
					(0.0001)
<b>Year (2004= base year)</b>					
<b>2009</b>	0.339*	0.185*	0.995*	0.247*	0.139*
	(0.073)	(0.023)	(0.024)	(0.02)	(0.026)
<b>2011</b>	0.317*	0.199*	1.204*	0.200*	0.307*
	(0.075)	(0.023)	(0.024)	(0.021)	(0.027)
<b>Constant</b>	-6.326*	-1.739*	-1.855*	-2.689*	-4.084*
	(0.255)	(0.093)	(0.088)	(0.079)	(0.092)

**Number of observations: 248,634**

**Wald chi2(300): 119763.21**

**Prob> chi2: 0.0000**

**Pseudo R2: 0.1780**

**Log pseudo likelihood : -274940.14**

*Notes: Figures in parenthesis are robust Standard Errors. \*, \*\* & \*\*\* indicates significance at 1%, 5% and 10% level of significance.*



## Chapter 4

### Determinants of specialization or diversification of occupation in rural India

The previous chapter examined the numerous factors that contributed to explaining the preference for rural non-farm occupations over agriculture. Diversification not only indicates choice of non-farm employment over farm but also refers to a situation where workers engage themselves in more than one economic activity either for survival or accumulation purposes (Unni, 1996; Start, 2001). Involvement of workers in a diverse portfolio of activities has been found to be beneficial in reducing risk and uncertainty of income (Fabusoro et al, 2010). Engaging in multiple activities also acts as an income stabilizer against sudden shocks and unfavorable events. But it is also undertaken to meet family expenditure that includes education of children or to take advantage of the available opportunities (Ellis, 1998). Therefore, diversification has become a norm for rural livelihoods in developing nations. However, on the contrary, certain studies (Deininger & Olinto, 2001), observe that while diversification is widespread, yet for individuals and households, specialization in either farm or non-farm activities yields greater benefits in terms of income and expenditure compared to diversification. In case of India, we found from the previous chapter that choice of non-farm employment differs across gender, education level, land ownership size, caste and other regional factors. Under the present debate of whether diversification or specialization has a welfare-enhancing impact on rural households, we examine the factors that affect rural farm households to shift from specialization in agriculture to diversification in non-farm activities and also additionally analyze the reasons for which non-farm workers diversify to farm activities. This aspect is important because even though non-farm employment pays better than agriculture, its heterogeneous nature does not imply equal returns from all sub-sectors (Scharf & Rahut, 2014). As such, a section of non-farm workers may also combine agriculture to maintain subsistence. We also found that share of non-farm workers combining farm activities is higher than farm workers combining non-farm activities. Again, Unni (1996) points out that in the absence of a well-functioning land market, non-farm workers in rural Gujarat engage in part-time farm activities. Therefore, this motivates us to examine what type of non-farm workers diversify to agriculture.

The chapter is divided into the following four sections. Section 4.1 discusses the nature and characteristics of workers who diversify and specialize. Section 4.2 elaborates on the method

applied to analyze the determinants of diversification and specialization while section 4.3 includes the findings of this chapter. Section 4.4 sums up the entire discussion of this chapter.

#### 4.1. Nature and characteristics of rural workers

This section elaborates on the nature and characteristics of workers who have chosen to either specialize in agriculture or non-agriculture sector or have diversified for 2004–05, 2009–10 and 2011–12.

**Table 4. 1 Percentage share of workers in occupational specialization and diversification during 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds.**

Year	Specialise in Farm	Diversify from Farm to Non-Farm
2004	94.55	5.45
2009	91.5	8.5
2011	88.52	11.48
Year	Specialise in Non-Farm	Diversify from non-Farm to Farm
2004	75.29	24.71
2009	84.14	15.86
2011	83.93	16.07

*Source: Author's calculation from NSSO EUS data.*

From table 4.1 it is seen that there is a growing tendency among the farming community to diversify to non-farm activities whereas, the proportion of individuals diversifying from non-farm to farm activities has declined. But looking at the share of diversified individuals, we see that the share of non-farm workers diversifying to farm activities is higher in all three time periods compared to farm workers diversifying to non-farm. This signifies that not only farm households and individuals diversify from farm to non-farm activities which is witnessed in many developing nations, even non-farm workers are combining agriculture for a livelihood.

**Table 4. 2 Distribution of male and female workers across different specialization and diversification categories.**

Farm specialization/diversification					
		Male		Female	
Year	Specialise	Diversify	Specialise	Diversify	
2004	92.33	7.67	97.61	2.39	
2009	90.46	9.54	93.31	6.69	
2011	87.57	12.43	90.24	9.76	
Non-farm specialization/diversification					
		Male		Female	
Year	Specialise	Diversify	Specialise	Diversify	

<b>2004</b>	73	27	83.28	27
<b>2009</b>	82.66	17.34	90.09	9.91
<b>2011</b>	82.1	17.9	90.72	9.28

Source: Author's calculation from NSSO EUS data.

Table 4.2 demonstrates that the share of both male and female workers specializing in agriculture has declined while their share in non-farm activities has increased over time. In other words, more male and female workers have started specializing in non-farm occupations. Again, if we look at the share of workers who diversify, then a growing tendency of workers to diversify from farm to non-farm activities can be seen for both male and female workers. Although the share of male workers diversifying from farm to non-farm sector is high compared to females, the rate of increase is greater among rural females. For instance, there is a 4.3% rise in the share of females who combine farm with non-farm activities between 2004–05 and 2009–10 but for males, the change is 1.87%. And between 2009–10 and 2011–12, the rise in share of diversified female workers is 3.07% while it is 2.89% for males. From this, it can be inferred that more females are diversifying to non-farm employment compared to males. Furthermore, diversification from non-farm to farm activities has considerably declined during 2004–05 and 2011–12 irrespective of gender. Here again, the decline is higher for females compared to males.

**Table 4. 3 Percentage share of workers who specialize or diversify as per their educational qualification.**

<b>2004</b>	<b>Illiterate</b>	<b>BP primary</b>	<b>and Middle &amp; secondary</b>	<b>HS &amp; above</b>
<b>Specialise in Farm</b>	78.41	66.92	59.22	40.71
<b>Specialise in Non-Farm</b>	12.38	22.17	28.46	44.27
<b>Diversify to Non-Farm</b>	3.8	4.03	4.29	3.76
<b>Diversify to Farm</b>	5.41	6.88	8.03	11.26
<b>2009</b>	<b>Illiterate</b>	<b>BP primary</b>	<b>and Middle &amp; secondary</b>	<b>HS &amp; above</b>
<b>Specialise in Farm</b>	70.54	62.37	56.92	43.32
<b>Specialise in Non-Farm</b>	18.59	26.7	32.16	46.43
<b>Diversify to Non-Farm</b>	6.75	5.94	5.03	3.16
<b>Diversify to Farm</b>	4.12	5	5.88	7.09
<b>2011</b>	<b>Illiterate</b>	<b>BP primary</b>	<b>and Middle &amp; secondary</b>	<b>HS &amp; above</b>
<b>Specialise in Farm</b>	65.22	56.59	52.22	38.99

<b>Specialise in Non-Farm</b>	20.59	29.7	35.54	50.78
<b>Diversify to Non-Farm</b>	9.09	7.63	6.15	3.76
<b>Diversify to Farm</b>	5.1	6.08	6.1	6.47

Source: Author's calculation from NSSO EUS data.

From table 4.3, it is evident that share of workers specializing in agriculture has shown a decreasing trend for workers of all educational category and the share of these workers has increased in non-farm specialization. Among these specialized non-farm workers, the share is highest among higher secondary and above level of education which shows that non-farm activities are mostly preferred by highly educated workers. Looking at the share of diversified workers, we find that illiterate workers and those with below primary and primary level education combine agriculture with non-farm activities and their share is increasing over time. On the contrary, diversification of non-farm workers towards farming has shown a declining trend 2004–05 and 2009–10 irrespective of education level but between 2009–10 and 2011–12, their share has increased except for graduate and above-educated workers. The figures also show that specialization in agriculture is high among workers who are illiterate and have middle and secondary level of education. But for HS level of educated workers, their share is highest in non-farm specialization. Unni (1996) also found that educated workers tend to specialize in non-farm activities as they are capable of earning higher returns by engaging in lucrative non-farm jobs.

**Table 4. 4 Share of workers belonging to different land-owning households.**

	<b>2004</b>				
	Landless	Marginal	Small	Medium	large
<b>Specialise in Farm</b>	58.8	63.5	83.2	86.59	88.08
<b>Specialise in Non-Farm</b>	32.67	24.25	7.56	6.25	6.01
<b>Diversify to Non- Farm</b>	3.58	4.15	4.04	3.43	2.81
<b>Diversify to Farm</b>	4.96	8.11	5.2	3.74	3.1
	<b>2009</b>				
	Landless	Marginal	Small	Medium	Large
<b>Specialise in Farm</b>	49.16	57.02	78.07	84.76	84.35
<b>Specialise in Non-Farm</b>	41.72	31.23	10.4	8.18	11.38
<b>Diversify to Non- Farm</b>	5.31	5.82	7.21	4.67	3.03
<b>Diversify to Farm</b>	3.81	5.93	4.32	2.4	1.24
	<b>2011</b>				
	Landless	Marginal	Small	Medium	Large
<b>Specialise in Farm</b>	44.13	50.57	77.42	81.71	84.4
<b>Specialise in Non-Farm</b>	47.2	34.99	9.76	8.85	7.59

<b>Diversify to Non- Farm</b>	6.91	7.56	8.46	6.2	4.61
<b>Diversify to Farm</b>	1.75	6.88	4.36	3.23	3.4

Source: Author's calculation from NSSO EUS data.

It is observed from table 4.4 that overall, there is a decline in the share of workers specializing in farm activities and an increase in the share of workers in non-agriculture whether they belong to landless or large land-owning households. However, if we look at each land-owning household type, then we found that by 2011–12, landless households have the highest share specializing in non-farm activities. Their share has also increased in case of diversification from farm to non-farm activities. For land-owning households, more than 50% of workers are solely engaged in agriculture. Among them, specialization in non-farm is undertaken mostly by marginal land-owning households. Therefore, it implies that land is an important income-earning asset in rural India and non-farm occupations are undertaken by landless and marginal households. Again, diversification to either sector is highest among landless and up to medium landholding size while it is lowest among large landed households. Examining the pattern of diversification, we observe that from landless to medium land-owning households, there is a rising share of workers diversifying from farm to non-farm and a decreasing share from non-farm to farm diversification. But in case of large land-owning households, their share has not only increased from farm to non-farm diversification but also from non-farm to farm diversification indicating that these households try to engage in agriculture even if they principally work in non-farm pursuits.

**Table 4. 5 Distribution of workers belonging to different social groups**

<b>2004</b>	<b>ST</b>	<b>SC</b>	<b>OBC</b>	<b>OTHERS</b>
Specialise in Farm	78.71	67.72	68.46	64.93
Specialise in Non-Farm	8.98	21.23	21.04	25.07
Diversify to Non- Farm	5.3	4.03	3.71	3.67
Diversify to Farm	7.01	7.02	6.79	6.33
<b>2009</b>	<b>ST</b>	<b>SC</b>	<b>OBC</b>	<b>OTHERS</b>
Specialise in Farm	69.17	57.75	62.87	61.53
Specialise in Non-Farm	16.07	29.53	27.25	29.75
Diversify to Non- Farm	10.55	6.52	5.03	3.74
Diversify to Farm	4.22	6.2	4.85	4.97
<b>2011</b>	<b>ST</b>	<b>SC</b>	<b>OBC</b>	<b>OTHERS</b>
Specialise in Farm	64.22	51.43	57.84	55.32
Specialise in Non-Farm	17.85	33.07	29.94	34.68
Diversify to Non- Farm	11.98	8.13	6.96	4.83
Diversify to Farm	5.96	7.37	5.26	5.18

Source: Author's calculation from NSSO EUS data.

Here the trend of specialization and diversification is similar to that of workers of different education and land-owning categories. Additionally, we observe that ST workers have the highest share in farm specialization and lowest share in non-farm specialization compared to OBC, SC and upper caste. A greater representation of STs in agriculture and their low share in non-farm can be due to their easy access to land and other resources (Srivastava & Srivastava, 2010). They may even have lesser access to information about non-farm employment opportunities which confine them to agriculture employment (Nakajima et al, 2018). Share of workers in non-farm specialization is highest among upper-caste workers. ST and SC are also more likely to combine both farm and non-farm activities compared to OBC and upper caste households. STs and SCs are not only resource poor but they also lack adequate human capital required to compete for high-return non-farm jobs (Madheswaran & Attewell, 2007). Therefore, to maintain the minimum level of living, they are more likely to combine multiple economic activities rather than focus on a single sector.

## **4.2. Methodology**

### **4.2.1. Data source**

To examine this aspect of specialization or diversification of rural individuals, we have used the nationally representative employment and unemployment data of NSSO for the period 2004–04 (61<sup>st</sup> round), 2009–10 (66<sup>th</sup> round) and 2011–12 (68<sup>th</sup> round) pooled together. NSSO collects extensive information on employment and unemployment status of workers both in rural and urban areas. We have taken the rural data since our study is focused on rural employment diversification. Employment status of workers is measured through major time and priority criteria. In our study, we will be classifying workers who specialize and those who diversify based on the major time criteria. According to this criterion, an individual is regarded as principally employed in one economic activity when he/she spends at least 180 days in that activity. Again, the worker is considered to be employed in a subsidiary status when they spend at least 30 days in that activity (Kumar et al, 2020). Specialization in any economic activity implies that the individual has devoted all his/her time either for a major part of the year or partially to only one economic activity. On the other hand, diversified workers are those who engaged in one activity (say agriculture) in a principal status but also work in other sector (non-farm) in a subsidiary status. These individuals who combine both activities are regarded as diversified workers. Taking this concept into account, we have classified workers into the following four categories- specialization in agriculture, specialization in non-agriculture, diversification from farm to non-farm and diversification from non-farm to farm.

#### 4.2.2. Method

The determinants of specialization or diversification is estimated with the help of a binary logistic regression model separately for farm and non-farm workers. Here, the comparison group is those who specialize in one economic activity and the other group is those who diversify, i.e. combine both farm and non-farm activities. Binary logit model is a common econometric method used when the dependent variable is a binary variable taking values "0" and "1". In one model, we examine factors that determine agricultural workers to diversify to non-farm activities. In the second, model, we analyze factors that affect non-farm workers to diversify to agriculture activities. We also examine the effect of gender, education, caste and land ownership size over time by interacting them with year dummies. The binary logistic regression model is given below-

$$\text{logit}(Y) = \ln \left[ \frac{p}{1-p} \right] = \beta X + \mu \dots \dots \dots (1).$$

Here, Y is the dependent variable taking values 0 and 1. The expression  $\ln \left[ \frac{p}{1-p} \right]$  is the log of the odds ratio. The odds ratio is the ratio of the probability that an individual would diversify to the probability that he/she would specialize.  $\beta$ s are the coefficients to be estimated and X is the vector of explanatory variables. Also, robust standard errors are applied to account for the issue of heteroscedasticity. The covariates used for the analysis are given below.

**Table 4. 6 Description of explanatory variables used in the analysis.**

Variable name	Variable description	Mean	S. D <sup>3</sup>
<b>Continuous variables</b>			
<b>Age</b>	Age of working members (in years)	27.43	19.21
<b>HH size</b>	Household size	6.01	2.91
<b>Dependency ratio</b>	Ratio of dependents to working-age members in a household	0.84	0.75
<b>Unemployment rate</b>	Ratio of unemployed people to total labor force in state-region <sup>4</sup> .	32.69	30.61
<b>Urbanization</b>	Percentage of urban population in a state region	33.67	12.08

<sup>3</sup> S.D means Standard Deviation

<sup>4</sup> State-region concept of NSSO represents a cluster of districts having similar geographical and population characteristics.

<b>Average dis</b>	The average distance of rural region from the urban centres (in kilometres)	306.58	214.76
<b>Categorical variables</b>		Percentage share	
<b>Gender</b>	male=1 female=0	51.102	
<b>Education (illiterate= base category)</b>			
<b>Edu1</b>	below primary and primary level education	33.310	
<b>Edu2</b>	middle and secondary level education	23.435	
<b>Edu3</b>	higher secondary and above education	5.902	
<b>Edu4</b>	Graduate and above	3.546	
<b>Vocation</b>	Receiving/received vocational training =1, not received=0	8.784	
<b>Married</b>	currently married=1, 0 otherwise	47.143	
<b>Household level factors</b>			
<b>Caste (unreserved category= base category)</b>			
<b>ST</b>	Schedule Tribe	16.150	
<b>SC</b>	Schedule Caste	16.979	
<b>OBC</b>	Other Backward Classes	38.973	
<b>Religion (other religion= base category)</b>			
<b>Hindu</b>	Hindu	75.432	
<b>Muslim</b>	Muslim	12.329	
<b>Size of land ownership (landless= base category)</b>			
<b>Marginal</b>	Land size< 1 hectare	66.359	
<b>Small</b>	1<land size<2 hectare	13.234	
<b>Medium</b>	2<land size<10 hectare	9.441	
<b>Large</b>	Land size>10 hectares	1.419	

### 4.3. Empirical findings

**Table 4. 7 Determinants of diversification of individuals from farm to non-farm.**

Variables	Model 1	Model 2	Model 3
	Coefficients	Coefficients	Coefficients
<b>Age</b>	-0.002** (0.0009)	0.002** (0.001)	0.001 (0.001)
<b>Gender</b>	0.696* (0.021)	0.744* (0.021)	0.899* (0.023)

<b>Education (illiterate= base category)</b>			
<b>Edu1</b>	0.033 (0.024)	0.107* (0.025)	-0.033 (0.027)
<b>Edu2</b>	-0.290* (0.025)	-0.092 (0.026)	-0.136* (0.028)
<b>Edu3</b>	-0.608* (0.044)	-0.295* (0.046)	-0.269* (0.048)
<b>Edu4</b>	-0.721* (0.064)	-0.345* (0.066)	-0.350* (0.069)
<b>Vocation=1</b>	0.371* (0.030)	0.453* (0.031)	0.399* (0.033)
<b>Married</b>	0.197* (0.026)	0.171* (0.027)	0.186* (0.029)
<b>Caste (other caste = base category)</b>			
<b>ST</b>		0.771* (0.030)	0.416* (0.036)
<b>SC</b>		0.379* (0.034)	0.286* (0.035)
<b>OBC</b>		0.259* (0.028)	0.159* (0.030)
<b>Religion (other religion = base category)</b>			
<b>Hindu</b>		0.272* (0.030)	0.193* (0.054)
<b>Muslim</b>		0.266* (0.046)	0.318* (0.067)
<b>Land ownership (landless households = base category)</b>			
<b>Marginal</b>		0.124** (0.061)	-0.143** (0.063)
<b>small</b>		-0.062 (0.065)	-0.314* (0.066)
<b>Semi-medium</b>		-0.432* (0.068)	-0.634* (0.070)
<b>Medium</b>		-0.542* (0.073)	-0.754* (0.075)
<b>Large</b>		-0.581* (0.109)	-0.944* (0.112)
<b>HH size</b>		-0.053* (0.004)	-0.034* (0.004)
<b>Dependency ratio</b>		0.204* (0.016)	0.257* (0.017)
<b>Unemployment rate</b>			-0.008* (0.0008)
<b>Urbanization</b>			-0.0007 (0.001)
<b>Average dis</b>			0.0001** (0.00004)
<b>Year</b>			
<b>2009</b>	0.481* (.030)	0.413 (.031)	0.452* (0.032)
<b>2011</b>	0.841* (0.030)	0.757 (0.031)	0.841* (0.032)

	(.030)	(.030)	(0.032)
<b>State code</b>	Yes	Yes	Yes
<b>Constant</b>	-3.159*	-3.833*	-3.469*
	(0.034)	(0.083)	(0.145)
<b>No. of observations</b>	138,663	135,504	135,416
<b>Wald chi2 (57)</b>	2741.69	4127.70	8189.05
<b>Probability&gt;chi2</b>	0.0000	0.0000	0.0000
<b>Pseudo R2</b>	0.0316	0.0529	0.1112
<b>Log pseudo likelihood</b>	-40491.865	-38633.51	-36250.626

Notes: Figures in parenthesis are robust standard errors. \*, \*\* & \*\*\* indicate significance at 1%, 5% and 10% level.

**Table 4. 8 Determinants of diversification from non-farm to farm sector.**

<b>Variables</b>	<b>Model 1</b>	<b>Model 2</b>	<b>Model 3</b>
	Coefficients	Coefficients	Coefficients
<b>Age</b>	0.006*	0.008*	0.009*
	(0.0008)	(0.0009)	(0.0009)
<b>Gender</b>	0.723*	0.757*	0.648*
	(0.021)	(0.022)	(0.023)
<b>Education (illiterate= base category)</b>			
<b>Edu1</b>	-0.295*	-0.268*	-0.124*
	(0.022)	(0.023)	(0.024)
<b>Edu2</b>	-0.422*	-0.424*	-0.318*
	(0.021)	(0.022)	(0.023)
<b>Edu3</b>	-0.673*	-0.740*	-0.652*
	(0.029)	(0.031)	(0.033)
<b>Edu4</b>	-0.792*	-0.921*	-0.893*
	(0.030)	(0.032)	(0.034)
<b>Vocation=1</b>	0.174*	0.217*	0.221*
	(0.019)	(0.020)	(0.021)
<b>Married</b>	0.389*	0.282*	0.316*
	(0.020)	(0.022)	(0.023)
<b>Caste (other caste = base category)</b>			
<b>ST</b>		0.309*	0.398*
		(0.027)	(0.030)
<b>SC</b>		-0.041***	0.029
		(0.024)	(0.026)
<b>OBC</b>		-0.103*	0.119*
		(0.020)	(0.022)
<b>Religion (other religion = base category)</b>			
<b>Hindu</b>		0.991*	0.211*
		(0.034)	(0.047)
<b>Muslim</b>		0.795*	-0.213*
		(0.041)	(0.054)

**Land ownership (landless households = base category)**

<b>Marginal</b>		1.040*	1.052*
		(0.050)	(0.051)
<b>small</b>		1.848*	1.843*
		(0.055)	(0.057)
<b>Semi-medium</b>		1.725*	1.782*
		(0.060)	(0.062)
<b>Medium</b>		1.537*	1.647*
		(0.072)	(0.074)
<b>Large</b>		1.294*	1.476*
		(0.134)	(0.139)
<b>HH size</b>		-0.016*	-0.044*
		(0.003)	(0.003)
<b>Dependency ratio</b>		0.246*	0.230*
		(0.013)	(0.014)
<b>Unemployment rate</b>			-0.006*
			(0.0006)
<b>Urbanization</b>			-0.004*
			(0.001)
<b>Average dis</b>			0.0001*
			(0.00003)
<b>Year</b>			
<b>2009</b>	-0.508*	-0.539*	-0.586*
	(.023)	(.024)	(0.026)
<b>2011</b>	-0.452*	-0.477*	-0.522*
	(.023)	(.024)	(0.026)
<b>State code</b>	Yes	Yes	Yes
<b>Constant</b>	-1.855*	-3.871*	-3.190*
	(0.035)	(0.075)	(0.108)
<b>No. of observations</b>	119,811	113,220	113,011
<b>Wald chi2 (57)</b>	2851.43	5275.662	10733.39
<b>Probability&gt;chi2</b>	0.0000	0.0000	0.0000
<b>Pseudo R2</b>	0.0256	0.0545	0.1229
<b>Log pseudo likelihood</b>	-55968.227	-52349.168	-48523.663

*Notes: Figures in parenthesis are robust standard errors. \*, \*\* & \*\*\* indicate significance at 1%, 5% and 10% level.*

Table 4.7 demonstrates the findings for those diversifying from farm to non-farm sector while table 4.8 includes determinants of diversification of non-farm workers into agriculture. Here, all the time periods are pooled together and a time dummy is included to examine the situation over time. In both tables 4.7 and 4.8, model 1 includes the individual characteristics, household determinants and regional factors are incorporated in model 2 and 3 respectively. From model

1 of tables 4.7 and 4.8, it is observed that with an increase in the age of a farm worker, he/she is less likely to diversify to non-farm activities. But for non-farm workers, age positively affects their chances of additionally working in farming. As there exists no age limit to work on the land, non-farm workers also engage in farm activities even with an increase in their age. Diversification regardless of the sector is higher among males than females. In other words, males are more likely to combine multiple activities compared to females. In addition to engaging in any economic activity, females are also responsible for looking after the family which might reduce their time to devote in additional subsidiary activities. It is interesting to note that education increases the chance of a worker to specialize in either sector rather than do multiple activities. In other words, with a rise in the level of human capital, individuals utilize their skills in one economic activity and by specializing they are capable of earning higher returns which lessens their requirements to engage in multiple pursuits. Deininger and Olinto (2001) also observed that educated individuals in rural Cambodia specialized in one economic activity which accrued them higher returns. Diversification is also high among individuals with any level of vocational training. Currently married individuals are more likely to combine both farm and non-farm activities. This may imply that marriage pushes people to engage in additional activities whether it is farm or non-farm sector.

With the inclusion of household-level determinants in model 2, we observe that the impact of age on diversification from farm to non-farm has become positive and significant. The effect of other individual-level determinants remains unchanged. From model 2 it is seen that ST, SC and OBC individuals engage in multiple economic activities rather than specializing in a single activity. Diversification of these individuals from farm to non-farm might imply their lack of ownership of adequate land which makes agriculture an unviable source of livelihood and forces them to engage in additional non-farm work (Mishra & Singh, 2018). Mishra and Singh (2018) also observe that with the advent of MGNREGA, ST/SC individuals have started shifting from agriculture to non-farm casual work in Uttar Pradesh. Again, their diversification from non-farm to farm may be a result of their low level of human capital which prevents them from engaging in relatively higher remunerative non-farm activities (Srivastava & Srivastava, 2010) and as such they are more likely to engage in agriculture as well. But it may also happen that they are still highly demanded by land-owning households as they were traditionally linked with agriculture by providing their labor supply (Mishra & Singh, 2018). Religion wise both Hindus and Muslims are more likely to work in both farm and non-farm activities. Again, land ownership has a significant influence on whether an individual would diversify or specialize.

It is observed that workers belonging to land-owning households are more likely to specialize in cultivation while those engaged in non-farm activities tend to diversify to farm sector employment with a rise in land ownership size. In other words, workers belonging to land-owning households specialize only in agriculture while those principally engaged in non-farm activities also supply their labour on farm when they own land compared to landless households. Again, household size has a negative impact on diversification whereas dependency ratio has a positive impact on either sector. Households with more dependent members tend to combine both farm and non-farm activities preferably to maintain their level of expenditure. On the other hand, they tend to specialize with a rise in the household size, implying that an additional member is more likely to follow the occupational path of other household members.

Furthermore, we observe a significant impact of region-level determinants on diversification probabilities in model 3. We included unemployment rate as one of the region-level determinants because it is an important indicator of the nature of economic activities taking place in a region. Also, a low unemployment rate represents a high level of economic activity in a region indicating that more people are getting employed. On the other hand, high unemployment rate represents low level of economic activities and hence lesser jobs. Our results show that unemployment rate has a negative impact on diversification for both farm and non-farm workers. Here also the issue of reverse causality remains as discussed in chapter 3.

Again, urbanization rate has a negative impact on diversification from non-farm to farm employment only. This shows that individuals residing in areas with a high level of urbanization are more likely to prefer working only in non-farm activities as residing in the vicinity of urban areas increases their chance of earning higher returns from non-farm employment. Average distance has a positive impact on diversification. Year dummies show that diversification from farm to non-farm has increased over time while diversification from non-farm to farm has declined indicating that people are shifting more towards non-agricultural activities which has been established by existing studies. Now, tables 4.9 to 4.12 below examine whether the effect of gender, education, caste and land ownership on the likelihood of diversification or specialization would change over time.

**Table 4. 9 Effect of gender on diversification or specialization of employment over time.**

Variables	Model 1 <sup>5</sup>		Model 2 <sup>6</sup>	
	Coefficients	Robust S.E	Coefficients	Robust S.E
Age	0.001	0.001	0.009*	0.001
Gender (male=1, female=0)	1.501*	0.061	0.556*	0.049
Gender_09	-0.629*	0.069	0.085	0.063
Gender_11	-0.768*	0.067	0.149**	0.062
<b>Education (illiterate= base category)</b>				
Edu1	-0.031	0.027	-0.124*	0.025
Edu2	-0.132*	0.029	-0.318*	0.024
Edu3	-0.259*	0.049	-0.653*	0.033
Edu4	-0.337*	0.069	-0.894*	0.035
Vocational=1	0.403*	0.034	0.220*	0.022
Married	0.210*	0.029	0.313*	0.023
<b>Caste (other caste = base category)</b>				
ST	0.418*	0.036	0.399*	0.031
SC	0.283*	0.035	0.029	0.026
OBC	0.158*	0.031	0.119*	0.023
<b>Religion (other religion= base category)</b>				
Hindu	0.190*	0.054	0.211*	0.047
Muslim	0.312*	0.067	-0.215*	0.054
<b>Land ownership (landless households = base category)</b>				
Marginal	-0.144**	0.064	1.052*	0.052
small	-0.314*	0.067	1.844*	0.057
Semi-medium	-0.631*	0.071	1.782*	0.062
Medium	-0.752*	0.076	1.649*	0.075
Large	-0.942*	0.113	1.476*	0.139
HH size	-0.035*	0.005	-0.044*	0.004
Dependency ratio	0.265*	0.017	0.230*	0.014
Unemployment rate	-0.009*	0.001	-0.007*	0.001
Urbanization	-0.001	0.001	-0.005*	0.001
Average dis	0.0001**	0.000	0.0001*	0.000
State	Yes		Yes	
<b>Year (2004–05= base year)</b>				
2009	0.912*	0.061	-0.656*	0.059
2011	1.389*	0.059	-0.648*	0.058
<b>State code</b>				
Constant	-3.904*	0.153	-3.112*	0.114
No. of observations	135,416		113,011	
Wald chi2 (59)	8025.13		10739.48	
Probability>chi2	0.0000		0.0000	
Pseudo R2	0.1129		0.1229	
Log pseudo likelihood	-36179.655		-48520.667	

<sup>5</sup> Model 1 refers to determinants that affect diversification from farm to non-farm.

<sup>6</sup> Model 2 refers to determinants that affect diversification from non-farm to farm.

Notes: Figures in parenthesis are robust standard errors. \*, \*\* & \*\*\* indicates significance at 1%, 5% and 10% level.

**Table 4. 10 Effect of education on diversification or specialization of employment over time.**

Variables	Model 1		Model 2	
	Coefficients	Robust S.E	Coefficients	Robust S.E
Age	0.001	0.001	0.010*	0.001
Gender (male=1, female=0)	0.902*	0.023	0.649*	0.024
<b>Education (illiterate= base category)</b>				
Edu1	-0.134**	0.066	-0.268*	0.055
Edu2	0.029	0.065	-0.484*	0.053
Edu3	-0.053	0.119	-0.917*	0.078
Edu4	-0.024	0.169	-1.147*	0.091
<b>Education (illiterate= base category)</b>				
Edu1_09	0.111	0.076	0.204*	0.067
Edu2_09	-0.167**	0.076	0.232*	0.063
Edu3_09	-0.233***	0.140	0.383*	0.092
Edu4_09	-0.184	0.202	0.445*	0.104
<b>Education (illiterate= base category)</b>				
Edu1_11	0.131***	0.074	0.147**	0.066
Edu2_11	-0.237*	0.074	0.174*	0.062
Edu3_11	-0.277**	0.135	0.265*	0.090
Edu4_11	-0.534*	0.196	0.169***	0.103
Vocational=1	0.398*	0.034	0.223*	0.022
Married	0.192*	0.029	0.308*	0.023
<b>Caste (other caste = base category)</b>				
ST	0.416*	0.037	0.399*	0.031
SC	0.284*	0.035	0.030	0.026
OBC	0.158*	0.031	0.120*	0.023
<b>Religion (other religion= base category)</b>				
Hindu	0.192*	0.054	0.212*	0.047
Muslim	0.317*	0.068	-0.216*	0.055
<b>Land ownership (landless households = base category)</b>				
Marginal	-0.147**	0.064	1.052*	0.052
small	-0.318*	0.067	1.845*	0.057
Semi-medium	-0.638*	0.071	1.786*	0.062
Medium	-0.759*	0.076	1.653*	0.075
Large	-0.949*	0.113	1.481*	0.139
HH size	-0.034*	0.005	-0.044*	0.004
Dependency ratio	0.259*	0.017	0.231*	0.014
Unemployment rate	-0.008*	0.001	-0.006*	0.001
Urbanization	-0.001	0.001	-0.005*	0.001
Average dis	0.0001**	0.000	0.0001*	0.000
State	Yes		Yes	
<b>Year (2004–05= base year)</b>				
2009	0.492*	0.057	-0.794*	0.052
2011	0.908*	0.055	-0.659*	0.051

State code	Yes	Yes	Yes	Yes
Constant	-3.499*	0.148	-3.072*	0.112
No. of observations	135,416		113,011	
Wald chi2 (65)	8284.65		10754.90	
Probability>chi2	0.0000		0.0000	
Pseudo R2	0.1117		0.1232	
Log pseudo likelihood	-36230.671		-48504.373	

Notes: Figures in parenthesis are robust standard errors. \*, \*\* & \*\*\* indicates significance at 1%, 5% and 10% level.

**Table 4. 11 Effect of caste on diversification or specialization of employment over time.**

Variables	Model 1		Model 2	
	Coefficients	Robust S.E	Coefficients	Robust S.E
Age	0.002	0.001	0.009*	0.001
Gender (male=1, female=0)	0.901*	0.023	0.648*	0.024
<b>Education (illiterate= base category)</b>				
Edu1	-0.035	0.027	-0.123*	0.025
Edu2	-0.139*	0.029	-0.317*	0.024
Edu3	-0.269*	0.049	-0.652*	0.033
Edu4	-0.346*	0.069	-0.895*	0.035
Vocational=1	0.397*	0.034	0.224*	0.022
Married	0.188*	0.029	0.313*	0.023
<b>Caste (other caste = base category)</b>				
ST	0.011	0.076	0.891*	0.067
SC	-0.025	0.080	0.135**	0.058
OBC	0.0003	0.069	0.255*	0.049
<b>Caste (other caste = base category)</b>				
ST_09	0.419*	0.086	-0.742*	0.078
SC_09	0.268*	0.095	-0.159**	0.069
OBC_09	0.141***	0.081	-0.213*	0.058
<b>Caste (other caste = base category)</b>				
ST_11	0.538*	0.085	-0.469*	0.076
SC_11	0.464*	0.093	-0.098	0.068
OBC_11	0.234*	0.079	-0.122**	0.057
<b>Religion (other religion= base category)</b>				
Hindu	0.189*	0.054	0.207*	0.047
Muslim	0.306*	0.068	-0.215*	0.055
<b>Land ownership (landless households = base category)</b>				
Marginal small	-0.144**	0.064	1.056*	0.052
Semi-medium	-0.315*	0.067	1.855*	0.057
Medium	-0.633*	0.071	1.789*	0.063
Large	-0.756*	0.076	1.656*	0.075
HH size	-0.946*	0.113	1.491*	0.139
HH size	-0.034*	0.005	-0.044*	0.004
Dependency ratio	0.258*	0.017	0.231*	0.014
Unemployment rate	-0.009*	0.001	-0.006*	0.001
Urbanization	-0.001	0.001	-0.005*	0.001
Average dis	0.0001***	0.0001	0.0001*	0.000

State	Yes	Yes	Yes	Yes
Year (2004–05= base year)				
2009	0.236*	0.066	-0.366*	0.047
2011	0.527*	0.065	-0.390*	0.047
State code	Yes	Yes	Yes	Yes
Constant	-3.175*	0.154	-3.370*	0.112
No. of observations	135,416		113,011	
Wald chi2 (63)	8335.416		10810.42	
Probability>chi2	0.0000		0.0000	
Pseudo R2	0.1118		0.1238	
Log pseudo likelihood	-36225.007		-48474.665	

Notes: Figures in parenthesis are robust standard errors. \*, \*\* & \*\*\* indicates significance at 1%, 5% and 10% level.

**Table 4. 12 Effect of land on diversification or specialization of employment over time.**

Variables	Model 1		Model 2	
	Coefficients	Robust S.E	Coefficients	Robust S.E
Age	0.002	0.001	0.009*	0.001
Gender (male=1, female=0)	0.902*	0.023	0.649*	0.024
<b>Education (illiterate= base category)</b>				
Edu1	-0.032	0.027	-0.125*	0.025
Edu2	-0.136*	0.029	-0.318*	0.024
Edu3	-0.268*	0.049	-0.654*	0.033
Edu4	-0.346*	0.069	-0.899*	0.035
Vocational=1	0.405*	0.034	0.221**	0.022
Married	0.187*	0.029	0.315*	0.023
<b>Caste (other caste = base category)</b>				
ST	-0.129*	0.036	-0.369*	0.032
SC	-0.259*	0.032	-0.278*	0.029
OBC	-0.418*	0.037	-0.397*	0.031
<b>Religion (other religion= base category)</b>				
Hindu	0.194*	0.054	0.214*	0.047
Muslim	0.321*	0.068	-0.213*	0.055
<b>Land ownership (landless households = base category)</b>				
Marginal	-0.182	0.148	1.073*	0.110
small	-0.312**	0.156	1.688*	0.122
Semi-medium	-0.243	0.159	1.596*	0.132
Medium	-0.477*	0.169	1.529*	0.153
Large	-0.859*	0.264	1.155*	0.294
<b>Land ownership (landless households = base category)</b>				
Marginal_09	0.243	0.178	-0.288**	0.132
Small_09	0.259	0.188	-0.076	0.146
Semi-medium_09	-0.190	0.194	-0.004	0.159
Medium_09	-0.167	0.207	-0.185	0.189
Large_09	0.048	0.320	-0.074	0.368
<b>Land ownership (landless households = base category)</b>				
Marginal_11	-0.180	0.176	0.369**	0.149
Small_11	-0.277	0.185	0.600*	0.161

<b>Semi-medium_11</b>	-0.787*	0.192	0.617*	0.172
<b>Medium_11</b>	-0.544*	0.204	0.628*	0.199
<b>Large_11</b>	-0.283	0.311	1.073*	0.366
<b>HH size</b>	-0.035*	0.005	-0.044*	0.004
<b>Dependency ratio</b>	0.259*	0.017	0.232*	0.014
<b>Unemployment rate</b>	-0.008*	0.001	-0.007*	0.001
<b>Urbanization</b>	-0.001	0.001	-0.005*	0.001
<b>Average dis</b>	0.0001**	0.000	0.0001*	0.000
<b>Year (2004–05= base year)</b>				
<b>2009</b>	0.290***	0.174	-0.356*	0.129
<b>2011</b>	1.122*	0.173	-0.938*	0.147
<b>State code</b>	Yes	Yes	Yes	Yes
<b>Constant</b>	-3.151*	0.189	-2.762*	0.139
<b>No. of observations</b>	135,416		113,011	
<b>Wald chi2 (68)</b>	8308.87		10763.26	
<b>Probability&gt;chi2</b>	0.0000		0.0000	
<b>Pseudo R2</b>	0.1120		0.1234	
<b>Log pseudo likelihood</b>	-36217.664		-48494.773	

Notes: Figures in parenthesis are robust standard errors. \*, \*\* & \*\*\* indicates significance at 1%, 5% and 10% level.

From table 4.9, we observe that for those principally engaged in agriculture, diversification to non-farm activities increased for females in later years while it was the males who used to diversify more during 2004–05. This could be due to the increased availability of employment opportunities outside of agriculture, due to the initiation of various employment generating schemes like MGNREGA. Alternatively, a surge in educational attainment of females and falling fertility rates might have facilitated them to diversify to non-farm pursuits more than before (Sarkar et al, 2018). Again, the effect of education demonstrates that educated individuals are less likely to diversify and more likely to specialize in either agriculture or non-farm activities during 2004–05. However, in the next time periods, we observe that diversification by non-farm workers towards agriculture has increased but for farm workers, diversification to non-farm activities increased only among those with primary level of education. Since non-farm employment is undertaken only as a subsidiary status activity, therefore, those with low level of education diversify from farm to non-farm. Hence, workers with low level of education combine both farm and non-farm activities. Further, diversification towards agriculture by educated non-farm workers may indicate their capacity to involve in farming which does not require any special skills.

The impact of social group on occupational diversification over time shows that diversification from farm to non-farm employment has increased while it has decreased from non-farm to farm. This depicts the preferences of low caste workers towards non-farm occupations as

diversification to this sector is high among them compared to upper caste workers. The reasons behind their high diversification and specialization in non-farm work can be linked to their economic condition where majority of them belong to landless households and lack adequate human capital requirements (Nakajima et al, 2018, Srivastava & Srivastava, 2010). Therefore, they are more likely to combine farm with non-farm activities to meet their expenses. Again, landlessness may limit their ability to diversify to agricultural activities.

The effect of land ownership remained unchanged over time. Workers belonging to land-owning households specialize in agriculture rather than dividing their labor between farm and non-farm activities. Similarly, individuals primarily engaged in non-farm activities diversify to agriculture with a rise in landowning size compared to landless households. Deininger and Olinto (2001) observe in their study that ownership of land leads to specialization in either farm or non-farm activities in Colombia. However, in India, a lack of well-functioning land markets may discourage households from investing in non-farm pursuits (Vyas & Mathai, 1978).

#### **4.3.1. Robustness of regression results:**

In order to check the robustness of our findings given in table 4.7 and 4.8 for farm and non-farm diversification, we add long-run mean rainfall deviation for each survey round at the state region level of NSSO. Here, rainfall deviation data is incorporated as an explanatory variable as several studies have pointed out a close association between weather variability and occupational diversification in rural regions (Demeke & Zeller, 2012; Rose, 2001; Mathenge, 2008; Rosenzweig & Stark, 1989; Lamb, 2003). These studies point out that in order to mitigate risk in farm production associated with uncertain climatic conditions, farm households diversify to non-farm and off-farm activities. Therefore, adverse climatic condition is likely to affect both agricultural production and income due to which farm households might combine farm with non-farm activities. Again, for non-farm workers, rainfall shock would reduce their likelihood to combine agricultural activities as this sector is likely to generate lower returns. Therefore, we include this rainfall deviation variable to examine whether the inclusion of such a variable would alter the effect of existing factors. We first added the rainfall deviation data without interacting it with year dummies while in the second analysis, we interacted rainfall values with time dummies. We observe that the inclusion of this variable has not led to any significant change in the coefficient values and signs of all the determinants remained unchanged for both farm and non-farm diversification. This implies that any form of shock in the economy which affects income is not correlated with the determinants of diversification

considered in the model. However, it affects the decision of diversification or specialization by individuals. The findings are provided in table 4A.1 in the Appendix 4A of this chapter.

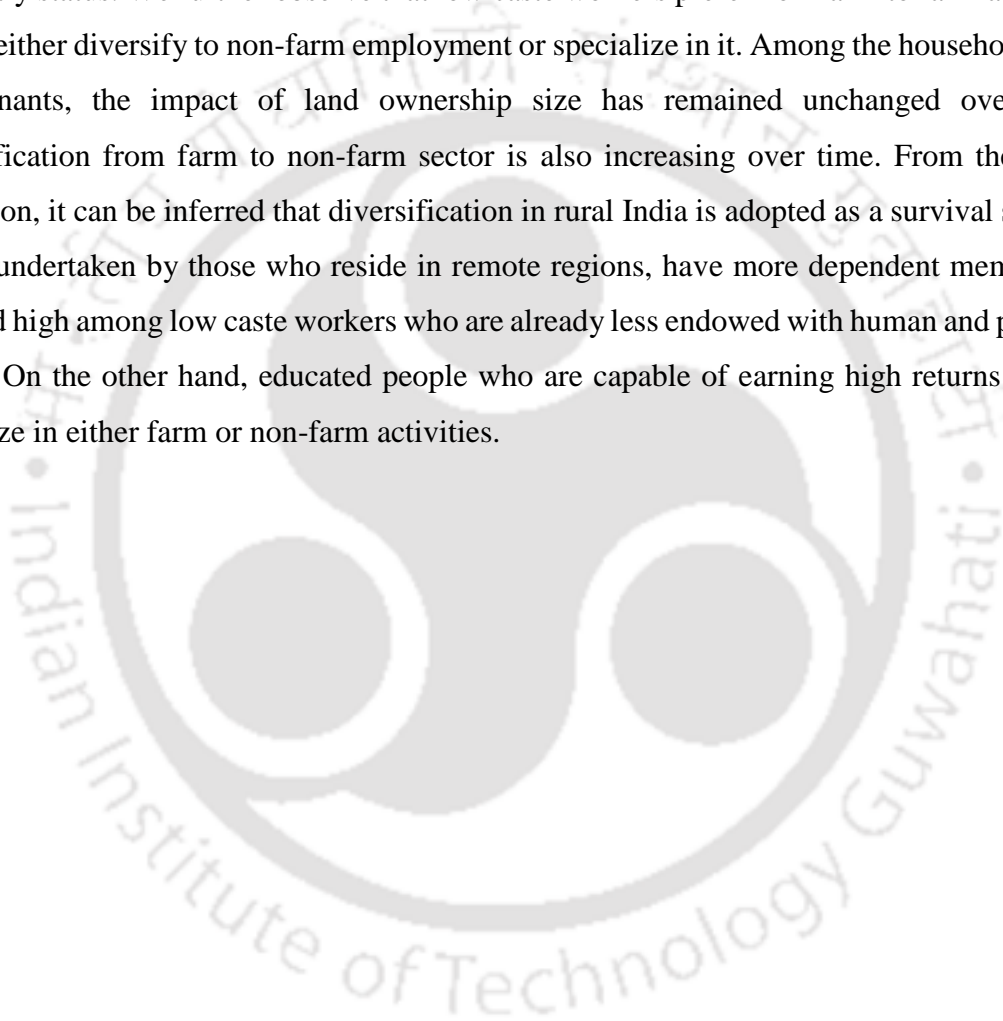
#### **4.3.2. Limitation of the present analysis:**

In this chapter, we examined the factors that influence an individual to specialize in either farm or non-farm activities or diversify. Here also, in estimating the determinants we cannot rule out the possibility of reverse causality, omitted variable bias, measurement error and simultaneity that leads to endogeneity as several unobserved factors might also be related to some of the observed determinants which may make it difficult to interpret the effects of determinants as causal. For instance, factors such as an individual's attitude towards risk, extent of debt burden or a financial shock experienced by the household might affect the decision of whether an individual should diversify or not. But we do not have information on all these variables in our data set and therefore we cannot rule out the possibility of omitted variable bias in our analysis. Hence, the effect of determinants should be interpreted as correlational and not causal.

#### **4.4. Summing up**

The importance of rural non-farm diversification is widely accepted by extant literature. Farm households can no longer be identified with only farming. Rather they have started combining farm with non-farm activities and the motives behind their diversification depend on various factors. Some diversify to reduce risk and uncertainty related to farm production and agricultural prices. Absence of well-functioning credit and factor markets also limits the capacity to expand activity in agriculture or any other particular non-farm activities. On the other hand, it is also observed that diversification is undertaken to accumulate income and uplift the financial status of households. Despite the rising importance of diversification as a livelihood strategy, some studies found that specialization in either farm or non-farm activities can significantly enhance household welfare rather than diversification. Therefore, we examine in this chapter the factors that affect individuals to diversify or specialize in farm and non-farm activities. Although the common phenomenon is diversification from farm to non-farm employment, but we found that in rural India, even non-farm workers engage in farm activities and their share is higher than those who diversify from farm to non-farm. Our findings showed that for all the three time periods, diversification is high among rural males. But with education level, individuals tend to specialize in either farm or non-farm employment. Diversification is also high among currently married individuals and those belonging to ST, SC and OBC

households. However, the effect of land ownership varies. Land ownership reduces the likelihood of farm workers to diversify to non-farm activities while non-farm workers tend to combine agriculture activities with an increase in land holding size. Households with a greater number of dependent members also combine both activities. The time effect demonstrates that diversification from farm to non-farm is high among females while males are more likely to diversify from non-farm to farm activities. This might point towards the tradition of inheritance of land mostly by males which increases their likelihood to engage in agriculture activities at a subsidiary status. We further observe that low caste workers prefer non-farm to farm activities as they either diversify to non-farm employment or specialize in it. Among the household-level determinants, the impact of land ownership size has remained unchanged over time. Diversification from farm to non-farm sector is also increasing over time. From the above discussion, it can be inferred that diversification in rural India is adopted as a survival strategy as it is undertaken by those who reside in remote regions, have more dependent members to feed and high among low caste workers who are already less endowed with human and physical capital. On the other hand, educated people who are capable of earning high returns tend to specialize in either farm or non-farm activities.



## Appendix 4A

**Table 4A. 1 Determinants of farm and non-farm diversification with district-level rainfall data.**

Variables	Model A1	Model A2	Model A3	Model A4
	Coefficients	Coefficients	Coefficients	Coefficients
<b>Age</b>	0.001 (0.001)	0.001 (0.001)	0.009* (0.001)	0.009* (0.001)
<b>Gender</b>	0.899* (0.023)	0.904* (0.023)	0.648* (0.024)	0.648* (0.024)
<b>Education (illiterate= base category)</b>				
<b>Edu1</b>	-0.032 (0.027)	-0.034 (0.027)	-0.125* (0.025)	-0.126* (0.025)
<b>Edu2</b>	-0.138* (0.029)	-0.143* (0.029)	-0.319* (0.024)	-0.319* (0.024)
<b>Edu3</b>	-0.270* (0.049)	-0.277* (0.049)	-0.651* (0.033)	-0.654* (0.033)
<b>Edu4</b>	-0.351* (0.069)	-0.359* (0.069)	-0.894* (0.035)	-0.895* (0.035)
<b>Vocation=1</b>	0.409* (0.034)	0.411* (0.034)	0.222* (0.022)	0.220* (0.022)
<b>Married</b>	0.183* (0.029)	0.187* (0.029)	0.319* (0.023)	0.320* (0.023)
<b>Caste (other caste = base category)</b>				
<b>ST</b>	0.418* (0.037)	0.418* (0.037)	0.394* (0.031)	0.386* (0.031)
<b>SC</b>	0.287* (0.035)	0.289* (0.035)	0.029 (0.026)	0.029 (0.026)
<b>OBC</b>	0.161* (0.031)	0.164* (0.031)	0.119* (0.023)	0.118* (0.023)
<b>Religion (other religion = base category)</b>				
<b>Hindu</b>	0.189* (0.054)	0.187* (0.054)	0.208* (0.047)	0.199* (0.047)
<b>Muslim</b>	0.313* (0.068)	0.312* (0.068)	-0.217* (0.054)	-0.225* (0.054)
<b>Land ownership (landless households = base category)</b>				
<b>Marginal</b>	-0.142** (0.063)	-0.144** (0.063)	1.053* (0.052)	1.047* (0.052)
<b>small</b>	-0.315* (0.067)	-0.317* (0.067)	1.844* (0.057)	1.840* (0.057)
<b>Semi-medium</b>	-0.634* (0.071)	-0.636* (0.071)	1.785* (0.062)	1.781* (0.062)
<b>Medium</b>	-0.755* (0.076)	-0.757* (0.076)	1.652* (0.075)	1.649* (0.075)
<b>Large</b>	-0.944* (0.113)	-0.943* (0.113)	1.483* (0.139)	1.483* (0.139)
<b>HH size</b>	-0.034* (0.005)	-0.034* (0.005)	-0.044* (0.004)	-0.044* (0.003)
<b>Dependency ratio</b>	0.257* (0.017)	0.257* (0.017)	0.231* (0.014)	0.229* (0.014)

<b>Unemployment rate</b>	-0.008*	-0.008*	-0.007*	-0.007*
	(0.001)	(0.001)	(0.001)	(0.001)
<b>Urbanization</b>	-0.001	-0.001	-0.004*	-0.005*
	(0.001)	(0.001)	(0.001)	(0.001)
<b>Average dis</b>	0.0001**	0.0001**	0.0001*	0.0001*
	(0.000)	(0.000)	(0.000)	(0.000)
<b>Rainfall deviation</b>	-0.0002*	0.0002**	0.0002*	0.0002**
	(0.000)	(0.0001)	(0.000)	(0.000)
<b>Rainfall deviation 09</b>	-	-0.001*	-	-0.0004*
		(0.0001)		(0.0001)
<b>Rainfall deviation 11</b>	-	-0.0003*	-	0.0002**
		(0.0001)		(0.0001)
<b>Year (2004–05 = Base year)</b>				
<b>2009</b>	0.454*	0.443*	-0.581*	-0.606*
	(0.033)	(0.033)	(0.026)	(0.026)
<b>2011</b>	0.829*	0.829*	-0.517*	-0.506*
	(0.033)	(0.033)	(0.026)	(0.026)
<b>State code</b>	Yes	Yes	Yes	Yes
<b>Constant</b>	-3.487*	-3.439*	-3.151*	-3.015*
	(0.145)	(0.145)	(0.109)	(0.11)
<b>Number of observations:</b>	135,416	135,416	113,011	113,011
<b>Wald chi2(58):</b>	8189.44	8235.27	10733.88	10696.54
<b>Prob&gt; chi2:</b>	0.0000	0.0000	0.0000	0.0000
<b>Pseudo R2:</b>	0.1114	0.1120	0.1231	0.1238
<b>Log pseudo likelihood:</b>	-36239.518	-36218.245	-48508.486	-48473.781

Notes: Figures in parenthesis are robust standard errors. \*, \*\* & \*\*\* indicate significance at 1%, 5% and 10% level.

Model A1 and A2 consist of the determinants of diversification or specialization of rural farm workers and Model A3 and A4 include the findings for rural non-farm workers.

## Chapter 5

### **Impact of employment diversification on household's magnitude and pattern of consumption expenditure in rural India**

This chapter focuses on how rural household's strategy of employment diversification affects the magnitude and share of household food and non-food consumption expenditure. Here, employment diversification implies that households either engage in more than one economic activity or they completely shift from one activity to the other, specifically from farm to the RNFS. Although our primary focus is on farm households, we also evaluate the well-being of non-farm household's diversification towards agriculture in order to determine if specializing only in non-farm activities is better than diversifying to farm. We further classified farm households into self-employed and casual farm households as the economic status of both these classes of farm workers differ (Rahman & Mishra, 2020). Being the producer of food, self-employed farm households are more food secure and have low incidence of poverty compared to casual farm households which are the most marginalized group (Dzanku, 2019; Chandrasekhar, Dev & Pandey, 2015; Rahman & Mishra, 2020). Poverty is also prevalent among agricultural labor households as they account for 41% of the rural poor while for self-employed farm households, incidence of poverty has reduced from 32% to 21.6% (Chandrasekhar et al, 2015). This clearly will have a diverse effect on their spending patterns. Therefore, in this chapter, we fill this gap in the literature. Also, by diversification, we mean households where at least one member is engaged in an economic activity apart from the household's principal occupation. It also includes households that have completely shifted from one occupation to the other. We measure household well-being in terms of the household's food and non-food consumption expenditure as consumption expenditures are closely linked with wellbeing and wealth (Hossain & Al-Amin, 2019; Zeeshan et al, 2021). Here consumption expenditure is used as a means to quantify welfare. For our analysis, we applied a propensity score matching (PSM) method which estimates the effect of diversification by comparing diversified and non-diversified households based on their observed characteristics and then estimate the treatment effect.

The chapter is organized into the following sections. Section 5.1 contains the methodology while section 5.2 elaborates on the various covariates used for the analysis. Descriptive statistics is included in section 5.3 while section 5.4 explains the propensity score matching

method. Section 5.5 elaborates on the covariate balancing test control and treatment group. The findings are included in section 5.6 and section 5.7 sums up the discussion of this chapter.

## **5.1. Methodology**

### **5.1.1. Data Source**

The data source for this analysis is obtained from the employment and unemployment survey (EUS) of NSSO for 61<sup>st</sup> (2004-05), 66<sup>th</sup> (2009-10) and 68<sup>th</sup> (2011-12) rounds. With a total sample size of 198,134 households for the three survey rounds for rural India, NSSO's EUS data is one of the most comprehensive and reliable data at the national level. The EUS data also collects detailed information on expenditures made by households on various food and non-food items. The recall period for all the food items is 30 days while for non-food items the recall period is 365 days for most of the durable goods and it is 30 days for items like house rent, expenditure on entertainment, etc. The non-food items which had a recall period of 365 days were converted into monthly expenditure and therefore, all the food and non-food expenditures represent the monthly consumption expenditure of the household. The absolute value of food and non-food expenditure is taken to understand whether actual spending on these items has increased or not. This would signify whether increase in income due to diversification results in an increase in consumption spending. Also, the study examines the pattern of diversification by taking the shares of food and non-food expenditure to total household expenditure. This is incorporated to understand whether or not diversification affects the consumption behaviour of households.

Diversified households are those households where the principal occupation of at least one household working member differs from the household's major income earning source and it also includes households that completely shifted away from traditional activities like farming to other non-traditional activities like in the RNFS (Start, 2001). Again, non-diversified households are those households where all the working-age members are involved in the household's principal income-earning occupation. Furthermore, for empirical analysis, only those households are considered where all the members are engaged in only one activity in the principal status. Households where members also work in subsidiary status are discarded as inclusion of these household types may confuse and confound the results (Dey, 2018).

We analyze the diversification impact on four different household types in rural India that incorporate self-employed farm, casual farm, self-employed non-farm and casual non-farm households. However, for the years 2004–05 and 2009–10, there is no such classification as

casual non-farm household. Therefore, the analysis of this household type is restricted to the year 2011–12. These household types are classified based on the major income derived from that activity. For instance, self-employed farm households derive at least 50 percent of their income from cultivation.

### 5.1.2. Conceptual Framework and Empirical Method

Following Owusu et al (2011) and Seng (2015) the decision of a household to adopt a diversified strategy takes place when the returns or income from that activity is higher than the income derived from their current activity. In our study, we assume that the decision of a farm household to diversify would be driven by either pull or push factors. For households lacking in basic capital endowment or resources would mostly diversify out of compulsion to maintain the subsistence level of income. While, for some others, diversification is undertaken for accumulation purposes. Whatever the reasons behind this diversification process, we assume that it has a favorable impact on household consumption expenditure. Similarly, diversification's impact on consumption expenditure of non-farm households is examined to test the efficiency of non-farm occupations for those principally engaged in it. Therefore, households are classified as either "diversified" or "specialized". Diversified households are referred to as the "treatment" group while non-diversified households comprise the "control" group. Hence, the decision to diversify or specialize is a binary indicator variable that is expressed as a function-

$$L_i^* = \beta X_i + \varepsilon_i \dots \dots \dots (1)$$

$$L_i = 1 \text{ if } L_i^* > 0 \text{ and } L_i = 0 \text{ if } L_i^* \leq 0$$

Where  $L_i$  takes value 1 if the household diversifies and 0, otherwise.  $X_i$  is the vector of household and locational characteristics that are expected to affect diversification decision. The outcome equation is considered to be a linear function of the explanatory variables and the binary treatment indicator which is given as below-

$$Y_i = \alpha X_i + \delta L_i + \mu_i \dots \dots \dots (2)$$

Here,  $Y_i$  is the outcome variable which is food and non-food consumption expenditure in our case,  $X_i$  represents the vector of covariates and  $\mu_i$  is the random disturbance term. However, simple linear regression estimates of equation (2) will lead to biased results as the decision of diversification is a deliberate process determined by several factors. To account for sample

selection bias arising out of non-randomized allocation of households to the treatment, our study adopts the Propensity Score Matching (PSM) method. PSM method is commonly used to estimate the causal effect of a treatment for observational or non-experimental studies where random assignment to treatment is not possible and units self-select themselves into the treatment. Under self-selection, difference in outcomes between the treated and the control unit does not necessarily reflect the effect of treatment but may be due to differences in their observed characteristics (Rosenbaum, 2005). This selection bias problem is taken into account by the PSM method when it matches units from the treatment and control group based on their observed characteristics (Becker & Ichino, 2002). Ignoring this self-selection problem may result in inconsistent or biased estimates.

Under observational studies, a binary treatment indicator represents whether the individual receives the treatment or not. Let  $Z_i$  be the binary indicator that takes a value 1 if the person participates and 0 if he/she does not participate. Then let the potential outcomes associated with treatments be denoted by  $Y_i^1$  and  $Y_i^0$  where  $Y_i^1$  is the outcome associated with treatment  $Z_i=1$  and  $Y_i^0$  is the outcome related to treatment  $Z_i = 0$ . Therefore, the treatment outcome for individual 'i' is given below as

$$Y_i = ZY^1 - (1 - Z)Y^0 \dots\dots\dots(3)$$

Since it is not possible to observe the actual and the counterfactual outcomes of the same individual at the same time. Hence, it is impossible to estimate the treatment effect for each and every individual under study. Therefore, PSM estimates the average treatment effects (Rosenbaum, 2005). The propensity score is defined as the conditional probability of receiving the treatment given pre-participation characteristics which is given as follows (Garrido et al, 2014; Rosenbaum, 2005; Austin, 2011)-

$$p(X_i) = P(Z_i = 1|X_i) = E(Z_i|X_i), p(X_i) = F\{h(X_i)\} \dots\dots\dots(4)$$

Here,  $p(X_i)$  is the propensity score estimated with the help of a logit model based on the vector of covariates denoted by  $X_i$ .  $Z_i$  is an indicator variable and is equal to 1 if the household diversifies and  $F\{.\}$  is a normal or logistic cumulative distribution function.

The predicted propensity score is then used to estimate treatment effects by matching treated units with control units. The three common treatment effects include: i) the Average Treatment Effect on the Treated (ATT) which estimates the effect of participation, ii) Average Treatment effect (ATE) which analyses the effect of participation on the sample as a whole and iii)

Average Treatment Effect on the untreated (ATU) which shows the effect of treatment on the untreated if they had actually received the treatment. The most important treatment effect among them is the ATT as it examines the effect of the intervention on those who actually got the treatment (Dehejia & Wahba, 2002). However, we estimated all the three treatment effects in our study.

The three treatment effects equations are given below

$$ATE = E[E\{Y_i^1 | Z_i = 1, p(X_i)\} - E\{Y_i^0 | Z_i = 0, p(X_i)\}] \dots \dots \dots (5)$$

$$ATT = E[E\{Y_i^1 | Z_i = 1, p(X_i)\} - E\{Y_i^0 | Z_i = 0, p(X_i)\} | Z_i = 1] \dots \dots \dots (6)$$

$$ATU = E[E\{Y_i^1 | Z_i = 1, p(X_i)\} - E\{Y_i^0 | Z_i = 0, p(X_i)\} | Z_i = 0] \dots \dots \dots (7)$$

The treatment effects are obtained after matching the participants with non-participants using different matching algorithms based on the propensity scores. There are different types of matching algorithms which include nearest neighbour, kernel, radius, and stratification matching (Becker & Ichino, 2002). The study adopts the nearest neighbour (NN) matching method where we match 5 control units against each treated units in order to enhance the quality of match (Caliendo & Kopeinig, 2008). In NN matching, the control units with the closest propensity score are matched with the treatment unit. For robust estimation, we also applied kernel and radius matching algorithms. Kernel matching with a bandwidth of 0.01 and radius matching with a caliper of 0.002 is implemented. Our study adopts matching with replacement which reduces bias in estimation and also minimizes the propensity score distance of treated and control units (Owusu et al, 2011; Dehejia & Wahba, 2002). The advantage of these methods is that while nearest neighbour method matches units based on the closest propensity score, kernel method matches more non-participants against each participant thereby reducing the variance (Owusu et al, 2011; Caliendo & Kopeinig, 2008). Radius matching again, avoids the risk of bad matches by comparing units within the caliper (Caliendo & Kopeinig, 2008). Matching is done with replacement since it reduces bias as each control unit can be matched with more than one treatment unit. Matching with replacement also minimizes the distance based on propensity score so that each treated unit finds similar control units (Dehejia & Wahba, 2002).

There are two primary assumptions of the PSM method. The assumption of conditional independence (CIA) or unconfoundedness states that based on the propensity scores, outcomes

are independent of treatment assignment (Caliendo & Kopeinig, 2008). This assumption simply means that differences in outcomes between treated and control units with the same value of covariates are due to the treatment effect.

$$(Y_i^0, Y_i^1) \perp\!\!\!\perp Z_i \mid p(X) \dots \dots \dots (8)$$

The second assumption is the common support or overlap which implies that persons with the same value of covariates have a positive probability of being both participants and non-participants (Heckman et al., 1999), i.e.  $0 < P(Z=1|X) < 1$ . This common support condition improves the quality of matches (Becker & Ichino, 2002).

In order to ascertain the achievement of balance of covariates between the treatment and control groups, a t-test for mean difference before and after matching is done where an insignificant p-value after matching will indicate that there is no significant difference in covariates between the two treatment groups. Other test of balance includes pseudo R2 and p-values of log likelihood ratio test of joint significance before and after matching. The pseudo R2 shows how well the covariates explain the participation probability and as such after matching the pseudo R2 value should become very low suggesting the absence of any systematic difference in the covariate distribution between treated and control group (Caliendo & Kopeinig, 2008).

## 5.2. Variable choice

### 5.2.1. Key covariates used to match the treatment and control group

To match diversified households with non-diversified households, we have included covariates that affect both the treatment and the outcomes. These covariates are at the household and regional level. Demographic factors include age of the household head, gender of the household head, education and vocational training of the household head and marital status of the household head. Other household-level indicators include caste, religion, size of land ownership, household size and dependency ratio. At the regional level, the variables included are unemployment rate, urbanization rate and average distance of the district to its nearest urban centres.

### Justification for the use of the various individual, household and locational characteristics.

**Age:** It represents the life cycle effect on employment and also on consumption pattern. With an increase in the age of the household head, he/she is less likely to look for other employment

opportunities. Moreover, the magnitude of consumption also declines with an increase in age (Chang & Mishra, 2008; Seng, 2015, Kuwornu et al, 2018).

**Gender:** Gender forms an important aspect of occupational choice as well as consumption expenditure. Employment choice differs between gender due to differences in access to assets, opportunities and level of human capital (Kuwornu et al, 2018). Furthermore, Chang and Mishra (2008) also observe significant differences in household consumption expenditure between male and female workers.

**Education level:** Education level indicates human capital (Seng, 2015). There are more job opportunities for educated people and they are also aware of available employment opportunities and can easily build networks (Zeeshan et al, 2018). Therefore, educated people are more capable of working in non-farm sector (Chang & Mishra, 2008; Seng, 2015; Kuwornu et al, 2018). Education is also found to have a positive impact on household consumption expenditure (Akaakohol & Aye, 2014).

**Vocational training:** Vocational training facilitates workers to engage in non-farm activities and therefore, those with vocational training are expected to also have a positive impact on consumption expenditure.

**Marital status:** It is observed that married individuals have more family responsibilities and since they mostly inherit land from their parents (Bezu & Holden, 2014), it is assumed that married household head is more likely to focus on agriculture activities and less likely to diversify to non-farm occupations. This choice of occupation of the household head is also likely to affect their consumption spending.

**Caste:** Caste significantly affects both asset ownership rights and occupational choice in rural India where upper-caste individuals mostly do cultivation and ST/SCs are engaged as casual workers (Mishra & Singh, 2018). Therefore, it is hypothesized that while upper-caste individuals are more likely to do cultivation, other caste workers will engage in different non-farm activities (Zeeshan et al, 2018). This occupational choice is also hypothesised to affect the magnitude of consumption for different caste households.

**Religion:** This variable is found to have a significant effect on occupation in rural India. Mishra and Singh (2018) pointed out the domination of Muslims in casual work compared to other religion. Differences in occupational choice may also affect the magnitude and pattern of consumption expenditure.

**Dependency ratio:** Presence of dependent members can significantly affect the household's decision of diversification and also on household consumption expenditure (Seng, 2015). However, its effect cannot be ascertained a-priori. More number of dependents may force households to engage in multiple economic activities to meet household expenditure needs. But on the other hand, with more dependents, household members may need to devote more time taking care of them which might adversely affect their diversification decision and even their consumption spending (Zeeshan et al, 2018).

**Household size:** It is hypothesized that presence of more household members means more supply of labor and therefore greater ability to diversify (Canagarajah et al, 2001). Household members are also expected to contribute positively to consumption expenditure (Kuwornu et al, 2018).

**Size of land ownership:** Land holding size is hypothesized to have a negative effect on diversification to non-farm employment as households owning land are more likely to utilize their land for cultivation (Zeeshan et al, 2018). On the other hand, having land might encourage non-farm workers to also engage in agricultural activities (Seng, 2015).

**Average distance to urban centres:** This can adversely affect diversification to non-farm employment as people residing in remote regions may not be aware of employment opportunities outside agriculture (Seng, 2015; Kuwornu et al, 2018). Also, households residing further away from urban regions are less likely to engage in high-return non-farm activities which is likely to affect their consumption spending as well (Demeke & Zeller, 2012).

**Urbanization rate in a region:** This variable is defined as the percentage of urban population in a region which is used as a proxy for urbanization. This variable is hypothesized to have a favorable effect on generating non-farm employment in rural regions through sub-contracting or urban demand for rural goods and services (Jatav & Sen, 2013). Therefore, higher level of urbanization is expected to augment diversification to non-farm employment. It has also been instrumental in enhancing household expenditure (van de Walle & Cratty, 2004).

**Unemployment rate in a region:** This variable is hypothesized to increase the likelihood of engaging in multiple economic activities by rural households as a rise in unemployment rate would result in an overall decline in income levels and to cope with the falling income levels, households would diversify. On the other hand, a rise in unemployment rate is expected to have an adverse impact on consumption expenditure of the household.

### 5.3.Descriptive Statistics

In this section, we provide cross tabulation of the percentage of diversified and non-diversified households in rural India and their allocation of labor to farm and non-farm activities.

**Table 5. 1 Percentage share of diversified household by household type**

Household type	Non-diversified			Diversified		
	2004-05	2009-10	2011-12	2004-05	2009-10	2011-12
S.E <sup>7</sup> farm household	86.47	86.86	85.53	13.53	13.14	14.47
Casual farm household	85.74	84.92	84.17	14.26	15.08	15.83
S.E non-farm household	77.35	81.47	83.97	22.65	18.53	16.03
Casual non-farm household	-	-	83.44	-	-	16.56

Source: Author's computation based on NSSO EUS data for the 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> round.

Unlike existing literature that focused only on the diversification strategies of farm households, we find that the share of diversified non-farm households is higher than the share of diversified farm households. This means that not only farm households diversify to non-farm employment but non-farm households also work in the farm sector. Given that more than half of the rural population are employed in agriculture, it is still pursued by most of the rural households. Even Unni (1996) observes that in rural Gujarat non-farm households diversify mostly to agriculture activities. However, over time there is a gradual rise in farm households diversifying to non-farm activities and a fall in the share of non-farm households diversifying to agriculture.

**Table 5. 2 Distribution of land ownership size by household type in rural India (in percentages)**

Land ownership size	S.E farm household	S.E non-farm household	Casual farm household	Casual non-farm household
<b>61<sup>st</sup> round</b>				
Landless	0.34	7.10	11.75	-
Marginal	38.59	81.93	85.34	-

<sup>7</sup> S.E stands for Self-employed.

Small	22.60	5.69	1.79	-
Semi-medium	19.06	3.12	0.80	-
Medium	15.12	1.77	0.22	-
Large	4.29	0.39	0.10	-
<b>66<sup>th</sup> round</b>				
Landless	0.49	5.91	10.97	-
Marginal	34.77	81.79	83.77	-
Small	22.55	6.95	3.68	-
Semi-medium	20.99	3.77	0.95	-
Medium	16.90	1.28	0.62	-
Large	4.31	0.30	-	-
<b>68<sup>th</sup> round</b>				
Landless	0.43	4.83	8.61	8.56
Marginal	37.91	84.91	88.30	88.95
Small	22.22	5.46	1.92	1.64
Semi-medium	21.08	3.19	0.86	0.59
Medium	14.64	1.49	0.17	0.23
Large	3.72	0.13	0.14	0.03

Source: Author's computation based on NSSO EUS data for the 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds.

Land ownership being an important income-earning asset in rural India also determines the choice of occupation by rural households (Dey, 2018). Table 5.2 shows the land distribution pattern of rural households by household type and clearly, self-employment in farming is undertaken by those households that own relatively more land in the small, semi-medium, medium and large category. Rural households deriving their major income from either non-farm or casual farm employment possess more marginal land compared to self-employed farm households. Due to the absence of casual non-farm household type during 61<sup>st</sup> (2004–05) and 66<sup>th</sup> (2009–10) rounds, information on land ownership size is missing for this household type during these time periods.

**Table 5. 3 Household type wise distribution of principal occupation of individuals between farm and different non-farm sectors (in percentages).**

Occupational groups	S.E farm households	S.E non-farm household	Casual farm household	Casual non-farm household
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<b>61<sup>st</sup> round (2004–05)</b>				
Agriculture	95.10	13.15	94.73	-
Mining & quarrying	0.02	0.25	0.02	-
Manufacturing	1.38	26.60	2.06	-
Electricity, gas & water supply	0.01	0.07	0.02	-
Construction	0.49	5.90	0.99	-
Trade & transport	1.64	38.44	1.07	-
Services	1.36	15.59	1.11	-
<b>66<sup>th</sup> round (2009–10)</b>				
Agriculture	95.16	12.54	95	-
Mining & quarrying	0.01	0.94	0.02	-
Manufacturing	1.11	22.30	1.42	-
Electricity, gas & water supply	0.01	0.09	0.02	-
Construction	0.81	8.41	1.60	-
Trade & transport	1.40	40.54	0.97	-
Services	1.51	15.18	0.97	-
<b>68<sup>th</sup> round (2011-12)</b>				
Agriculture	94.22	8.98	92.81	11.38
Mining & quarrying	0.04	0.26	0.49	2.78
Manufacturing	1.20	22.97	2.04	14.69
Electricity, gas & water supply	0.02	0.23	0.00	0.27
Construction	1.10	9.50	2.32	57.46
Trade & transport	1.97	39.25	1.16	7.72
Services	1.46	18.79	1.18	5.69

*Source: Author's computation based on NSSO EUS data for the 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds.*

Table 5.3 describes the distribution of occupation in the principal status according to household type. Share of employment in agriculture is highest for self-employed farm and casual farm households as they derive more than 50 percent of their income from agriculture. But it is also

observed that the share of these households in cultivation has declined marginally and has increased in sectors like trade, transport and communication. For self-employed non-farm household, individuals are principally employed in trade, services and manufacturing whereas more than 50 percent of casual non-farm households are engaged in construction work. They also have a higher share in agriculture compared to workers from self-employed non-farm households.

**Table 5. 4 Percentage share of workers in different activity status of different household types for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> round**

Activity status	S.E farm households	S.E non-farm household	Casual farm household	Casual non-farm household
<b>61<sup>st</sup> round</b>				
1. Self-employed in farm	94.04	9.20	2.44	-
2. Regular in farm	0.16	0.08	2.47	-
3. Casual in farm	0.91	3.88	89.81	-
4. Self-employed in non-farm	2.28	78.25	1.63	-
5. Regular in non-farm	1.71	5.16	1.64	-
6. Casual in non-farm	0.91	3.44	2.01	-
<b>66<sup>th</sup> round</b>				
1. Self-employed in farm	93.20	9.09	3.25	-
2. Regular in farm	0.09	0.26	1.96	-
3. Casual in farm	1.87	3.74	89.79	-
4. Self-employed in non-farm	1.97	75.60	1.36	-
5. Regular in non-farm	1.77	6.22	1.44	-
6. Casual in non-farm	1.10	4.21	2.20	-
<b>68<sup>th</sup> round</b>				
1. Self-employed in farm	91.84	5.01	2.73	2.47
2. Regular in farm	0.08	0.25	0.37	0.36
3. Casual in farm	2.30	3.72	89.71	8.55
4. Self-employed in non-farm	2.42	78.95	1.73	4.74
5. Regular in non-farm	2.05	5.33	1.44	3.99
6. Casual in non-farm	1.31	6.74	4.02	79.90

Source: Author's computation based on NSSO EUS data for the 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds.

Table 5.4 examines the activity status of workers apart from working in their principal livelihood source. It is observed that for cultivator households, workers mostly diversify to self-employed non-farm activities, followed by casual farm work and regular non-farm

activities. Similarly, for casual farm households, diversification is highest towards casual non-farm activities followed by engagement as self-employed farm and non-farm workers. Again, workers of self-employed non-farm households diversify towards self-employed agriculture activities or engage in casual and regular non-farm activities. For casual non-farm households, they mostly diversify to casual farm followed by self-employed and regular non-farm activities.

Now, in estimating the impact of occupational diversification on household well-being, we have considered four outcomes- food expenditure, non-food expenditure, food expenditure shares and share of non-food expenditure. Food consumption spending includes items like cereal and cereal products, milk, vegetables, meat, fish, fruits etc. while non-food items include expenditure on fuel and light, entertainment, medical expenses, clothing, bedding and other durable goods. Tables 5.5 to 5.7, present the outcome variables and their descriptive statistics.

**Table 5. 5 Difference in the mean values of outcomes between diversified and non-diversified households across household types for 61<sup>st</sup> round.**

Outcome variable	Treatment		Control		Difference of means (t-test)
	Mean	S. E	Mean	S. E	
<b>61<sup>st</sup> round</b>					
<i>Self-employed farm household</i>					
1. Food expenditure	2899.46	17.874	2097.35	4.421	802.11*
2. Food expenditure share <sup>8</sup>	55.176	0.107	57.762	0.052	-2.585*
3. Non-food expenditure	2643.03	28.909	1616.16	5.897	1026.87*
4. Non-food expenditure share	42.345	0.111	39.970	0.077	2.374*
<i>Self-employed non-farm household</i>					
1. Food expenditure	2191.05	12.869	1760.05	4.992	431.001*
2. Food expenditure share	57.173	0.104	56.330	0.057	0.842*
3. Non-food expenditure	1711.04	16.35	1493.77	8.674	217.274*
4. Non-food expenditure share	39.894	0.106	41.142	0.059	-1.248*
<i>Self-employed farm to self-employed non-farm household</i>					
1. Food expenditure	1760.05	4.992	2098.09	4.422	-338.04*
2. Food expenditure share	56.330	0.057	57.567	0.040	-1.236*

<sup>8</sup> The addition of food expenditure share and non-food expenditure share does not sum up to 100% due to non-inclusion of tobacco consumption expenditure as a part of food consumption expenditure.

3. Non-food expenditure	1493.77	8.674	1616.55	5.893	-121.78*
4. Non-food expenditure share	41.142	0.059	39.610	0.041	1.532*

***Farm labor household***

1. Food expenditure	1609.59	13.98	1190.99	3.81	418.59*
2. Food expenditure share	58.59	0.171	60.45	0.061	-1.860*
3. Non-food expenditure	1191.28	19.13	746.71	3.46	444.56*
4. Non-food expenditure share	38.09	0.177	36.34	0.062	1.747*

*Source: Author's computation based on NSSO EUS data for the 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds. \* Implies significance at 1% level.*

**Table 5. 6 Difference in the mean values of outcomes between diversified and non-diversified households across household types for 66<sup>th</sup> round.**

Outcome variable	Treatment		Control		Difference of means (t-test)
	Mean	S. E	Mean	S. E	
<b>66<sup>st</sup> round</b>					
<b><i>Self-employed farm household</i></b>					
1. Food expenditure	4294.57	30.317	3168.32	7.620	1126.24*
2. Food expenditure share	54.26	0.135	55.10	0.049	-0.842*
3. Non-food expenditure	4018.21	46.174	2801.63	12.636	1216.58*
4. Non-food expenditure share	43.75	0.136	42.86	0.050	0.894*
<b><i>Self-employed non-farm household</i></b>					
1. Food expenditure	3146.71	18.176	2714.70	7.191	432.01*
2. Food expenditure share	55.17	0.118	54.95	0.057	0.226***
3. Non-food expenditure	2773.17	32.785	2455.10	13.153	318.07*
4. Non-food expenditure share	42.44	0.119	43.11	0.058	-0.671*
<b><i>Self-employed farm to self-employed non-farm household</i></b>					
1. Food expenditure	2714.70	7.191	3168.32	7.620	-453.62*
2. Food expenditure share	54.95	0.057	55.10	0.049	-0.153**
3. Non-food expenditure	2455.10	13.153	2801.63	12.636	-346.53*

4. Non-food expenditure share	43.11	0.058	42.86	0.050	0.256*
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***farm labor household***

1. Food expenditure	2567.71	24.570	1915.12	7.121	652.58*
2. Food expenditure share	55.02	0.232	58.17	0.081	-3.149*
3. Non-food expenditure	2374.12	55.335	1366.13	7.962	1007.99*
4. Non-food expenditure share	42.57	0.235	39.21	0.082	3.355*

Source: Author's computation based on NSSO EUS data for the 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds. \* Implies significance at 1% level.

**Table 5. 7 Difference in the mean values of outcomes between diversified and non-diversified households across household types for 68<sup>th</sup> round.**

Outcome variable	Treatment		Control		Difference of means (t-test)
	Mean	S. E	Mean	S. E	
<b>68<sup>th</sup> round</b>					
<b><i>Self-employed farm household</i></b>					
1. Food expenditure	4723.06	32.670	3845.25	10.893	877.80*
2. Food expenditure share	50.89	0.133	51.49	0.055	-0.607*
3. Non-food expenditure	5086.37	58.067	4060.84	19.875	1025.53*
4. Non-food expenditure share	47.13	0.135	46.38	0.056	0.748*
<b><i>Self-employed non-farm household</i></b>					
1. Food expenditure	3817.29	22.718	3369.41	9.974	447.87*
2. Food expenditure share	51.55	0.125	51.50	0.059	0.046
3. Non-food expenditure	3816.48	41.658	3521.04	18.407	295.43*
4. Non-food expenditure share	45.75	0.130	46.39	0.060	-0.637*
<b><i>Self-employed farm to self-employed non-farm household</i></b>					
1. Food expenditure	3369.41	9.974	3845.25	10.893	-475.84*
2. Food expenditure share	51.50	0.059	51.49	0.055	0.007
3. Non-food expenditure	3521.049	18.40	4060.84	19.875	-539.79*
4. Non-food expenditure share	46.39	0.060	46.38	0.056	0.010

**Casual farm household**

1. Food expenditure	3207.95	48.069	2383.83	10.869	824.12*
2. Food expenditure share	53.95	0.288	55.75	0.108	-1.803*
3. Non-food expenditure	2969.64	78.828	1913.87	14.856	1055.76*
4. Non-food expenditure share	42.96	0.290	41.41	0.108	1.557*

**Casual non-farm household**

1. Food expenditure	3086.70	23.528	2729.01	9.390	357.69*
2. Food expenditure share	53.35	0.179	54.75	0.082	-1.398*
3. Non-food expenditure	2755.64	39.729	2333.18	14.827	422.45*
4. Non-food expenditure share	42.77	0.183	42.52	0.082	0.246

**Casual farm to casual non-farm household**

1. Food expenditure	2729.01	9.39	2383.83	10.86	345.18*
2. Food expenditure share	54.75	0.082	55.75	0.108	-0.995*
3. Non-food expenditure	2333.18	14.82	1913.87	14.85	419.30*
4. Non-food expenditure share	42.52	0.082	41.41	0.108	1.113*

*Source: Author's computation based on NSSO EUS data for the 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds. \* implies significance at 1% level.*

It is observed that there exists significant difference in the outcomes of diversified and non-diversified households. For diversified cultivator, casual farm and casual non-farm households, the mean difference in their food expenditure, non-food expenditure and non-food expenditure share are positive and significant implying that diversified households could spend more on these items. But they have a significant negative spending on food expenditure share. On the other hand, for diversified self-employed non-farm households, it is found that apart from spending more on food and non-food expenditures by the treated group, they also tend to spend more on food items and lesser share of spending is devoted to non-food items. Again, for cultivator households that have completely shifted to self-employed non-farm activities, it is found that food and non-food expenditure is significantly low for the treated group compared to the control group. But for casual farm households that completely shifted to casual non-farm, higher spending on food, non-food and share of non-food expenditure increased for the treated group. However, their food expenditure share is low keeping other things constant.

From the above mean difference test of the outcome variables, it is found that there is significant difference in the outcome values between the treated and control groups. However, these findings cannot be considered causal inferences as the differences in attributes of diversified and non-diversified households are not taken into account. Therefore, observed characteristics that affect treatment indicator and the outcome need to be controlled for in order to avoid the issue of self-selection bias.

#### 5.4. Propensity score estimates

The first stage in analysing the impact of diversification on household consumption expenditure is to estimate the propensity scores. We applied a logistic regression model for propensity score estimates where the dependent variable takes value 1 if the household has diversified and 0 for non-diversified households. The selection of the explanatory variables for adoption of a diversified strategy is based on existing literature. Several individual, household and locational characteristics have been considered for the analysis. The logistic regression results for each household type across the three time periods are elaborated below from tables 5.8 to 5.12

**Table 5. 8 Determinants of diversification for 61<sup>st</sup> round**

<b>Variables</b>	<b>Self-employed farm</b>	<b>Farm labour</b>	<b>Self-employed non-farm</b>
<b>Age_head</b>	.029* (.002)	.010** (.004)	.026* (.002)
<b>Gender_head</b>	-.022 (.137)	-.088 (.211)	.412* (.145)
<b>Education_head (illiterate= base category)</b>			
<b>Below primary &amp; primary</b>	.181** (.074)	.319* (.110)	-.393* (.072)
<b>Middle &amp; secondary</b>	.510* (.080)	.559* (.153)	-.566* (.081)
<b>HS<sup>9</sup> &amp; diploma</b>	.817* (.137)	2.072* (.346)	-.978* (.152)
<b>Graduate &amp; above</b>	1.012* (.149)	2.508* (.486)	-.949* (.164)
<b>Married_head</b>	-.023 (.107)	-.006 (.190)	.245** (.118)
<b>Caste (unreserved= base category)</b>			
<b>ST</b>	-.547* (.115)	-.545* (.191)	.596* (.119)
<b>SC</b>	.174 (.106)	-.679* (.150)	.479* (.096)
<b>OBC</b>	-.095 (.069)	-.386* (.140)	.300* (.075)

<sup>9</sup> HS refers to Higher Secondary education.

<b>Religion (other religion= base category)</b>			
<b>Hindu</b>	-0.269** (.011)	-.123 (.179)	-.159 (.106)
<b>Muslim</b>	.061 (.132)	.054 (.236)	-.215 (.135)
<b>Size of land ownership (landless= base category)</b>			
<b>Marginal</b>	-.858** (.369)	-.013 (.154)	.038 (.113)
<b>Small</b>	-1.136* (.372)	.053 (.373)	1.645* (.153)
<b>Semi-medium</b>	-1.291* (.374)	-.352 (.617)	1.663* (.178)
<b>Medium</b>	-1.562* (.378)	-.701 (1.172)	1.957* (.230)
<b>Large</b>	-1.878* (.405)	-	1.818* (.445)
<b>Household size</b>	.239* (.010)	.352* (.025)	-
<b>Dependency ratio</b>	-.862* (.059)	-.871* (.090)	-.120* (.044)
<b>Unemployment rate</b>	.001* (.000)	.005* (.000)	-.001 (.000)
<b>Urbanization</b>	1.263* (.251)	.779** (.385)	.390 (.238)
<b>Average distance</b>	-.000 (.000)	-.000 (.000)	.0003** (.000)
<b>Constant</b>	-3.784* (.426)	-3.915* (.383)	-3.309* (.251)
<b>LR Chi2 (22)</b>	1273.01	464.76	796.82
<b>Probability&gt;Chi2</b>	0.000	0.000	0.000
<b>Pseudo R2</b>	0.1306	0.1258	0.0935
<b>Log likelihood</b>	-4236.7934	-1614.5879	-3861.2702
<b>No. of observations</b>	14,628	5,130	8,650

Source: Author's computation based on NSSO 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> EUS data.

Notes: \*, \*\* and \*\*\* indicate significant at 1%, 5% and 10% respectively. Figures in parenthesis are standard errors.

**Table 5. 9 Determinants of diversification for 66<sup>th</sup> round**

<b>Variables</b>	<b>Self-employed farm</b>	<b>Farm labour</b>	<b>Self-employed non-farm</b>
<b>Age_head</b>	.028* (.005)	.022* (.007)	.026* (.004)
<b>Gender_head</b>	-.014 (.213)	.480 (.307)	.269 (.192)
<b>Education_head (illiterate= base category)</b>			
<b>Below primary &amp; primary</b>	.290** (.119)	.055 (.140)	-.314* (.093)
<b>Middle &amp; secondary</b>	.387* (.119)	.445* (.156)	-.706* (.094)
<b>HS &amp; diploma</b>	.545* (.175)	.952* (.330)	-.946* (.148)

<b>Graduate &amp; above</b>	1.072* (.200)	2.677* (.412)	-1.118* (.172)
<b>Vocation_head</b>	.304*** (.178)	.287 (.334)	.134 (.106)
<b>Married_head</b>	-.335*** (.186)	-.313 (.263)	.008 (.164)
<b>Caste (unreserved= base category)</b>			
<b>ST</b>	.390* (.142)	-.716* (.243)	.579* (.130)
<b>SC</b>	.269*** (.159)	-.082 (.182)	.335* (.113)
<b>OBC</b>	.044 (.108)	-.258 (.168)	.149*** (.089)
<b>Religion (other religion= base category)</b>			
<b>Hindu</b>	-.089 (.138)	-.467** (.200)	.301** (.130)
<b>Muslim</b>	.227 (.196)	.117 (.258)	.075 (.165)
<b>Size of land ownership (landless= base category)</b>			
<b>Marginal</b>	-.196 (.460)	.041 (.188)	.433* (.162)
<b>Small</b>	-.686 (.465)	-.146 (.388)	1.628* (.192)
<b>Semi-medium</b>	-.737 (.467)	-1.552 (1.056)	1.959* (.217)
<b>Medium</b>	-1.122** (.475)	.057 (.760)	2.267* (.289)
<b>Large</b>	-1.343** (.554)	-	2.168* (.645)
<b>Household size</b>	.250* (.018)	.290*(.034)	-
<b>Dependency ratio</b>	-1.058* (.111)	-.801* (.132)	-.238* (.063)
<b>Unemployment rate</b>	.001**(.000)	.001 (.001)	-.002* (.000)
<b>Urbanization</b>	.520 (.331)	1.748* (.419)	.826* (.270)
<b>Average distance</b>	-.0001 (.000)	-.001* (.000)	.0001 (.000)
<b>Constant</b>	-4.304* (.591)	-3.841* (.513)	-3.603*(.343)
<b>LR Chi2 (23)</b>	444.67	276.31	463.65
<b>Probability&gt;Chi2</b>	0.000	0.000	0.000
<b>Pseudo R2</b>	0.0968	0.1141	0.0741
<b>Log likelihood</b>	-2075.6372	-1072.6992	-2895.6628
<b>No. of observations</b>	8,001	3,300	7,573

Source: Author's computation based on NSSO 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> EUS data.

Notes: \*, \*\* and \*\*\* indicate significant at 1%, 5% and 10% respectively. Figures in parenthesis are standard errors.

**Table 5. 10 Determinants of diversification for 68<sup>th</sup> round-**

<b>Variables</b>	<b>Self-employed farm</b>	<b>Casual farm</b>	<b>Self-employed non-farm</b>	<b>Casual non-farm</b>
<b>Age_head</b>	.010** (.005)	.007 (.009)	.028* (.244)	.008 (.006)
<b>Gender_head</b>	.314 (.205)	-.284 (.368)	.247 (.212)	-.355 (.241)
<b>Education_head (illiterate= base category)</b>				
<b>Below primary &amp; primary</b>	.057 (.108)	.301** (.158)	-.272* (.103)	-.314* (.115)
<b>Middle &amp; secondary</b>	.249 ** (.104)	-.067 (.217)	-.661* (.106)	-.309** (.128)
<b>HS &amp; diploma</b>	.168 (.166)	-.123 (.643)	-.922* (.172)	-.358 (.331)
<b>Graduate &amp; above</b>	.766* (.171)	1.145 (.763)	-1.270* (.207)	-.739 (.229)
<b>Vocation_head</b>	.286** (.117)	.332 (.269)	.136 (.099)	.190 (.156)
<b>Married_head</b>	-.260 (.172)	.026 (.357)	.085 (.182)	.272 (.219)
<b>Caste (unreserved= base category)</b>				
<b>ST</b>	-.216 (.137)	-.480 (.311)	.639* (.148)	-.116 (.160)
<b>SC</b>	.152 (.140)	.109 (.232)	.381* (.131)	-.154 (.161)
<b>OBC</b>	-.247* (.090)	-.070 (.215)	.174*** (.100)	-.291 (.198)
<b>Religion (other religion= base category)</b>				
<b>Hindu</b>	.026 (.140)	-.223 (.288)	.563* (.163)	-.636* (.170)
<b>Muslim</b>	.312*** (.177)	-.065 (.356)	.349*** (.199)	.003 (.183)
<b>Size of land ownership (landless= base category)</b>				
<b>Marginal</b>	-1.473* (.343)	.456 (.303)	.521* (.196)	.167 (.175)
<b>Small</b>	-2.149* (.350)	.298 (.686)	1.745* (.232)	.348 (.414)
<b>Semi-medium</b>	-2.392* (.355)	.848 (.923)	1.967* (.257)	1.465* (.536)
<b>Medium</b>	-2.696* (.367)	1.737 (1.280)	2.180* (.327)	2.281* (.817)
<b>Large</b>	-2.440* (.424)	-	2.425** (.966)	-
<b>Household size</b>	.216* (.017)	.384* (.046)	-	.200* (.030)
<b>Dependency ratio</b>	-.841* (.092)	-.892* (.161)	-.199* (.072)	-.518* (.098)
<b>Unemployment rate</b>	.000 (.000)	.007* (.001)	-.004* (.000)	.000 (.001)
<b>Urbanization</b>	1.302* (.288)	1.335* (.509)	.855* (.271)	1.322* (.374)
<b>Average distance</b>	-.000 (.000)	-.001** (.000)	.001* (.000)	.001* (.000)

<b>Constant</b>	-1.803* (.496)	-4.278* (.689)	-4.483* (.422)	-3.033* (.399)
<b>LR Chi2 (22)</b>	443.42	182.32	415.39	162.10
<b>Probability&gt;Chi2</b>	0.000	0.000	0.000	0.000
<b>Pseudo R2</b>	0.0838	0.1132	0.0791	0.0517
<b>Log likelihood</b>	-2423.3479	-713.89382	-2418.7544	-1485.8476
<b>No. of observations</b>	7,539	2,183	7,173	3,902

Source: Author's computation based on NSSO 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> EUS data.

Notes: \*, \*\* and \*\*\* indicate significant at 1%, 5% and 10% respectively. Figures in parenthesis are standard errors.

**Table 5. 11 Determinants of complete shift of occupation from self-employed farm to self-employed non-farm household for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds.**

<b>Variables</b>	<b>61<sup>st</sup> round</b>	<b>66<sup>th</sup> round</b>	<b>68<sup>th</sup> round</b>
<b>Age_head</b>	.011 (.024)	-.023* (.002)	-.023* (.002)
<b>Gender_head</b>	.360 (.262)	.224** (.092)	.270* (.094)
<b>Education_head (illiterate= base category)</b>			
<b>Below primary &amp; primary</b>	.080 (.157)	.327* (.053)	.337* (.055)
<b>Middle &amp; secondary</b>	.358** (.161)	.444* (.052)	.505* (.053)
<b>HS &amp; diploma</b>	.401 (.250)	.545* (.076)	.621* (.079)
<b>Graduate &amp; above</b>	.814** (.330)	1.080* (.094)	1.041* (.095)
<b>Vocation_head</b>	.638* (.173)	.873* (.072)	.586* (.057)
<b>Married_head</b>	-.062 (.172)	-.294* (.085)	-.490* (.088)
<b>Caste (unreserved= base category)</b>			
<b>ST</b>	-.564** (.220)	-.213* (.069)	-.190* (.071)
<b>SC</b>	1.228* (.199)	.814* (.064)	.777* (.069)
<b>OBC</b>	.337** (.145)	.389* (.045)	.245* (.046)
<b>Religion (other religion= base category)</b>			
<b>Hindu</b>	.205 (.221)	-.114*** (.068)	.070 (.072)
<b>Muslim</b>	1.379* (.145)	.684* (.088)	.874* (.091)
<b>Size of land ownership (landless= base category)</b>			
<b>Medium</b>	-4.400* (1.012)	-3.079* (.156)	.070 (.072)

<b>Large</b>	-2.675** (1.073)	-3.297* (.419)	.874* (.091)
<b>Dependency ratio</b>	-.120 (.097)	-.041 (.030)	-.015 (.032)
<b>Unemployment rate</b>	.004* (.001)	.002* (.000)	.004* (.000)
<b>Urbanization</b>	.536 (.542)	-.091 (.149)	.216 (.143)
<b>Average distance</b>	-.001** (.000)	-.0002* (.000)	-.001* (.000)
<b>Constant</b>	-1.566** (.679)	.361** (.164)	.347** (.180)
<b>LR Chi2 (19)</b>	365.02	2260.59	2125.39
<b>Probability&gt;Chi2</b>	0.000	0.000	0.000
<b>Pseudo R2</b>	0.1649	0.1184	0.1179
<b>Log likelihood</b>	-924.575	-8417.035	-7948.9375
<b>No. of observations</b>	1,606	13,812	13,009

Source: Author's computation based on NSSO 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> EUS data.

Notes: \*, \*\* and \*\*\* indicate significant at 1%, 5% and 10% respectively. Figures in parenthesis are standard errors.

**Table 5. 12 Determinants of complete shift of occupation from casual farm to casual non-farm household for the 68<sup>th</sup> round-**

<b>Variables</b>	<b>Casual farm to casual non-farm household</b>
<b>Age_head</b>	-.021* (.003)
<b>Gender_head</b>	.545* (.139)
<b>Education_head (illiterate= base category)</b>	
<b>Below primary &amp; primary</b>	.247* (.068)
<b>Middle &amp; secondary</b>	.564* (.082)
<b>HS &amp; diploma</b>	.726* (.221)
<b>Graduate &amp; above</b>	1.146* (.397)
<b>Vocation_head</b>	.468* (.117)
<b>Married_head</b>	-.498* (.128)
<b>Caste (unreserved= base category)</b>	
<b>ST</b>	-.043 (.117)
<b>SC</b>	.240** (.098)
<b>OBC</b>	.170*** (.090)
<b>Religion (other religion= base category)</b>	
<b>Hindu</b>	-.323** (.128)

<b>Muslim</b>	.194 (.154)
<b>Size of land ownership (landless= base category)</b>	
<b>Marginal</b>	-.081 (.101)
<b>Small</b>	-.527***(.252)
<b>Semi-medium</b>	-.353 (.458)
<b>Medium</b>	-.292 (.948)
<b>Large</b>	-1.697 (1.253)
<b>Household size</b>	.124* (.023)
<b>Dependency ratio</b>	-.117**(.056)
<b>Unemployment rate</b>	.001** (.000)
<b>Urbanization</b>	-.524**(.229)
<b>Average distance</b>	-.0003**(.000)
<b>Constant</b>	.976* (.277)
<b>LR Chi2 (23)</b>	251.07
<b>Probability&gt;Chi2</b>	0.000
<b>Pseudo R2</b>	0.0362
<b>Log likelihood</b>	-3338.2267
<b>No. of observations</b>	5,285

Source: Author's computation based on NSSO 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> EUS data.

Notes: \*, \*\* and \*\*\* indicate significant at 1%, 5% and 10% respectively. Figures in parenthesis are standard errors.

From the estimates of determinants of diversification for self-employed farm and casual farm households, it is observed that age has a positive and significant impact on diversification probabilities. Education and vocational training facilitate both cultivator and casual farm households to diversify to non-farm activities. Again, caste is found to have an insignificant impact on diversification during 2009–10 and 2011–12, but in 2004–05, SC workers from cultivator households diversified whereas their likelihood declined if they belonged to casual farm households.

Furthermore, land ownership exhibits an adverse impact for cultivator households to additionally engage in non-farm activities while for casual farm households, it has no significant impact. Also, it is seen that with a rise in household size, farm households are more likely to diversify but with an increase in the number of dependents, their chance of working

outside agriculture falls. Among the regional-level factors, unemployment and urbanization rates exhibit a positive impact whereas no significant impact is observed for the distance variable.

Again, the determinants of farm households, whether cultivators or casual workers, shifting completely towards self-employed non-farm and casual non-farm households respectively, show that males are more likely to shift compared to females. They are also more likely to shift with a rise in their educational level and vocational training facilities. However, shifting of occupation is not preferred by married individuals. Among the different castes, occupational shift is high among SC and OBC households and low for ST households. Here also, households with medium and large land ownership size do not completely shift to other occupations. Again, unemployment rate has a positive impact whereas distance exhibits an adverse impact on occupational shift.

Furthermore, among the factors that affect non-farm households to diversify towards farm activities, we found age to have a positive and significant impact. With an increase in age of the household head, there is a positive chance of engaging in agricultural activities. However, education has a negative impact on self-employed non-farm households diversifying to farm activities and no significant impact on casual non-farm households. Also, households having land would diversify towards farm activities compared to landless households. Again, diversifying to farm activities is higher among self-employed non-farm ST, SC and OBC households. Furthermore, diversification is also high among households residing in remote regions.

### **5.5.Covariate balancing test**

Before discussing the findings of the treatment impact on household consumption expenditure, this section elaborates on the quality of the matching process. A major objective of the propensity score matching is to attain balance among the covariates of the treated and control groups. The insignificant difference in the mean values of the covariates between the two groups after matching indicates that we can obtain counterfactuals for the treated group which enables us to estimate the effect of treatment on outcome. First, we will check the common support condition. The estimated propensity score lies between 0 and 1, i.e. [0.0001711, 0.8505906] with a mean value of 0.12 and standard deviation of 0.1029797. Considerable overlap of common support condition is observed as the predicted value of propensity scores ranges between 0.0019046 to 0.8505906 for diversified households with a mean and standard

deviation of 0.2098368 and 0.1537003 and for non-diversified households, propensity scores lie between 0.001711 to 0.8105741 with a mean of 0.1077495 and standard deviation of 0.0870975. Thus, following the minima and maxima criteria, the common support region would lie between 0.0019046 and 0.8105741. This region of common support is also evident in figure 5.1. Tables 5.13 through 5.18 present the covariate balancing test for the 68<sup>th</sup> round across the different household types. The covariate balancing test for 61<sup>st</sup> and 66<sup>th</sup> rounds is included in the appendix of this chapter as these are similar tests for the other two rounds.

**Table 5. 13 Covariate Balancing test for matched sample for self-employed farm household**

Variable	Unmatched sample			Five-nearest neighbour matching		
	Treated	Control	Diff. p-value	Treated	Control	Diff. p-value
<b>Self-employed farm</b>						
Age_head	46.108	43.531	0.000*	46.108	46.488	0.352
Gender_head	0.95	0.928	0.019**	0.95	0.942	0.489
<b>Education_head (illiterate= base category)</b>						
Below primary & primary	0.26	0.269	0.572	0.26	0.255	0.815
Middle & secondary	0.36	0.348	0.486	0.36	0.36	0.968
HS & diploma	0.068	0.082	0.178	0.068	0.071	0.849
Graduate & above	0.069	0.045	0.002*	0.069	0.073	0.792
Vocation_head	0.121	0.102	0.077***	0.121	0.114	0.641
Married_head	0.925	0.923	0.878	0.925	0.92	0.715
<b>Caste (unreserved= base category)</b>						
ST	0.149	0.207	0.000*	0.149	0.143	0.762
SC	0.104	0.079	0.014**	0.104	0.106	0.862
OBC	0.381	0.406	0.161	0.381	0.37	0.644
<b>Religion (other religion= base category)</b>						
Hindu	0.743	0.762	0.227	0.743	0.731	0.581
Muslim	0.14	0.091	0.000*	0.140	0.149	0.600
<b>Land (landless= base category)</b>						
Marginal	0.553	0.404	0.000*	0.553	0.56	0.777
Small	0.183	0.235	0.001*	0.183	0.18	0.870
Semi-medium	0.14	0.203	0.000*	0.140	0.144	0.824

<b>Medium</b>	0.078	0.128	0.000*	0.078	0.079	0.928
<b>Large</b>	0.024	0.024	0.929	0.024	0.023	0.900
<b>Household size</b>	5.55	4.868	0.000*	5.550	5.516	0.777
<b>Dependency ratio</b>	0.413	0.604	0.000*	0.413	0.391	0.324
<b>Unemployment rate</b>	66.196	62.255	0.006*	66.196	64.831	0.494
<b>Urbanization</b>	0.262	0.244	0.000*	0.262	0.257	0.441
<b>Average distance</b>	288.65	313.82	0.000*	288.65	291.82	0.662

Notes: \*, \*\* & \*\*\* indicates significance level at 1%, 5% and 10%. Figures in parenthesis are standard errors.

**Table 5. 14 Covariate Balancing test for matched sample for casual farm household**

Variable	Unmatched sample			Five-nearest neighbour matching		
	Treated	Control	Diff. p-value	Treated	control	Diff. p-value
<b>Casual farm household</b>						
<b>Age_head</b>	44.28	40.771	0.000*	44.228	44.509	0.716
<b>Gender_head</b>	0.893	0.875	0.403	0.893	0.896	0.91
<b>Education_head (illiterate= base category)</b>						
<b>Below primary &amp; primary</b>	0.401	0.33	0.023**	0.403	0.426	0.584
<b>Middle &amp; secondary</b>	0.14	0.175	0.157	0.14	0.13	0.741
<b>HS &amp; diploma</b>	0.011	0.015	0.594	0.011	0.007	0.654
<b>Graduate &amp; above</b>	0.011	0.004	0.122	0.011	0.006	0.513
<b>Vocation_head</b>	0.075	0.057	0.236	0.076	0.076	0.974
<b>Married_head</b>	0.886	0.854	0.159	0.885	0.889	0.89
<b>Caste (unreserved= base category)</b>						
<b>ST</b>	0.079	0.138	0.008*	0.079	0.095	0.519
<b>SC</b>	0.352	0.296	0.065***	0.349	0.311	0.345
<b>OBC</b>	0.401	0.402	0.981	0.403	0.409	0.887
<b>Religion (other religion= base category)</b>						
<b>Hindu</b>	0.791	0.834	0.085***	0.79	0.763	0.452
<b>Muslim</b>	0.14	0.112	0.189	0.14	0.17	0.349
<b>Land (landless= base category)</b>						
<b>Marginal</b>	0.924	0.877	0.025**	0.923	0.923	1.000

<b>Small</b>	0.011	0.019	0.344	0.011	0.012	0.936
<b>Semi-medium</b>	0.007	0.004	0.535	0.007	0.005	0.745
<b>Medium</b>	0.003	0.001	0.259	0.003	0.007	0.563
<b>Household size</b>	4.806	4.095	0.000*	4.775	4.813	0.817
<b>Dependency ratio</b>	0.451	0.648	0.000*	0.452	0.47	0.695
<b>Unemployment rate</b>	92.404	74.197	0.000*	92.472	92.68	0.965
<b>Urbanization</b>	0.294	0.263	0.001*	0.293	0.289	0.705
<b>Average distance</b>	243.96	287.97	0.005*	244.48	246.05	0.883

Notes: \*, \*\* & \*\*\* indicates significance level at 1%, 5% and 10%.

**Table 5. 15 Covariate Balancing test for matched sample for self-employed non-farm household**

Variable	Unmatched sample			Five-nearest neighbour matching		
	Treated	Control	Diff. p-value	Treated	Control	Diff. p-value
<b>Self-employed non-farm household</b>						
<b>Age_head</b>	44.366	41.318	0.000*	44.345	44.136	0.633
<b>Gender_head</b>	0.934	0.936	0.871	0.934	0.937	0.813
<b>Education_head (illiterate= base category)</b>						
<b>Below primary &amp; primary</b>	0.31	0.268	0.011**	0.309	0.301	0.729
<b>Middle &amp; secondary</b>	0.312	0.389	0.000*	0.314	0.308	0.786
<b>HS &amp; diploma</b>	0.062	0.089	0.009*	0.062	0.074	0.301
<b>Graduate &amp; above</b>	0.039	0.069	0.001*	0.039	0.046	0.49
<b>Vocation_head</b>	0.182	0.176	0.652	0.184	0.188	0.813
<b>Married_head</b>	0.91	0.915	0.588	0.909	0.914	0.707
<b>Caste (unreserved= base category)</b>						
<b>ST</b>	0.156	0.116	0.001*	0.157	0.151	0.758
<b>SC</b>	0.165	0.144	0.102	0.166	0.162	0.845
<b>OBC</b>	0.451	0.448	0.907	0.447	0.464	0.496
<b>Religion (other religion= base category)</b>						
<b>Hindu</b>	0.783	0.73	0.001*	0.783	0.786	0.869
<b>Muslim</b>	0.13	0.176	0.001*	0.13	0.127	0.874
<b>Land (landless= base category)</b>						
<b>Marginal</b>	0.758	0.873	0.000*	0.76	0.747	0.522

<b>Small</b>	0.106	0.039	0.000*	0.105	0.115	0.517
<b>Semi-medium</b>	0.067	0.02	0.000*	0.065	0.063	0.875
<b>Medium</b>	0.029	0.007	0.000*	0.029	0.028	0.954
<b>Large</b>	0.002	0	0.053***	0.002	0.003	0.715
<b>Dependency ratio</b>	0.522	0.662	0.000*	0.523	0.508	0.583
<b>Unemployment rate</b>	64.941	72.773	0.000*	65.065	64.809	0.891
<b>Urbanization</b>	0.262	0.246	0.003*	0.261	0.259	0.687
<b>Average distance</b>	335.75	280.91	0.000*	311.87	326.47	0.276

Notes: \*, \*\* & \*\*\* indicates significance level at 1%, 5% and 10%. Figures in parenthesis are standard errors.

**Table 5. 16 Covariate Balancing test for matched sample for casual non-farm household**

Variable	Unmatched sample			Five-nearest neighbour matching		
	Treated	Control	Diff. p-value	Treated	Control	Diff. p-value
<b>Casual non-farm household</b>						
<b>Age_head</b>	41.679	39.052	0.000*	41.649	41.563	0.883
<b>Gender_head</b>	0.907	0.925	0.136	0.907	0.907	0.966
<b>Education_head (illiterate= base category)</b>						
<b>Below primary &amp; primary</b>	0.294	0.345	0.021**	0.295	0.291	0.883
<b>Middle &amp; secondary</b>	0.218	0.253	0.086***	0.219	0.219	1.000
<b>HS &amp; diploma</b>	0.022	0.025	0.677	0.022	0.019	0.733
<b>Graduate &amp; above</b>	0.007	0.01	0.482	0.007	0.009	0.691
<b>Vocation_head</b>	0.109	0.093	0.238	0.109	0.102	0.722
<b>Married_head</b>	0.884	0.884	0.965	0.884	0.898	0.481
<b>Caste (unreserved= base category)</b>						
<b>ST</b>	0.129	0.11	0.176	0.13	0.139	0.643
<b>SC</b>	0.337	0.302	0.103	0.338	0.349	0.71
<b>OBC</b>	0.408	0.419	0.628	0.407	0.405	0.97
<b>Religion (other religion= base category)</b>						
<b>Hindu</b>	0.823	0.765	0.003*	0.823	0.822	0.975
<b>Muslim</b>	0.096	0.165	0.000*	0.096	0.093	0.868
<b>Land (landless= base category)</b>						

<b>Marginal</b>	0.884	0.885	0.987	0.886	0.887	0.969
<b>Small</b>	0.016	0.011	0.353	0.016	0.014	0.768
<b>Semi-medium</b>	0.011	0.003	0.016**	0.011	0.011	0.954
<b>Medium</b>	0.007	0	0.001*	0.005	0.002	0.513
<b>Household size</b>	4.786	4.327	0.000*	4.778	4.78	0.988
<b>Dependency ratio</b>	0.576	0.706	0.000*	0.576	0.578	0.972
<b>Unemployment rate</b>	77.663	77.262	0.859	77.737	77.839	0.973
<b>Urbanization</b>	0.276	0.255	0.000*	0.277	0.275	0.833
<b>Average distance</b>	290.35	266.64	0.001*	290.61	289.29	0.896

Notes: \*, \*\* & \*\*\* indicates significance level at 1%, 5% and 10%. Figures in parenthesis are standard errors.

**Table 5. 17 Covariate balancing test for self-employed farm households shifting to self-employed non-farm household**

variable	unmatched sample		Diff. p-value	five-nearest neighbour matching		
	treated	control		treated	control	diff. p-value
<b>S.E farm to S.E non-farm</b>						
<b>Age_head</b>	41.318	43.531	0.000*	41.324	41.532	0.187
<b>Gender_head</b>	0.936	0.928	0.085***	0.936	0.934	0.701
<b>Education_head (illiterate= base category)</b>						
<b>Below primary &amp; primary</b>	0.268	0.269	0.937	0.269	0.263	0.459
<b>Middle &amp; secondary</b>	0.389	0.348	0.000*	0.39	0.397	0.39
<b>HS &amp; diploma</b>	0.089	0.082	0.114	0.089	0.092	0.59
<b>Graduate &amp; above</b>	0.069	0.045	0.000*	0.068	0.075	0.143
<b>Vocation_head</b>	0.176	0.102	0.000*	0.176	0.166	0.162
<b>Married_head</b>	0.915	0.923	0.085***	0.916	0.91	0.25
<b>Caste (unreserved= base category)</b>						
<b>ST</b>	0.116	0.207	0.000*	0.116	0.114	0.734
<b>SC</b>	0.144	0.079	0.000*	0.144	0.144	0.98
<b>OBC</b>	0.448	0.406	0.000*	0.448	0.452	0.637
<b>Religion (other religion= base category)</b>						
<b>Hindu</b>	0.73	0.762	0.000*	0.73	0.737	0.346
<b>Muslim</b>	0.176	0.091	0.000*	0.176	0.172	0.561
<b>Land (landless= base category)</b>						

<b>Medium</b>	0.007	0.128	0.000*	0.007	0.007	0.836
<b>Large</b>	0	0.024	0.000*	0.000	0.000	0.759
<b>Dependency ratio</b>	0.662	0.604	0.000*	0.662	0.644	0.128
<b>Unemployment rate</b>	72.773	62.255	0.000*	72.694	72.539	0.847
<b>Urbanization</b>	0.246	0.244	0.360	0.246	0.243	0.199
<b>Average distance</b>	280.91	313.82	0.000*	280.92	282.04	0.699

Notes: \*, \*\* & \*\*\* indicates significance level at 1%, 5% and 10%. Figures in parenthesis are standard errors.

**Table 5. 18 Covariate balancing test for casual farm households shifting to casual non-farm household**

Variable	Unmatched sample			Five-nearest neighbour matching		
	Treated	Control	Diff. p-value	treated	Control	Diff. p-value
<b>Casual farm to Casual non-farm household</b>						
<b>Age_head</b>	39.056	40.78	0.000*	39.057	38.842	0.333
<b>Gender_head</b>	0.925	0.876	0.000*	0.925	0.929	0.522
<b>Education_head (illiterate= base category)</b>						
<b>Below primary &amp; primary</b>	0.345	0.331	0.280	0.345	0.343	0.813
<b>Middle &amp; secondary</b>	0.253	0.174	0.000*	0.253	0.256	0.758
<b>HS &amp; diploma</b>	0.025	0.015	0.018**	0.025	0.026	0.805
<b>Graduate &amp; above</b>	0.01	0.004	0.012**	0.01	0.009	0.573
<b>Vocation_head</b>	0.093	0.057	0.000*	0.093	0.083	0.161
<b>Married_head</b>	0.884	0.854	0.002*	0.884	0.882	0.849
<b>Caste (unreserved= base category)</b>						
<b>ST</b>	0.109	0.138	0.002*	0.11	0.110	0.907
<b>SC</b>	0.302	0.2967	0.653	0.302	0.309	0.575
<b>OBC</b>	0.419	0.402	0.226	0.419	0.400	0.12
<b>Religion (other religion= base category)</b>						
<b>Hindu</b>	0.765	0.833	0.000*	0.765	0.766	0.954
<b>Muslim</b>	0.165	0.112	0.000*	0.165	0.159	0.53
<b>Land (landless= base category)</b>						
<b>Marginal</b>	0.884	0.876	0.338	0.884	0.893	0.267
<b>Small</b>	0.011	0.019	0.022**	0.011	0.01	0.498

<b>Semi-medium</b>	0.003	0.004	0.534	0.003	0.002	0.32
<b>Medium</b>	0.001	0.001	0.865	0.001	0.0002	0.259
<b>Large</b>	0.0003	0.001	0.275	0.0003	0.0001	0.752
<b>Household size</b>	4.327	4.097	0.000*	4.327	4.303	0.564
<b>Dependency ratio</b>	0.706	0.648	0.002*	0.706	0.700	0.739
<b>Unemployment rate</b>	77.245	74.185	0.021**	77.208	75.724	0.178
<b>Urbanization</b>	0.255	0.263	0.042**	0.255	0.253	0.521
<b>Average distance</b>	266.61	287.86	0.000*	266.6	262.33	0.251

Notes: \*, \*\* & \*\*\* indicates significance level at 1%, 5% and 10%. Figures in parenthesis are standard errors.

It is observed that in the unmatched group, there is a significant difference in the values of most of the observed covariates across the treated and control sample. But the difference in those covariates after matching is not present. This implies that after the implementation of the matching procedure, the covariates of the treated and control groups do not have any statistically significant difference.

Again, literatures suggest some more measures to ascertain the quality of good matching between the treated and control groups. This assessment of the matching quality is done by examining the value of pseudo-R square and LR chi-square. The pseudo-R square shows how well the covariates explain the probability of diversification (Caliendo & Kopeinig, 2008). Another measure is the likelihood ratio (LR) test which examines the joint significance of all the regressors (Caliendo & Kopeinig, 2008). Balance is achieved when pseudo-R square value becomes considerably low after matching. Again, the test for likelihood ratio should be rejected after matching (Bayan, 2018). Tables 5.19 to 5.21 depict the indicators of matching quality before and after matching for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds.

**Table 5. 19 Indicators of matching quality before and after matching for 61<sup>st</sup> round**

<b>Outcome</b>	<b>Pseudo R2 before match</b>	<b>Pseudo R2 after match</b>	<b>LR chi2 (p-value before match)</b>	<b>LR chi2 (p-value after match)</b>	<b>Mean S. B<sup>10</sup> before match</b>	<b>Mean S.B after match</b>
<b>Household type- self-employed farm household</b>						
<b>NNM</b>	0.133	0.001	1292.69* (p=0.000)	2.49 (p=1.00)	14.1	0.9
<b>KBM</b>	0.133	0.000	1292.47* (p=0.000)	1.95 (p=1.00)	14	0.7

<sup>10</sup> S.B. stands for Standardised Bias.

<b>RM</b>	0.133	0.001	1292.93* (p=0.000)	3.93 (p=1.00)	14.1	1.2
<b>Household type- self-employed non-farm household</b>						
<b>NNM</b>	0.094	0.002	797.01* (p=0.000)	7.43 (0.997)	13.7	1.7
<b>KBM</b>	0.094	0.001	797.01* (p=0.000)	3.85 (p=1.00)	13.7	1.2
<b>RM</b>	0.094	0.001	797.01* (p=0.000)	6.02 (p=0.999)	13.7	1.4
<b>Household type- self-employed farm to self-employed non-farm household</b>						
<b>NNM</b>	0.163	0.005	361.43* (p=0.000)	10.80 (p=0.93)	19.8	2.5
<b>KBM</b>	0.163	0.006	361.43* (p=0.000)	12.69 (p=0.854)	19.8	2.8
<b>RM</b>	0.163	0.004	361.43* (p=0.000)	7.85 (p=988)	19.8	2.5
<b>Household type- casual farm household</b>						
<b>NNM</b>	0.128	0.004	473.89* (p=0.000)	6.61 (p=0.999)	15.4	2.6
<b>KBM</b>	0.128	0.001	473.89* (p=0.000)	2.02 (p=1.00)	15.4	1.3
<b>RM</b>	0.128	0.001	473.89* (p=0.000)	1.37 (p=1.00)	15.4	1.2

Source: Author's estimation based on 61<sup>st</sup> round NSSO data

Note: \* denotes significance at 1% level.

NNM= five nearest neighbour matching with replacement and common support.

KBM= kernel based matching with bandwidth 0.01 and on common support

RM= radius matching with caliper 0.002 and on common support.

**Table 5. 20 Indicators of matching quality before and after matching for 66<sup>th</sup> round**

<b>Outcome</b>	<b>Pseudo R2 before match</b>	<b>Pseudo R2 after match</b>	<b>LR chi2 (p-value before match)</b>	<b>LR chi2 (p-value after match)</b>	<b>Mean S. B<sup>11</sup> before match</b>	<b>Mean S.B after match</b>
<b>Household type- self-employed farm household</b>						
<b>NNM</b>	0.097	0.003	448 (p=0.000)	5 (p=1.00)	11	1.7
<b>KBM</b>	0.097	0.001	448 (p=0.000)	1.59 (p=1.00)	11	1.0
<b>RM</b>	0.097	0.002	448 (p=0.000)	3.02 (p=1.00)	11	1.7
<b>Household type- self-employed non-farm household</b>						

<sup>11</sup> S.B. stands for Standardised Bias.

<b>NNM</b>	0.074	0.001	465.14 (p=0.000)	2.45 (p=1.00)	12.6	1.0
<b>KBM</b>	0.074	0.000	465.14 (p=0.000)	0.59 (p=1.00)	12.6	0.5
<b>RM</b>	0.074	0.001	465.14 (p=0.000)	1.68 (p=1.00)	12.6	1.0
<b>Household type- self-employed farm to self-employed non-farm household</b>						
<b>NNM</b>	0.118	0.001	2253.76 (p=0.000)	26.37 (p=0.120)	14.8	1.3
<b>KBM</b>	0.118	0.001	2253.76 (p=0.000)	17.71 (p=0.542)	14.8	1.0
<b>RM</b>	0.118	0.001	2253.76 (p=0.000)	18.58 (p=0.484)	14.8	1.0
<b>Household type- casual farm household</b>						
<b>NNM</b>	0.112	0.003	271.63 (p=0.000)	2.99 (p=1.00)	15.6	2.0
<b>KBM</b>	0.112	0.001	271.63 (p=0.000)	1.11 (p=1.00)	15.6	1.4
<b>RM</b>	0.112	0.003	271.63 (p=0.000)	3.30 (1.00)	15.6	2.2

Source: Author's estimation based on 66<sup>th</sup> round NSSO data

Note: \* denotes significance at 1% level.

NNM= five nearest neighbour matching with replacement and common support.

KBM= kernel based matching with bandwidth 0.01 and on common support

RM= radius matching with caliper 0.002 and on common support.

**Table 5. 21 Indicators of matching quality before and after matching for 68<sup>th</sup> round**

<b>Outcome</b>	<b>Pseudo R2 before match</b>	<b>Pseudo R2 after match</b>	<b>LR chi2 (p-value before match)</b>	<b>LR chi2 (p-value after match)</b>	<b>Mean S. B<sup>12</sup> before match</b>	<b>Mean S.B after match</b>
<b>Household type- self-employed farm household</b>						
<b>NNM</b>	.085	.003	452.07 (p=0.000)	6.39(p=1.00)	12.8	1.9
<b>KBM</b>	0.085	0.001	452.07 (p=0.000)	1.54 (p=1.00)	12.8	0.9
<b>RM</b>	0.085	0.001	452.07 (p=0.000)	3.16 (p=1.00)	12.8	0.8
<b>Household type- self-employed non-farm household</b>						
<b>NNM</b>	0.078	0.002	409.59 (p=0.000)	5.59 (p=1.00)	13.7	2.1
<b>KBM</b>	0.078	0.001	409.59	2.02	13.7	1.4

<sup>12</sup> S.B. stands for Standardised Bias.

			(p=0.000)	(p=1.00)		
<b>RM</b>	0.078	0.002	409.59	3.71	13.7	1.8
			(p=0.000)	(1.00)		
<b>Household type- self-employed farm to self-employed non-farm household</b>						
<b>NNM</b>	0.118	0.001	2123.9	16.63	15.1	1.3
			(p= 0.000)	(p= 0.615)		
<b>KBM</b>	0.118	0.001	2123.91	18.69	15.1	1.4
			(p=0.000)	(p=0.477)		
<b>RM</b>	0.118	0.001	2123.91	17.15	15.1	1.4
			(p=0.000)	(p=0.579)		
<b>Household type- casual farm household</b>						
<b>NNM</b>	.111	.005	179	3.93	15	3.3
			(p=0.000)	(p=1.00)		
<b>KBM</b>	0.112	0.005	181.03	3.55	15.1	3.4
			(p=0.000)	(p=1.00)		
<b>RM</b>	0.111	0.007	179	4.77	15	3.8
			(p=0.000)	(p=1.00)		
<b>Household type- casual non-farm household</b>						
<b>NNM</b>	.052	.002	163.95	3.31	9.8	1.5
			(p=0.000)	(p=1.00)		
<b>KBM</b>	0.052	0.001	163.95	0.85	9.8	1.0
			(p=0.000)	(p=1.00)		
<b>RM</b>	0.052	0.001	163.95	1.31	9.8	1.0
			(p=0.000)	(p=1.00)		
<b>Household type- casual farm household to casual non-farm household</b>						
<b>NNM</b>	0.036	0.002	251.04	15.45	8.7	1.6
			(p=0.000)	(p=0.878)		
<b>KBM</b>	0.036	0.001	251.04	9.05	8.7	1.1
			(p=0.000)	(p=0.996)		
<b>RM</b>	0.036	0.001	251.04	8.67	8.7	1.2
			(p=0.000)	(p=0.995)		

Source: Author's estimation based on 68<sup>th</sup> round NSSO data

Note: \* denotes significance at 1% level.

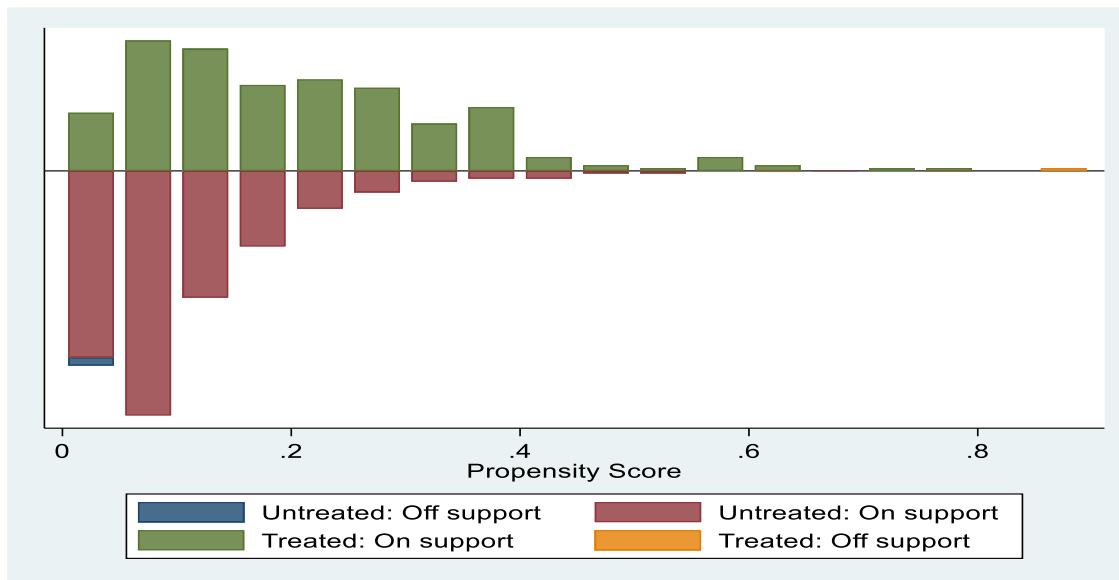
NNM= five nearest neighbour matching with replacement and common support.

KBM= kernel-based matching with bandwidth 0.01 and on common support

RM= radius matching with caliper 0.002 and on common support.

It is seen from tables 5.19 to 5.21 that the value of pseudo-R-square for self-employed farm households for 68<sup>th</sup> round which was 8.5% before matching, decreased to 0.1–0.3% after matching. Again, p-values of the likelihood ratio test which represents the joint significance of

covariates show that covariates were jointly significant before matching but became insignificant after matching. Also, the standardized mean difference of covariates of 12.8% before matching was reduced to 0.8–1.9% after matching. This test, therefore, demonstrates that the matching procedure considerably reduces observed bias between diversified and non-diversified households.



**Figure 5. 1 Distribution of propensity scores after imposition of common support condition.**

The figure indicates a symmetrical distribution of the propensity scores between the treated and control samples and this symmetrical distribution can be observed within the region of common support indicated by the green and red histograms. Sample units that have no suitable match are denoted as treated: off support.

### 5.6. Treatment effect estimation

The effect of diversification (treatment) for the different household types is estimated using nearest neighbour, kernel and radius matching estimator. Common support condition is implemented so that the control and treated sample have similar propensity scores and adequate matches can be found for analysis. The significance of outcome variables is based on z-value obtained by bootstrapping standard errors using 50 replications.

**Table 5. 22 Estimation of ATT, ATE and ATU for food and non-food expenditure across different household types**

#### Self-employed farm household

**61<sup>st</sup> round (2004-05)**

Matching estimator	Food expenditure			Non-food expenditure		
	ATT	ATE	ATU	ATT	ATE	ATU
<b>NN</b>	102.37** (2.10)	177* (4.79)	186.44* (4.86)	316* (3.89)	275.79* (4.90)	271.03* (4.42)
<b>Kernel</b>	101.85* (2.92)	177.45* (6.23)	186.36* (5.40)	307.51* (4.50)	284.36* (5.48)	281.63* (6.26)
<b>Radius</b>	91.13** (2.55)	181.58* (5.19)	192.12* (4.73)	284.81* (4.15)	289.61* (4.71)	290.17* (4.75)

**66<sup>th</sup> round (2009-10)**

<b>NN</b>	181.74** (2.48)	235.13*** (1.81)	240.10*** (1.72)	201.03 (1.44)	373.83* (2.56)	389.92* (3.53)
<b>Kernel</b>	193.43* (3.27)	204.44*** (1.84)	205.46 (1.61)	275.26* (2.74)	315.14** (2.53)	318.83** (2.18)
<b>Radius</b>	189.19* (3.07)	263.56*** (1.79)	270.40** (2.16)	287.03* (2.82)	388.58* (2.72)	397.92** (2.17)

**68<sup>th</sup> round (2011-12)**

<b>NN</b>	89.01 (0.80)	176.52** (1.98)	187.69*** (1.86)	329.43*** (1.69)	567.54* (2.67)	597.92** (2.56)
<b>Kernel</b>	105.29 (1.59)	207.65* (2.66)	220.69* (2.65)	363.79** (1.99)	532.47* (3.09)	553.96* (3.73)
<b>Radius</b>	110.98 (1.35)	221.88* (3.18)	236.13** (2.41)	366.53** (2.26)	527.44** (2.55)	547.94* (2.87)

**Self-employed non-farm household****61<sup>st</sup> round (2004-05)**

Matching estimator	Food expenditure			Non-food expenditure		
	ATT	ATE	ATU	ATT	ATE	ATU
<b>NN</b>	216.28* (6.08)	158.16* (6.30)	144.15* (5.50)	-12.14 (-0.23)	-24.76 (-0.56)	-27.81 (-0.64)
<b>Kernel</b>	215.11* (7.74)	153.87* (7.20)	139.14* (5.54)	-28.52 (-0.49)	-24.79 (-0.69)	-23.89 (-0.66)
<b>Radius</b>	212.36* (5.98)	159.58* (6.24)	147.13* (6.17)	-31.35 (-0.60)	-28.14 (-0.71)	-27.39 (-0.76)

**66<sup>th</sup> round (2009–10)**

<b>NN</b>	140.29** (2.41)	155.21* (3.20)	157.74* (2.77)	72.59 (0.70)	-52.63 (-0.67)	-73.89 (-1.07)
<b>Kernel</b>	122.66* (2.90)	147.68* (4.20)	151.93* (4.28)	22.24 (0.31)	-41.11 (-0.64)	-51.87 (-0.71)
<b>Radius</b>	139.46* (3.10)	152.21* (3.60)	154.33* (3.64)	18.83 (0.23)	-58.32 (-0.91)	-71.17 (-1.20)

**68<sup>th</sup> round (2011–12)**

<b>NN</b>	292.68* (3.71)	263.06* (4.57)	259.03* (3.65)	66.46 (0.55)	-13.68 (-0.18)	-24.59 (-0.23)
<b>Kernel</b>	285.25* (4.76)	246.62* (4.68)	241.39* (4.10)	64.19 (0.76)	-42.45 (-0.54)	-56.90 (-0.67)
<b>Radius</b>	253.13* (3.94)	243.22* (4.19)	241.91* (4.26)	5.08 (0.05)	-30.63 (-0.35)	-35.36 (-0.39)

**Self-employed farm to self-employed non-farm**

<b>Matching estimator</b>	<b>Food expenditure</b>			<b>Non-food expenditure</b>		
	<b>ATT</b>	<b>ATE</b>	<b>ATU</b>	<b>ATT</b>	<b>ATE</b>	<b>ATU</b>
<b>61<sup>st</sup> round (2004-05)</b>						
<b>NN</b>	-130.59* (-2.97)	-94.51** (-2.41)	-63.62 (-1.27)	-11.08 (-0.23)	58.56 (1.16)	118.20 (1.54)
<b>Kernel</b>	-148.76* (-3.77)	-86.69** (-2.10)	-33.35 (-0.64)	-18.92 (-0.43)	14.88 (0.26)	43.93 (0.86)
<b>Radius</b>	-104.87* (-2.76)	-78.84** (-2.24)	-54.36 (-1.30)	-11.58 (-0.22)	16.45 (0.39)	42.80 (0.70)
<b>66<sup>th</sup> round (2009-10)</b>						
<b>NN</b>	-124.37* (-5.66)	-135.90* (-4.79)	-146.27* (-3.87)	-18.35 (-0.39)	-33.60 (-0.53)	-47.31 (-0.50)
<b>Kernel</b>	-126.55* (-5.44)	-127.71* (-5.67)	-128.75* (-4.33)	-14.61 (-0.44)	-8.91 (-0.14)	-3.77 (-0.05)
<b>Radius</b>	-133.98* (-7.24)	-130.83* (-5.63)	-127.96* (-4.07)	-22.84 (-0.49)	-10.22 (-0.17)	1.27 (0.01)
<b>68<sup>th</sup> round (2011-12)</b>						
<b>NN</b>	-180.72* (-5.66)	-149.83* (-4.79)	-120.54** (-3.87)	-238.41* (-7.24)	-179.50** (-5.63)	-123.67 (-3.87)

	(-4.79)	(-4.65)	(-2.40)	(-2.66)	(-2.55)	(-1.11)
<b>Kernel</b>	-176.19*	-144.72*	-114.91**	-241.07*	-169.51**	-101.69
	(-5.48)	(-5.17)	(-2.53)	(-3.18)	(-3.74)	(-0.84)
<b>Radius</b>	-193.19*	-154.81*	-118.12*	-272.81*	-218.82*	-167.20**
	(-7.03)	(-4.74)	(-3.08)	(-3.11)	(-3.64)	(-2.28)

#### Casual farm/farm labor household

Matching estimator	Food expenditure			Non-food expenditure		
	ATT	ATE	ATU	ATT	ATE	ATU

#### 61<sup>st</sup> round (2004-05)

<b>NN</b>	131.02*	155.17*	158.48*	205.76*	135.24*	125.60*
	(4.62)	(5.70)	(5.51)	(5.28)	(5.02)	(4.27)
<b>Kernel</b>	117.58*	150.58*	154.98*	141.37*	122.54*	120.03*
	(6.41)	(5.65)	(6.55)	(4.25)	(5.31)	(4.08)
<b>Radius</b>	117.10*	156.49*	161.64*	130.55*	123.58*	122.67*
	(4.77)	(6.01)	(5.16)	(4.17)	(4.44)	(4.29)

#### 66<sup>th</sup> round (2009-10)

<b>NN</b>	257.88*	186.32*	176.58*	709.21*	428.90*	390.75*
	(3.39)	(3.63)	(4.18)	(4.34)	(3.78)	(3.28)
<b>Kernel</b>	295.49*	193.41*	179.76*	702.24*	442.02*	407.22*
	(5.02)	(3.87)	(3.66)	(6.03)	(4.11)	(3.54)
<b>Radius</b>	268.97*	171.99*	159.19*	503.86*	385.76*	370.18*
	(4.78)	(4.00)	(3.04)	(3.02)	(3.26)	(3.40)

#### 68<sup>th</sup> round (2011-12)

<b>NN</b>	276.67**	207.56***	197.99	593.76**	249.29***	201.56
	(2.00)	(1.69)	(1.22)	(2.52)	(1.95)	(1.38)
<b>Kernel</b>	297.71**	228.39**	218.96	639.45*	277.70**	228.48**
	(2.50)	(2.03)	(1.62)	(2.64)	(2.27)	(2.32)
<b>Radius</b>	268.02***	136.48	117.80	554.35*	192.25	140.82
	(1.88)	(1.19)	(0.93)	(2.76)	(1.61)	(1.09)

#### Casual non-farm household

Matching estimator	Food expenditure			Non-food expenditure		
	ATT	ATE	ATU	ATT	ATE	ATU

#### 68<sup>th</sup> round (2011-12)

<b>NN</b>	134.12** (2.41)	164.55* (2.95)	169.44* (3.16)	136.22 (1.22)	194.58*** (1.92)	203.96** (2.24)
<b>Kernel</b>	150.34* (2.78)	153.58* (3.56)	154.10* (3.20)	154.37*** (1.95)	173.94** (2.26)	177.07*** (1.91)
<b>Radius</b>	150.95* (2.69)	146.13* (2.97)	145.35** (2.57)	210.51*** (1.85)	191.87*** (1.91)	188.86** (2.29)

#### Casual farm to casual non-farm household

Matching estimator	Food expenditure			Non-food expenditure		
	ATT	ATE	ATU	ATT	ATE	ATU
<b>68<sup>th</sup> round (2011-12)</b>						
<b>NN</b>	180.84* (6.01)	171.00* (6.72)	153.74* (5.81)	284.11* (4.89)	272.08* (6.49)	250.97* (3.80)
<b>Kernel</b>	176.54* (6.43)	165.01* (6.60)	144.76* (4.95)	257.48* (5.56)	252.19* (5.08)	242.89* (4.96)
<b>Radius</b>	176.60* (7.01)	169.17* (6.57)	156.11* (6.34)	260.21* (5.52)	261.04* (6.88)	262.52* (4.75)

Source: Author's calculation based on NSSO EUS data for the 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds.

**Table 5. 23 Estimation of ATT, ATE and ATU for food and non-food expenditure shares across different household types**

#### Self-employed farm household

##### 61<sup>st</sup> round (2004-05)

Matching estimator	Food expenditure share			Non-food expenditure share		
	ATT	ATE	ATU	ATT	ATE	ATU
<b>NN</b>	-1.44* (-3.59)	-1.04** (-2.29)	-0.99** (-1.84)	1.54* (3.66)	0.97*** (1.68)	0.90** (1.89)
<b>Kernel</b>	-1.53* (-4.71)	-1.29* (-3.24)	-1.26* (-2.97)	1.65* (4.84)	1.25* (2.72)	1.21* (2.91)
<b>Radius</b>	-1.49* (-4.96)	-1.23* (-2.56)	-1.20* (-2.67)	1.63* (4.96)	1.18* (3.06)	1.13** (2.33)

##### 66<sup>th</sup> round (2009-10)

<b>NN</b>	-0.88 (-1.59)	-1.40** (-2.16)	-1.45** (-2.24)	0.85 (1.25)	1.27*** (1.72)	1.31*** (1.80)
<b>Kernel</b>	-0.98**	-1.11**	-1.12	1.00***	1.01	1.01***

	(-2.22)	(-2.00)	(-1.58)	(1.89)	(1.49)	(1.69)
<b>Radius</b>	-1.09**	-1.31**	-1.34	1.07**	1.19***	1.20***
	(-2.26)	(-2.04)	(-1.63)	(2.47)	(1.70)	(1.92)
<b>68<sup>th</sup> round (2011-12)</b>						
<b>NN</b>	-0.88	-1.95*	-2.08*	0.82	2.04*	2.19*
	(-1.41)	(-3.56)	(-3.69)	(1.43)	(3.69)	(3.11)
<b>Kernel</b>	-1.11**	-1.77*	-1.85*	1.09**	1.83*	1.93*
	(-2.57)	(-3.24)	(-2.86)	(2.54)	(3.31)	(3.21)
<b>Radius</b>	-1.25*	-1.85*	-1.93*	1.25*	1.89*	1.97*
	(-2.78)	(-2.97)	(-3.85)	(2.69)	(3.31)	(3.41)
<b>Self-employed non-farm household</b>						
<b>61<sup>st</sup> round (2004-05)</b>						
<b>Matching</b>	Food expenditure share			Non-food expenditure share		
<b>estimator</b>	ATT	ATE	ATU	ATT	ATE	ATU
<b>NN</b>	1.33*	1.26*	1.24*	-1.45*	-1.47*	-1.48*
	(2.69)	(3.73)	(3.98)	(-3.84)	(-4.89)	(-4.30)
<b>Kernel</b>	1.43*	1.21*	1.16*	-1.58*	-1.43*	-1.39*
	(4.27)	(4.13)	(4.14)	(-4.02)	(-4.75)	(-5.61)
<b>Radius</b>	1.45*	1.28*	1.24*	-1.58*	-1.50*	-1.48*
	(3.53)	(3.93)	(4.08)	(-4.92)	(-4.16)	(-4.52)
<b>66<sup>th</sup> round (2009-10)</b>						
<b>NN</b>	0.06	0.71***	0.83***	-0.58	-1.28*	-1.40*
	(0.13)	(1.81)	(1.84)	(-1.16)	(-3.04)	(-2.96)
<b>Kernel</b>	0.13	0.56	0.64***	-0.63	-1.11**	-1.19*
	(0.43)	(1.38)	(1.73)	(-1.57)	(-2.20)	(-3.41)
<b>Radius</b>	0.21	0.65	0.73**	-0.72***	-1.21*	-1.29*
	(0.60)	(1.47)	(2.15)	(-1.92)	(-3.18)	(-3.01)
<b>68<sup>th</sup> round (2011-12)</b>						
<b>NN</b>	0.62	0.48	0.46	-1.15**	-1.00**	-0.98**
	(1.25)	(1.09)	(1.07)	(-2.09)	(-2.22)	(-2.09)
<b>Kernel</b>	0.44	0.54	0.55	-1.00*	-1.09*	-1.10**
	(1.10)	(1.22)	(1.39)	(-2.70)	(-2.75)	(-2.34)
<b>Radius</b>	0.45	0.42	0.42	-1.06**	-0.98*	-0.97**

	(1.07)	(1.04)	(1.28)	(-2.46)	(-2.86)	(-2.01)
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**Self-employed farm to self-employed non-farm household**

**61<sup>st</sup> round (2004-05)**

Matching estimator	Food expenditure share			Non-food expenditure share		
	ATT	ATE	ATU	ATT	ATE	ATU
<b>NN</b>	-1.18** (-1.93)	-2.02* (-3.56)	-2.73** (-2.54)	1.22 (1.64)	1.93*** (2.55)	2.53* (2.81)
<b>Kernel</b>	-1.33** (-2.26)	-1.37*** (-1.95)	-1.41 (-1.46)	1.35** (2.21)	1.44*** (1.84)	1.51 (1.45)
<b>Radius</b>	-0.83 (-1.21)	-1.34** (-1.95)	-1.81** (-2.34)	1.10*** (1.83)	1.49** (1.96)	1.86** (2.09)

**66<sup>th</sup> round (2009-10)**

<b>NN</b>	-0.65* (-2.85)	-0.56** (-2.52)	-0.48*** (-1.91)	0.53** (2.49)	0.49** (2.41)	0.46 (1.26)
<b>Kernel</b>	-0.66* (-2.67)	-0.61* (-2.67)	-0.57*** (-1.93)	0.57* (3.00)	0.57* (3.060)	0.57** (2.04)
<b>Radius</b>	-0.67* (-3.68)	-0.57* (-3.08)	-0.49 (-1.55)	0.58* (3.28)	0.56** (2.56)	0.53 (1.56)

**68<sup>th</sup> round (2011-12)**

<b>NN</b>	-0.23 (-0.96)	-0.32 (-1.39)	-0.40 (-0.99)	0.11 (0.41)	0.15 (0.61)	0.19 (0.51)
<b>Kernel</b>	-0.31 (-1.31)	-0.39*** (-1.67)	-0.47 (-1.30)	0.17 (0.83)	0.22 (0.87)	0.27 (0.82)
<b>Radius</b>	-0.28 (-1.39)	-0.27 (-1.17)	-0.27 (-1.02)	0.16 (0.82)	0.10 (0.41)	0.04 (0.14)

**Casual farm/farm labor household**

**61<sup>st</sup> round (2004-05)**

Matching estimator	Food expenditure share			Non-food expenditure share		
	ATT	ATE	ATU	ATT	ATE	ATU
<b>NN</b>	-1.55* (-2.98)	-0.69 (-1.20)	-0.57 (-0.89)	1.34* (2.68)	0.47 (0.93)	0.35 (0.76)
<b>Kernel</b>	-1.00** (-2.08)	-0.51 (-0.94)	-0.45 (-0.79)	0.79 (1.90)	0.32 (0.62)	0.25 (0.46)

<b>Radius</b>	-0.81***	-0.47	-0.43	0.58	0.27	0.24
	(-1.68)	(-0.83)	(-0.85)	(1.09)	(0.51)	(0.41)

#### 66<sup>th</sup> round (2009-10)

<b>NN</b>	-2.77*	-1.21	-1.00	2.63*	1.42**	1.26
	(-3.71)	(-1.34)	(-1.23)	(3.03)	(2.16)	(1.47)

<b>Kernel</b>	-2.44*	-1.41***	-1.27	2.42*	1.63***	1.52***
	(-2.64)	(-1.77)	(-1.38)	(3.71)	(1.93)	(1.70)

<b>Radius</b>	-1.77*	-1.44***	-1.40	1.75**	1.66**	1.64
	(-2.98)	(-1.79)	(-1.64)	(2.19)	(2.33)	(1.62)

#### 68<sup>th</sup> round (2011-12)

<b>NN</b>	-1.73***	-0.62	-0.46	1.40	1.02	0.97
	(-1.80)	(-0.62)	(-0.48)	(1.53)	(1.14)	(0.87)

<b>Kernel</b>	-1.73**	-0.62	-0.47	1.57	1.04	0.97
	(-2.00)	(-0.70)	(-0.53)	(1.46)	(1.10)	(1.20)

<b>Radius</b>	-1.58	-0.34	-0.16	1.33	0.78	0.71
	(-1.64)	(-0.30)	(-0.17)	(1.28)	(0.87)	(0.69)

#### Casual non-farm household

##### 68<sup>th</sup> round (2011-12)

<b>Matching estimator</b>	Food expenditure share			Non-food expenditure share		
	ATT	ATE	ATU	ATT	ATE	ATU
<b>NN</b>	-1.38**	-1.53*	-1.56*	0.36	0.66	0.71
	(-2.15)	(-2.65)	(-2.59)	(0.57)	(1.33)	(1.32)
<b>Kernel</b>	-1.22**	-1.44**	-1.48*	0.19	0.52	0.57
	(-2.37)	(-2.47)	(-2.72)	(0.36)	(0.90)	(0.99)
<b>Radius</b>	-1.38**	-1.50**	-1.52**	0.34	0.62	0.66
	(-2.43)	(-2.31)	(-2.35)	(0.57)	(1.14)	(1.37)

#### Casual farm to casual non-farm household

##### 68<sup>th</sup> round (2011-12)

<b>Matching estimator</b>	Food expenditure share			Non-food expenditure share		
	ATT	ATE	ATU	ATT	ATE	ATU
<b>NN</b>	-.991*	-.916*	-.784**	.865**	.753**	.557
	(-3.23)	(-2.66)	(-1.99)	(2.26)	(2.09)	(1.42)
<b>Kernel</b>	-.873***	-.861**	-.841**	.766**	.722**	.645***

	(-3.00)	(-2.52)	(-2.46)	(2.51)	(2.37)	(1.93)
<b>Radius</b>	<b>-0.873**</b>	<b>-0.848**</b>	<b>-0.805**</b>	<b>0.778**</b>	<b>0.731**</b>	<b>0.649**</b>
	(-2.86)	(-2.29)	(-2.19)	(2.12)	(2.31)	(2.09)

Source: Author's calculation based on NSSO EUS data for the 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> rounds.

### 5.6.1. Explanation of ATT for food and non-food expenditure

First, we discuss the effect of diversification represented through the Average Treatment Effect on the Treated (ATT) which is the primary focus of our analysis. It demonstrates the effect of diversification for the sample of diversified households. Focusing first on the household's magnitude of expenditure between food and non-food items, our findings show that diversification has a positive and significant impact on food and non-food consumption expenditure for self-employed farm households during 2004–05 and 2009–10, but by 2011–12, it only enhanced farm household's non-food expenditure without having any significant impact on food. Cultivator households were able to spend rupees 101.85 on food and rupees 307.51 on non-food during 2004–05 if they diversified (kernel matching). The magnitude of food and non-food spending increased to rupees 193.43 and 275.26 respectively during 2009–10.

Similarly, for both casual farm and casual non-farm households, diversification increases consumption expenditure across all periods. It is also observed that the magnitude of food expenditure by diversified casual farm households has increased overtime from rupees 131 in 2004–05 to rupees 276 in 2011–12 (NN matching). Similarly, non-food spending also increased by rupees 205 and rupees 593 during the same period. This demonstrates the benefits of diversification for casual workers. Furthermore, for self-employed non-farm households, diversification towards farm employment only significantly increased food expenditure without having any impact on their non-food expenditure. For instance, during 2011–12, they could spend rupees 292.68 more on food if they diversify. This is feasible because the number of self-employed non-farm households with small, semi-medium, and medium land is larger when compared to casual non-farm households, allowing them to work on land. Again, because food consumption spending also includes the monetary value of one's production, the sole reason for self-employed non-farm households to diversify into agriculture may be to meet their food consumption needs. Since self-employed non-farm households could spend more on food although non-food expenditure is not significantly different from the control group, we can say that there has been an overall increase in consumption spending.

Again, with regard to the second definition of diversification, which relates to a household's complete transition from one activity to another, our findings reveal that self-employed farm households are better off specializing in farm activities rather than switching completely to self-employed non-farm work as this transition results in a considerable decline in their consumption expenditure. For instance, food and non-food expenditures of self-employed farm households declined by rupees 180 and rupees 238 respectively during 2011–12 when they shifted completely to non-farm occupations. In rural Cambodia, Deininger and Olinto (2001) observe that specialization in either farm or non-farm activities results in an increase in household consumption spending between 10% to 36%. Contrarily, our findings show that a complete shift from casual farm to casual non-farm work leads to an upward movement in both food and non-food expenditures. They could spend rupees 180.84 and 284.11 (NN matching) more on food and non-food respectively if they shift completely to non-farm casual activities. This points towards the fact that casual farm worker households are the most marginalized section and any shift away from agriculture would significantly enhance their economic well-being. Scharf and Rahut (2014) also demonstrate the benefits of engaging even in low-return non-farm occupations as it contributes to reducing income inequality. Chandrasekhar et al (2015) also observe the significance of rural non-farm employment for landless and marginal land-holding households as yield growth remained insignificant in reducing poverty and undernourishment. For self-employed farm households, specializing in cultivation is a better option than leaving it to pursue non-farm occupation. Therefore, it seems that diversification is not always welfare-enhancing and depends critically on the household's principal source of occupation and the type of diversification strategy applied.

#### **Explanation of ATT for food and non-food expenditure share**

Apart from consumption expenditure, diversification has a considerable impact on the pattern of food and non-food expenditure share. A larger share of household's spending on non-food items relative to food items is allocated only when the household experiences an overall rise in their economic status (Rahman & Mishra, 2020). As per the findings from table 5.23, we observe that diversification enhances the non-food consumption spending while reducing the expenditure share on food items for self-employed farm households who have either combined agriculture with non-farm activities or have completely shifted towards self-employed non-farm occupations. But in 2011–12, no significant impact on food and non-food expenditure share is observed for cultivator households shifting to self-employed non-farm occupations.

Again, for casual farm and casual non-farm households, diversification reduces their food expenditure share while having no significant impact on non-food consumption share. On the other hand, a shift from casual farm to casual non-farm occupations enables them to spend a larger share on non-food items while spending less on food consumption share. They spend 0.991% lesser share on food and 0.865% more on non-food expenditure share. Rahman and Mishra (2020) also found a negative effect of non-farm income on food expenditure share for diversified farm households. Furthermore, for self-employed non-farm households, diversification results in a significant rise in the share of food expenditure only during 2004–05 and it results in a reduction in their share in non-food expenditure for all three time periods. This negative expenditure shares of non-food items by these diversified non-farm self-employed households may be because these households are already earning very low income from non-farm and whatever income they earn from agriculture is spent entirely to meet food consumption needs. From this analysis, it can be inferred that cultivator households, who are considered food secure (Dzanku, 2019) tend to devote a larger share of expenditure on non-food items when they diversify. Whereas, non-farm self-employed households spend a larger share of income on food and less on non-food as a result of diversification. Again, it can be demonstrated that casual non-farm households have a better economic situation than casual agricultural workers because a transition to casual non-farm work improves household consumption expenditure.

#### **5.6.2. Findings for ATE and ATU**

The ATE and ATU results show the impact of occupational diversification on the overall sample and the untreated group respectively. The ATE demonstrates the effect of diversification on consumption expenditure between the diversified and non-diversified households. The ATE results show that diversification enhanced the food and non-food expenditure of all types of farm and non-farm households compared to non-diversified households. But for cultivator households, shifting completely towards self-employed non-farm activities declined their consumption expenditure compared to those who did not shift. For instance, in 2011–12, food expenditure declined by rupees 149 as a result of shifting from farm to non-farm employment. On the contrary, diversification is always a better option for casual farm workers compared to non-diversified casual farm households as they could spend rupees 207 and 249 more on food and non-food (NN matching, 68<sup>th</sup> round). Diversification also results in a greater spending on food and non-food items by casual non-farm households but for self-employed non-farm households, it only significantly enhances food expenditure.

The ATE findings for food and non-food expenditure share are similar to that of ATT for all household types. Here also, all types of diversified households have a lower food expenditure share and a higher non-food expenditure share compared to non-diversified households except for self-employed non-farm households where diversification significantly reduces their expenditure share for non-food items.

The ATU, which depicts the benefits accruing to non-diversified households had they actually participated, is another key matching estimator. The benefits of diversification for non-diversified households through ATU can be analysed by comparing its value with the ATT findings. Our results demonstrate that greater benefits in terms of higher consumption expenditure would have accrued to the non-diversified self-employed farm households had they actually participated. For instance, non-diversified self-employed farm households could have increased their food and non-food expenditure by an amount of rupees 187.69 and 597.92 (NN matching, 68<sup>th</sup> round) if they diversified. They would have benefitted more from diversification as their magnitude is greater than the ATT values which are rupees 89 and rupees 329 for food and non-food respectively. But for casual farm households, diversification would have lowered the consumption expenditure of the non-diversified households had they actually diversified. In other words, non-diversified casual farm households could spend only rupees 197.92 on food through diversification whereas those who actually diversified could increase food spending by rupees 276.67 (NN matching, 68<sup>th</sup> round). These findings are consistent across all three time periods. Furthermore, we observe that cultivator households that did not shift would have been worse off as a result of a complete switch towards non-farm self-employed occupations as this would significantly lower their food spending. But their loss is lower than those who actually shifted. We see that the ATU value for food expenditure is rupees -120.54 while the ATT is rupees -180.72 (NN matching, 68<sup>th</sup> round). The ATU for non-food expenditure is insignificant.

Among the non-farm households, it is observed that diversification would have accrued lower benefits to self-employed workers if they had participated in agriculture. But, for casual non-farm households, even non-diversified households would have benefitted from diversification in terms of higher spending on food and non-food items. The ATU value for food expenditure is rupees 169 while it is rupees 134 in the case of ATT which implies that they could have spent rupees 169 more on food through diversification (nearest neighbour matching). Similar findings are obtained for self-employed non-farm households.

For food and non-food expenditure shares, the ATU figures demonstrate that diversification would have led to higher spending on non-food items while lowering expenditure on food for the non-diversified self-employed farm and casual non-farm households. For self-employed non-farm households, diversification would have increased the share of food expenditure by 0.83% for the control group and this value is higher than the ATT value of 0.06. Again, in case of self-employed farm households, a complete shift towards self-employed non-farm employment would have significantly lowered food expenditure share while increasing their share of non-food shares during 2004–05 and 2009–10 if they would have actually shifted. However, the findings for 2011–12 are not significant. Further, for casual farm households, a complete shift to casual non-farm activities would not have lowered their food expenditure share or have raised the non-food share as much as it did for those who actually shifted. Casual farm households could spend 0.645% (ATU, Kernel matching) more on non-food if they shift to non-farm occupations but those who actually shifted were able to spend 0.766% (ATT, Kernel matching) more on non-food.

### **5.6.3. Limitations of the model**

The PSM is based on the conditional independence assumption (CIA) which states that given a vector of observable factors, treatment is independent of outcome. However, a major limitation of this assumption is its inability to identify the presence of any unobserved factor that might also influence both the treatment and the outcome. Also, the matching procedure that makes the treatment and control groups comparable cannot balance these unobserved factors (Rosenbaum, 1984). Hence, a major limitation of PSM is its inability to account for unobserved heterogeneity.

Some of the unobserved factors that might influence both treatment and outcome may be related to household and locational characteristics. For instance, working-age members of a household may acquire entrepreneurial skills and risk-taking behaviour from their family which are not directly observable but exhibit a considerable impact on diversification as well as on the outcome (Hoang et al, 2014). Family members with these traits are more capable of diversifying to remunerative non-farm jobs which would also accrue higher returns. Such households are also more likely to spend more on food and non-food items such as education, health or recreation. Further, non-farm networks also play a crucial role in finding suitable opportunities in the non-farm sector (Hoang et al, 2014). Information on non-farm jobs provided by fellow villagers or employers prioritising workers coming from same locality also increases the diversification of a household. Again, Van de Walle and Cratty (2004) observe

that different forms of risks affect both the decision of diversification as well as consumption expenditure. Natural calamities like flood and drought may increase the likelihood of farm households to diversify to non-farm activities but for non-farm households, diversifying to agriculture may decline. The effect of diversification on household consumption spending may also be likely to fall as it will be undertaken as a coping strategy.

Further, physical and institutional infrastructures like information on job availability, markets, transport and communication facilities all contribute to lower transportation costs and increase the chances of getting not only remunerative jobs but even ease the availability of different forms of goods and services (Van de Walle & Cratty, 2004). Therefore, households residing in regions that are characterized by a lack of physical and institutional infrastructures, would have lesser opportunities to diversify to non-farm occupations.

Also, we have tried many variables as possible instruments for the treatment variable which is whether to diversify or not, to control any bias due to the correlation of the treatment variable with some of the explanatory variables considered in the model. The variables that were tried as Instrumental Variable (IV) from NSSO employment and unemployment data for 68<sup>th</sup> round include- 1) Whether the household has MGNREGA job card; 2) Whether the enterprise uses electricity or not; 3) Percentage of male workers in a household; 4) Whether the household has any savings bank account; 5) Average education index of a household. We also used information from Census data to find a suitable IV and these variables are - 1) Percentage of rural households having any vehicle; 2) Literacy rate; 3) Percentage of households with mobile. We further tried to use night-time light intensity data which was also used by Rahman and Mishra (2019) in their paper. However, all the above-mentioned variables failed the falsification test due to which we were not able to use any of them as an IV for the treatment variable which is whether the household would diversify or specialize using NSSO data.

### **5.7. Summing up**

This study looks at how employment diversification adopted as a livelihood strategy impacts rural households' welfare evaluated through consumption expenditures. A propensity score matching method is used to quantify the impact of diversification on rural household's welfare. Our study not only differentiates between self-employed and casual farm households, which was hitherto considered a single entity but also analyses the effect of diversification to farm activities by non-farm households as our descriptive statistics found a higher share of non-farm households combining farm activities. Our findings reveal that not all household types have benefitted from diversification. Although households with more than one economic activity

could increase their food and non-food expenditure, cultivator households, on the contrary, would be better off specializing in agricultural activities rather than moving entirely to self-employed non-farm work. For cultivator households to continue specialization in agriculture, government intervention to support this sector is required. Not only consumption expenditure, but even expenditure shares of diversified households have shifted towards non-food items like education, health and other services which again vary across household types. While cultivator households spend a greater portion of earnings on non-food items, non-farm self-employed households spend more on food as a result of diversification. Furthermore, our results demonstrate that the economic status of casual farm households could be improved with the adoption of a diversified livelihood strategy rather than confining solely to casual farm work.

Our study demonstrates the growing significance of non-farm sector in rural India, especially for the marginalised farming community which crucially depends on this sector for livelihood and is even found to benefit from this sector. We also found the positive consequences of combining both farm and non-farm activities by the casual non-farm households in terms of higher consumption expenditure. Therefore, there should be a simultaneous effort to develop both farm and non-farm sector. From a policy perspective, focus should be placed on establishing small- and medium scale industries, specifically developing the agro-processing industries. This would not only absorb labor force in the non-farm sector but would even boost growth linkages with the farm sector (Owusu et al, 2011). Rural infrastructural development like construction of roads, electrification and better transport facilities together with provision for formal and vocational training (Scharf & Rahut, 2014; Zeeshan et al, 2018) would enhance the scope of rural households to diversify towards non-agricultural employment avenues.

**Appendix 5A**  
**Covariate balancing test for 66<sup>th</sup> round**

**Table 5A. 1 Covariate balancing test for self-employed farm household**

Variable	Unmatched sample			Five-nearest neighbour matching		
	Treated	Control	Diff. p-value	Treated	Control	diff. p-value
<b>Self-employed farm household</b>						
<b>Age_head</b>	47.397	43.083	0.000*	47.397	47.766	0.400
<b>Gender_head</b>	0.934	0.930	0.701	0.934	0.932	0.895
<b>Education_head (illiterate= base category)</b>						
<b>Below primary &amp; primary</b>	0.282	0.264	0.293	0.282	0.289	0.790
<b>Middle &amp; secondary</b>	0.339	0.354	0.458	0.339	0.343	0.881
<b>HS &amp; diploma</b>	0.083	0.085	0.911	0.083	0.083	0.984
<b>Graduate &amp; above</b>	0.064	0.04	0.004*	0.064	0.064	1.000
<b>Vocation_head</b>	0.061	0.048	0.144	0.061	0.081	0.155
<b>Married_head</b>	0.910	0.923	0.208	0.910	0.905	0.748
<b>Caste (unreserved= base category)</b>						
<b>ST</b>	0.232	0.213	0.259	0.232	0.229	0.928
<b>SC</b>	0.100	0.092	0.512	0.100	0.096	0.811
<b>OBC</b>	0.353	0.370	0.385	0.353	0.361	0.767
<b>Religion (other religion= base category)</b>						
<b>Hindu</b>	0.723	0.762	0.021**	0.723	0.717	0.808
<b>Muslim</b>	0.106	0.084	0.057***	0.106	0.107	0.930
<b>Land (landless= base category)</b>						
<b>Marginal</b>	0.476	0.395	0.000*	0.476	0.469	0.81
<b>Small</b>	0.208	0.237	0.087***	0.208	0.209	0.957
<b>Semi-medium</b>	0.181	0.200	0.237	0.181	0.188	0.746
<b>Medium</b>	0.103	0.139	0.010**	0.103	0.101	0.928
<b>Large</b>	0.022	0.021	0.933	0.022	0.023	0.942
<b>Household size</b>	6.053	4.963	0.000*	6.053	5.943	0.471
<b>Dependency ratio</b>	0.393	0.633	0.000*	0.393	0.382	0.655
<b>Unemployment rate</b>	82.018	78.936	0.098***	82.018	81.952	0.980

<b>Urbanization</b>	0.24	0.232	0.134	0.24	0.237	0.707
<b>Average distance</b>	302.98	314.14	0.195	302.98	306.71	0.726

Notes: \*, \*\* & \*\*\* indicates significance at 1%, 5% and 19% level of significance.

**Table 5A. 2 Covariate balancing test for farm labour household**

Variables	Unmatched sample			Five-nearest neighbour matching		
	Treated	Control	Diff. p-value	Treated	Control	Diff. p-value
<b>Casual farm household</b>						
<b>Age_head</b>	44.104	40.213	0.000*	44.053	44.125	0.913
<b>Gender_head</b>	0.921	0.871	0.004*	0.921	0.925	0.831
<b>Education_head (illiterate= base category)</b>						
<b>Below primary &amp; primary</b>	0.287	0.318	0.223	0.289	0.285	0.912
<b>Middle &amp; secondary</b>	0.219	0.185	0.108	0.220	0.220	1.000
<b>HS &amp; diploma</b>	0.035	0.021	0.091***	0.035	0.026	0.46
<b>Graduate &amp; above</b>	0.042	0.004	0.000*	0.038	0.034	0.76
<b>Vocation_head</b>	0.032	0.02	0.123	0.032	0.027	0.679
<b>Married_head</b>	0.883	0.847	0.058***	0.883	0.883	1.000
<b>Caste (unreserved= base category)</b>						
<b>ST</b>	0.083	0.164	0.000*	0.083	0.087	0.859
<b>SC</b>	0.3257	0.297	0.257	0.324	0.337	0.706
<b>OBC</b>	0.378	0.377	0.947	0.378	0.355	0.506
<b>Religion (other religion= base category)</b>						
<b>Hindu</b>	0.734	0.823	0.000*	0.733	0.74	0.821
<b>Muslim</b>	0.161	0.107	0.001*	0.162	0.159	0.908
<b>Size of land ownership (landless= base category)</b>						
<b>Marginal</b>	0.858	0.834	0.221	0.86	0.861	0.951
<b>small</b>	0.03	0.031	0.883	0.027	0.027	0.965
<b>semi-medium</b>	0.002	0.008	0.183	0.002	0.003	0.893
<b>Medium</b>	0.007	0.004	0.339	0.007	0.006	0.866
<b>Household size</b>	4.886	4.18	0.000*	4.88	5.013	0.388
<b>Dependency ratio</b>	0.467	0.665	0.000*	0.47	0.475	0.896

<b>Unemployment rate</b>	104.53	97.155	0.011**	104.6	103.95	0.876
<b>Urbanization</b>	0.293	0.254	0.000*	0.292	0.288	0.683
<b>Average distance</b>	254.13	291.16	0.004*	253.68	260.03	0.570

Notes: \*, \*\* & \*\*\* indicates significance at 1%, 5% and 19% level of significance.

**Table 5A. 3 Covariate balancing test for self-employed farm to self-employed non-farm household**

Variables	Unmatched sample			Five-nearest matching		neighbour	
	Treated	Control	Diff. p-value	Treated	Control	diff. p-value	
<b>Self-employed farm to Self-employed non-farm household</b>							
<b>Age_head</b>	40.763	43.083	0.000*	40.764	40.748	0.923	
<b>Gender_head</b>	0.94	0.93	0.012**	0.940	0.938	0.531	
<b>Education_head (illiterate= base category)</b>							
<b>Below primary &amp; primary</b>	0.268	0.264	0.558	0.268	0.269	0.893	
<b>Middle &amp; secondary</b>	0.386	0.354	0.000*	0.386	0.394	0.357	
<b>HS &amp; diploma</b>	0.091	0.085	0.205	0.091	0.089	0.797	
<b>Graduate &amp; above</b>	0.067	0.04	0.000*	0.067	0.072	0.252	
<b>Vocation_head</b>	0.116	0.048	0.000*	0.116	0.101	0.008	
<b>Married_head</b>	0.922	0.923	0.783	0.922	0.916	0.227	
<b>Caste (unreserved= base category)</b>							
<b>ST</b>	0.114	0.213	0.000*	0.114	0.102	0.031	
<b>SC</b>	0.156	0.092	0.000*	0.156	0.153	0.607	
<b>OBC</b>	0.432	0.37	0.000*	0.432	0.433	0.960	
<b>Religion (other religion= base category)</b>							
<b>Hindu</b>	0.729	0.762	0.000*	0.729	0.731	0.821	
<b>Muslim</b>	0.166	0.084	0.000*	0.166	0.172	0.389	
<b>Size of land ownership (landless= base category)</b>							
<b>Medium</b>	0.006	0.139	0.000*	0.006	0.007	0.849	
<b>Large</b>	0.001	0.021	0.000*	0.001	0.001	0.715	
<b>Dependency ratio</b>	0.677	0.633	0.000*	0.677	0.68	0.810	

<b>Unemployment rate</b>	87.471	78.936	0.000*	87.469	86.862	0.472
<b>Urbanization</b>	0.234	0.232	0.425	0.234	0.23	0.059
<b>Average distance</b>	286.22	314.14	0.000*	286.23	286.09	0.968

Notes: \*, \*\* & \*\*\* indicates significance at 1%, 5% and 10% level of significance.

**Table 5A. 4 Covariate balancing test of self-employed non-farm household**

Variable	Unmatched sample			Five-nearest neighbour matching		
	Treated	Control	Diff. p-value	Treated	Control	Diff. p-value
<b>self-employed non-farm household</b>						
<b>Age_head</b>	43.547	40.763	0.000*	43.536	43.572	0.926
<b>Gender_head</b>	0.938	0.94	0.799	0.938	0.939	0.957
<b>Education_head (illiterate= base category)</b>						
<b>Below primary &amp; primary</b>	0.295	0.268	0.067***	0.295	0.29	0.793
<b>Middle &amp; secondary</b>	0.308	0.386	0.000*	0.309	0.321	0.544
<b>HS &amp; diploma</b>	0.073	0.091	0.051***	0.073	0.076	0.758
<b>Graduate &amp; above</b>	0.049	0.067	0.027**	0.049	0.048	0.905
<b>Vocation_head</b>	0.115	0.116	0.897	0.114	0.118	0.779
<b>Married_head</b>	0.911	0.922	0.205	0.911	0.903	0.555
<b>Caste (unreserved= base category)</b>						
<b>ST</b>	0.174	0.114	0.000*	0.174	0.186	0.491
<b>SC</b>	0.174	0.156	0.127	0.174	0.179	0.779
<b>OBC</b>	0.412	0.432	0.201	0.411	0.403	0.695
<b>Religion (other religion= base category)</b>						
<b>Hindu</b>	0.759	0.729	0.038**	0.759	0.762	0.849
<b>Muslim</b>	0.121	0.166	0.000*	0.121	0.116	0.722
<b>Size of land ownership (landless= base category)</b>						
<b>Marginal</b>	0.721	0.85	0.000*	0.721	0.723	0.932
<b>Small</b>	0.127	0.05	0.000*	0.127	0.125	0.928
<b>Semi-medium</b>	0.074	0.021	0.000*	0.075	0.075	0.948
<b>Medium</b>	0.03	0.006	0.000*	0.029	0.028	0.939
<b>Large</b>	0.004	0.001	0.003*	0.004	0.004	1
<b>Dependency ratio</b>	0.539	0.677	0.000*	0.539	0.534	0.852

<b>Unemployment rate</b>	81.021	87.471	0.000*	81.055	81.094	0.984
<b>Urbanization</b>	0.241	0.234	0.075***	0.241	0.241	0.961
<b>Average distance</b>	304.75	286.22	0.016**	304.75	305.03	0.98

Notes: \*, \*\* & \*\*\* indicates significance at 1%, 5% and 19% level of significance.

### Covariate balancing test for 61<sup>st</sup> round

**Table 5A. 5 Covariate balancing test for self-employed farm household**

Variable	Unmatched sample			Five-nearest neighbour matching		
	Treated	Control	Diff. p-value	Treated	Control	Diff. p-value
<b>Self-employed farm household</b>						
<b>Age_head</b>	54.495	47.676	0.000*	54.495	54.781	0.515
<b>Gender_head</b>	0.938	0.907	0.000*	0.938	0.935	0.811
<b>Education_head (illiterate= base category)</b>						
<b>Below primary &amp; primary</b>	0.313	0.332	0.136	0.313	0.312	0.975
<b>Middle &amp; secondary</b>	0.276	0.243	0.005*	0.276	0.279	0.821
<b>HS &amp; diploma</b>	0.056	0.041	0.006*	0.056	0.056	0.975
<b>Graduate &amp; above</b>	0.047	0.028	0.000*	0.047	0.047	0.986
<b>Married_head</b>	0.886	0.874	0.165	0.886	0.884	0.882
<b>Caste (unreserved= base category)</b>						
<b>ST</b>	0.113	0.226	0.000*	0.113	0.111	0.863
<b>SC</b>	0.102	0.082	0.010**	0.102	0.102	1
<b>OBC</b>	0.384	0.369	0.247	0.384	0.386	0.905
<b>Religion (other religion= base category)</b>						
<b>Hindu</b>	0.74	0.737	0.810	0.74	0.741	0.96
<b>Muslim</b>	0.129	0.085	0.000*	0.129	0.124	0.655
<b>Size of land ownership (landless= base category)</b>						
<b>Marginal</b>	0.431	0.435	0.765	0.431	0.432	0.965
<b>Small</b>	0.219	0.225	0.602	0.219	0.212	0.647
<b>Semi-medium</b>	0.172	0.18	0.423	0.172	0.174	0.833
<b>Medium</b>	0.133	0.124	0.310	0.133	0.135	0.84

<b>Large</b>	0.036	0.03	0.144	0.036	0.036	0.954
<b>Household size</b>	7.134	5.231	0.000*	7.134	7.026	0.415
<b>Dependency ratio</b>	0.539	0.752	0.000*	0.539	0.53	0.624
<b>Unemployment rate</b>	96.054	83.22	0.000*	96.054	97.188	0.628
<b>Urbanization</b>	0.225	0.204	0.000*	0.225	0.226	0.759
<b>Average distance</b>	305.11	325.9	0.000*	305.11	303.96	0.86

Notes: \*, \*\* & \*\*\* indicates significance at 1%, 5% and 19% level of significance.

**Table 5A. 6 Covariate balancing test for farm labour household**

Variable	Unmatched sample			Five-nearest neighbour matching		
	Treated	Control	Diff. p-value	Treated	Control	Diff. p-value
<b>farm labour household</b>						
<b>Age_head</b>	46.754	42.995	0.000*	46.702	46.876	0.792
<b>Gender_head</b>	0.881	0.848	0.033**	0.881	0.879	0.929
<b>Education_head (illiterate= base category)</b>						
<b>Below primary &amp; primary</b>	0.297	0.251	0.015**	0.296	0.303	0.801
<b>Middle &amp; secondary</b>	0.123	0.089	0.007*	0.123	0.126	0.875
<b>HS &amp; diploma</b>	0.026	0.006	0.000*	0.026	0.022	0.628
<b>Vocation_head</b>	0.021	0.001	0.000*	0.021	0.009	0.084
<b>Married_head</b>	0.847	0.805	0.013**	0.847	0.852	0.795
<b>Caste (unreserved= base category)</b>						
<b>ST</b>	0.098	0.13	0.029**	0.098	0.094	0.814
<b>SC</b>	0.295	0.368	0.001*	0.296	0.306	0.705
<b>OBC</b>	0.386	0.358	0.188	0.385	0.376	0.757
<b>Religion (other religion= base category)</b>						
<b>Hindu</b>	0.782	0.844	0.000*	0.782	0.797	0.505
<b>Muslim</b>	0.135	0.09	0.000*	0.135	0.122	0.513
<b>Land (landless= base category)</b>						
<b>Marginal</b>	0.872	0.843	0.059***	0.872	0.878	0.779
<b>Small</b>	0.02	0.013	0.182	0.02	0.019	0.934

<b>Semi-medium</b>	0.008	0.005	0.437	0.008	0.005	0.58
<b>Medium</b>	0.001	0.001	0.870	0.001	0.001	0.752
<b>Household size</b>	5.224	4.137	0.000*	5.196	5.326	0.363
<b>Dependency ratio</b>	0.536	0.738	0.000*	0.536	0.559	0.487
<b>Unemployment rate</b>	141.89	121.96	0.000*	141.87	142.57	0.857
<b>Urbanization</b>	0.262	0.244	0.001*	0.262	0.264	0.784
<b>Average distance</b>	276.68	290.72	0.091***	276.34	273.11	0.699

Notes: \*, \*\* & \*\*\* indicates significance at 1%, 5% and 10% level of significance.

**Table 5A. 7 Covariate balancing test for self-employed farm to self-employed non-farm household**

Variable	Unmatched sample			Five-nearest neighbour matching		
	Treated	Control	Diff. p-value	Treated	Control	Diff. p-value
<b>S.E farm to S.E non-farm</b>						
<b>Age_head</b>	25.825	25.825	0.996	25.825	25.898	0.576
<b>Gender_head</b>	0.948	0.924	0.054***	0.948	0.956	0.463
<b>Education_head (illiterate= base category)</b>						
<b>Below primary &amp; primary</b>	0.313	0.357	0.066***	0.313	0.323	0.695
<b>Middle &amp; secondary</b>	0.357	0.316	0.081***	0.357	0.384	0.275
<b>HS &amp; diploma</b>	0.075	0.071	0.758	0.075	0.078	0.829
<b>Graduate &amp; above</b>	0.047	0.027	0.032**	0.047	0.04	0.492
<b>Vocation_head</b>	0.166	0.089	0.000*	0.166	0.16	0.778
<b>Married_head</b>	0.856	0.862	0.739	0.856	0.829	0.151
<b>Caste (unreserved= base category)</b>						
<b>ST</b>	0.091	0.317	0.000*	0.091	0.093	0.871
<b>SC</b>	0.195	0.08	0.000*	0.195	0.183	0.567
<b>OBC</b>	0.435	0.356	0.001*	0.435	0.429	0.833
<b>Religion (other religion= base category)</b>						
<b>Hindu</b>	0.732	0.693	0.081***	0.732	0.738	0.813
<b>Muslim</b>	0.188	0.066	0.000*	0.188	0.196	0.682
<b>Medium</b>	0.001	0.099	0.000*	0.001	0.003	0.502

<b>Large</b>	0.001	0.014	0.004*	0.001	0.001	0.893
<b>Dependency ratio</b>	0.676	0.74	0.058***	0.676	0.649	0.411
<b>Unemployment rate</b>	92.78	70.214	0.000*	92.78	92.514	0.923
<b>Urbanization</b>	0.217	0.197	0.000*	0.217	0.217	0.973
<b>Average distance</b>	292.84	339.62	0.000*	292.84	298.71	0.538

Notes: \*, \*\* & \*\*\* indicates significance at 1%, 5% and 19% level of significance.

**Table 5A. 8 Covariate balancing test for self-employed non-farm household**

Variable	Unmatched sample			Five-nearest neighbour matching		
	Treated	Control	Diff. p-value	Treated	Control	diff. p-value
<b>S.E non-farm household</b>						
<b>Age_head</b>	48.252	42.984	0.000*	48.195	48.185	0.982
<b>Gender_head</b>	0.935	0.917	0.013**	0.935	0.937	0.854
<b>Education_head (illiterate= base category)</b>						
<b>Below primary &amp; primary</b>	0.318	0.331	0.340	0.318	0.318	0.982
<b>Middle &amp; secondary</b>	0.233	0.289	0.000*	0.233	0.224	0.516
<b>HS &amp; diploma</b>	0.041	0.06	0.002*	0.041	0.044	0.721
<b>Graduate &amp; above</b>	0.036	0.046	0.087***	0.036	0.046	0.148
<b>Married_head</b>	0.891	0.88	0.198	0.892	0.892	0.991
<b>Caste (unreserved= base category)</b>						
<b>ST</b>	0.155	0.093	0.000*	0.154	0.169	0.242
<b>SC</b>	0.171	0.155	0.105	0.171	0.162	0.494
<b>OBC</b>	0.425	0.436	0.401	0.426	0.43	0.818
<b>Religion (other religion= base category)</b>						
<b>Hindu</b>	0.722	0.734	0.311	0.723	0.712	0.49
<b>Muslim</b>	0.126	0.167	0.000*	0.126	0.122	0.714
<b>Land (landless= base category)</b>						
<b>Marginal</b>	0.703	0.862	0.000*	0.704	0.709	0.744
<b>Small</b>	0.119	0.028	0.000*	0.119	0.117	0.856
<b>Semi-medium</b>	0.067	0.017	0.000*	0.067	0.061	0.528
<b>Medium</b>	0.039	0.006	0.000*	0.038	0.037	0.942
<b>Large</b>	0.007	0.001	0.000*	0.007	0.011	0.246

<b>Dependency ratio</b>	0.686	0.773	0.000*	0.686	0.672	0.545
<b>Unemployment rate</b>	95.699	101.79	0.000*	95.768	95.272	0.812
<b>Urbanization</b>	0.226	0.223	0.446	0.226	0.228	0.589
<b>Average distance</b>	315.85	294.84	0.000*	315.51	316.59	0.886

Notes: \*, \*\* & \*\*\* indicates significance at 1%, 5% and 10% level of significance.



## Chapter 6

### **Determinants and linkage between farm and non-farm wages in rural India**

This chapter investigates the linkage between real farm wage and non-farm wage of rural casual workers. Wages in rural India, particularly agricultural wages are regarded as an indicator of household well-being and poverty status since they represent the lowest level of earning at which workers are willing to supply their labor (Himanshu & Kundu, 2016; Himanshu, 2018). Although agriculture has remained the primary source of employment for more than half of the rural population, yet its declining productivity, profitability and a fall in its share of GDP renders this sector unviable as a prime source of livelihood. Therefore, farm laborers are in a disadvantageous position compared to other workers. As such, a rise in real wage rates would contribute significantly to economic upliftment and poverty reduction. One major pathway through which wages in the agriculture sector can witness an upward trend is through the availability of employment opportunities in the rural non-farm sector which would result in a tightening of the rural labor market (Vyas & Mathai, 1978). Several studies (Berg et al, 2012; Narayanamoorthy & Bhattarai, 2013; Kumar et al, 2020) have also demonstrated a positive impact on farm wages due to an expansion in rural non-farm employment opportunities particularly in the construction sector after 2005–06 through implementation of MGNREGA. Therefore, growth in the rural non-farm sector is expected to have a positive impact on farm wages. But, on the contrary, Lanjouw and Murgai (2009) demonstrate that the establishment of non-farm sectors like construction and manufacturing generally occurs in regions where cheap labor is available and in such a situation, the non-farm wages may be determined based on the prevailing farm wages in that region. In this case, existing farm wages might have a reverse impact on non-farm wages. This implies that wages in both markets may have a direct impact or they may influence each other through some other channel. As such, both rural farm and non-farm wages may be linked directly or indirectly. This aspect of the relation between farm and non-farm wages in rural India has remained unexplored. Therefore, the objective of this chapter is to empirically examine the determinants of farm and non-farm wages and study the relationship between them. In other words, how wages in one market respond when there are changes in the wage rates in the other market. Therefore, this chapter is devoted to analyzing the nature of the linkage between farm and non-farm labor markets through their impact on wages for the period 2004–05, 2009–10 and 2011–12.

The rest of this chapter is divided into five sections. Section 6.1 provides a brief description of the pattern of farm and non-farm casual wages across gender and states of India followed by

methodology in section 6.2. The regression results are provided in section 6.3 and section 6.4 consists of robustness check of the regression results. Section 6.5 sums up the discussion of this chapter.

### 6.1. Patterns of rural farm and non-farm wages of casual workers across the three time periods and for each state

Tables 6.1 and 6.2 depict the nominal and real average daily wage rates of casual agricultural and non-agricultural workers.

**Table 6. 1 Average nominal daily wages of male and female workers in agricultural and non-agricultural sector**

Nominal wage	61st round		66th round		68th round	
	Farm wage	Non-farm wage	Farm wage	Non-farm wage	Farm wage	Non-farm wage
<b>Male</b>	51.27	71.34	93.05	125.57	135.81	181.95
<b>Female</b>	33.94	45.15	66.98	87.82	100.31	124.38
<b>Person</b>	44.51	67.15	83.33	120.62	121.99	175.94

Source: computed from NSSO EUS data.

**Table 6. 2 Average real daily wages of male and female workers in agricultural and non-agricultural sector**

Real wage	61st round		66th round		68th round	
	Farm wage	Non-farm wage	Farm wage	Non-farm wage	Farm wage	Non-farm wage
<b>Male</b>	92.13	123.86	110.82	150.22	135.81	181.95
<b>Female</b>	60.99	78.39	79.77	105.06	100.31	124.38
<b>Person</b>	79.98	116.58	99.24	144.29	121.99	175.94

Source: computed from NSSO EUS data.

**Table 6. 3 Growth rate of real agricultural and non-agricultural wages of male and female workers**

	Real growth rate					
	Farm wage			Non-farm wage		
	2004-05	2009-10	% Growth rate	2009-10	2011-12	% Growth rate
<b>Male</b>	92.13	110.82	20.28	110.82	135.81	22.55
<b>Female</b>	60.99	79.77	30.79	79.77	100.31	25.74

<b>Person</b>	79.98	99.24	24.08	99.24	121.99	22.92
<b>non-farm wage</b>						
	2004-05	2009-10	% Growth rate	2009-10	2011-12	% Growth rate
<b>Male</b>	123.86	150.22	21.28	150.22	181.95	21.12
<b>Female</b>	78.39	105.06	34.02	105.06	124.38	18.38
<b>Person</b>	116.58	144.29	23.76	144.29	175.94	21.93

*Source: computed from NSSO EUS data.*

From tables 6.1 and 6.2, it is seen that both nominal and real non-farm wages are higher than farm wages for both male and female workers. However, there is an upward trend in both nominal and real wages in farm and rural non-farm sectors. Again, regardless of the sector of employment, wages of female workers are always lower than their male counterparts. Swaminathan (2020) also points out the presence of gender gap in wage rates in both farm and non-farm markets which can be reduced through provision of better remunerative jobs for women. The reason behind the low level of female wages compared to males is attributed to the lesser number of days of work. They also remain unemployed for a longer period than male workers which might lead to their lower earnings (Srivastava & Srivastava, 2010). Roy (2020) additionally stated that this wage disparity is more pronounced in agriculture than in the non-farm sector. However, when we look at the growth rate of real farm and non-farm wages from table 6.3, we observe that the growth rate of female wages in agriculture is higher than that of male wages resulting in a fall in wage gaps across gender over time. This higher growth of female wages and wage convergence in agriculture across gender which was more pronounced after the post-MGNREGA period is also pointed out by Himanshu and Kundu (2016) and Narayanamoorthy and Bhattarai (2013). Other reasons for this wage convergence demonstrated by them include a rise in public expenditure and expansion of non-farm employment opportunities. Eswaran et al (2009) also observed that the rise in farm wages was higher for females compared to males between 1983 and 2004 due to greater dependence on the former group in agriculture.

Again, Gulati et al (2014) pointed out several growth-induced factors that are responsible for this rise in farm wages in the post-MGNREGA period. Apart from MGNREGA which has led to a rise in demand for laborers, other growth-induced factors that have contributed to this rise in wages include the overall increase in Gross Domestic Product (GDP), agriculture GDP and construction GDP. The growth rate of overall GDP which was 5.7 percent during the 1990s increased to 7.6 percent between 2001–02 to 2011–12. Similarly, agriculture GDP increased

from 3 percent between 2000–01 to 2006–07 to 3.7 percent in the latter half of the decade. In case of the construction sector, not only GDP but growth of employment also augmented by three-fold from 3.1% in 1993–94 to 9.6% in 2009–10. Lanjouw and Murgai (2009) also observed a convergence of real wages of agricultural and non-agricultural sectors, particularly after the implementation of MGNREGA. Reddy (2015) found that the growth rate of wages which was negligible in both farm and non-farm sectors before 2006, increased at a high rate after this period. Furthermore, we found from table 6.3 that in the case of real non-agricultural wages, the growth rate for females declined from 34.02 percent during 2004–05 to 2009–10 to 18.38 percent during 2009–10 and 2011–12, while for males, the growth rate remained same at 21 percent. Tables 6.4 and 6.5 below demonstrate the state-level average daily wages in farm and non-farm sectors and the ratio of non-farm to farm wages in order to understand whether convergence of wages has occurred between these sectors or not as pointed out by extant studies.

**Table 6. 4 Average real agricultural and non-agricultural wages across states**

State	61st round		66th round		68th round	
	Farm wage	Non-farm wage	Farm wage	Non-farm wage	Farm wage	Non-farm wage
<b>Jammu &amp; Kashmir</b>	182.473	166.92	196.425	197.019	211.013	207.691
<b>Himachal Pradesh</b>	156.038	152.629	149.167	164.539	155	177.768
<b>Punjab</b>	126.184	135.764	151.59	155.085	195.919	197.965
<b>Chandigarh</b>	0	173.142	97.381	221.319	0	189.285
<b>Uttarakhand</b>	101.909	122.904	129.825	152.828	148.121	187.823
<b>Haryana</b>	120.328	132.622	138.676	191.214	179.913	208.041
<b>Delhi</b>	197.676	119.883	0	231.171	0	107.142
<b>Rajasthan</b>	107.945	110.004	132.065	153.745	141.873	169.581
<b>Uttar Pradesh</b>	78.273	95.435	102.858	121.961	113.103	144.983
<b>Bihar</b>	72.753	95.925	82.716	103.661	109.426	151.531
<b>Sikkim</b>	131.472	152.837	88.071	150.265	107.142	213.82
<b>Arunachal Pradesh</b>	129.718	230.859	100.898	179.258	160.095	283.179
<b>Nagaland</b>	269.558	218.307	33.745	188.42	108	206.761

<b>Manipur</b>	95.674	127.033	152.614	127.847	170.531	198.491
<b>Mizoram</b>	135.367	170.797	80.505	165.833	154.545	250.8
<b>Tripura</b>	103.642	105.327	116.095	127.318	150.724	161.926
<b>Meghalaya</b>	89.796	135.35	120.011	184.054	149.655	207.448
<b>Assam</b>	99.111	107.685	93.817	113.275	102.14	147.152
<b>West Bengal</b>	79.963	94.304	101.772	105.213	115.954	127.206
<b>Jharkhand</b>	70.837	90.531	77.31	124.616	85.106	134.103
<b>Orissa</b>	63.922	81.339	79.139	105.341	98.392	132.444
<b>Chhattisgarh</b>	51.624	76.715	79.245	114.059	76.859	100.699
<b>Madhya Pradesh</b>	58.581	86.392	72.752	104.54	92.692	121.896
<b>Gujarat</b>	83.065	124.916	92.339	135.67	103.209	152.821
<b>Daman &amp; Diu</b>	132.881	137.808	121.901	119.631	130.606	275
<b>Dadra &amp; Nagar</b>	91.065	113.991	117.95	151.584	160	179.285
<b>Haveli</b>						
<b>Maharashtra</b>	62.624	94.328	80.681	123.387	106.641	161.234
<b>Andhra Pradesh</b>	65.696	98.84	105.656	154.73	123.513	186.547
<b>Karnataka</b>	69.127	114.814	94.134	139.917	122.52	189.266
<b>Goa</b>	167.66	151.215	150.516	151.637	175.285	180.213
<b>Lakshadweep</b>	199.125	268.665	173.702	296.861	187.5	345.676
<b>Kerala</b>	205.389	210.828	226.013	253.198	273.894	336.117
<b>Tamil Nadu</b>	89.889	133.706	113.268	174.769	143.596	221.454
<b>Puducherry</b>	102.428	129.764	118.363	181.83	154.876	213.771
<b>A &amp; N island</b>	137.716	157.577	159.639	174.137	172.913	184.363
<b>All India</b>	80.822	118.695	100.976	146.397	123.403	178.189

Source: computed from NSSO EUS data.

Consistent with extant literature, it is observed from table 6.4 that in states like Kerala, Haryana, Punjab, Himachal Pradesh, Tamil Nadu, Jammu and Kashmir and all North-Eastern States except Assam, real daily wages of both farm and non-farm workers are higher than the national average for all three time periods. In the case of Assam, wages in both sectors are lower than the all-India average during 2009–10 and 2011–12. Among the north-eastern states, Mizoram has the highest wage rate followed by Sikkim and Arunachal Pradesh. An exception is the case of Nagaland where both farm and non-farm wages were high during 2004–05 but in the next two periods, farm wages fell below the national average. Rural wages are also found

to be high in the union territories of Lakshadweep, Delhi, Puducherry and Andaman and Nicobar Islands. Several studies (Reddy, 2015; Jose, 2013, Srivastava & Singh, 2006; Venkatesh, 2013) have observed high wages in both agriculture and non-agriculture sectors in developed states like Kerala, Tamil Nadu, Himachal Pradesh, Rajasthan, Gujarat, Haryana and Punjab, and that the growth of wages accelerated in the post-liberalization period in these states. Jose (2013) also found that Kerala has remained consistently the highest wage rate state for both males and females between 1999–00 to 2009–10. Factors that have contributed to this high level of wages in these developed states include high growth of urbanization, a greater share of non-farm sector, fewer differences between rural and urban areas and high per capita income (Reddy, 2015).

Again, states where wages in both sectors are lower than the all-India average include Andhra Pradesh, Karnataka, Odisha, West Bengal, Uttar Pradesh, Bihar, Madhya Pradesh, Maharashtra and Gujarat. Although wages in the low-wage rate states have risen over time, it has remained below the national average even after 2006 when there has been an acceleration in the growth of wages in both sectors (Reddy, 2015). Several reasons were attributed which include a lower share of non-farm net state domestic product and negligible impact of structural change in raising wages in addition to higher dependence of rural households on agriculture for livelihood (Reddy, 2015). It is also demonstrated by Gulati et al (2014) that the growth of real farm wages which was negative in the pre-MGNREGA period registered positive growth during 2007–08 and 2011–12. Among the states, the growth of wages has been high in Andhra Pradesh, Odisha, Tamil Nadu and Rajasthan where MGNREGA was actively implemented.

**Table 6. 5 Ratio of non-farm to farm wages for 61<sup>st</sup>, 66<sup>th</sup> and 68<sup>th</sup> round.**

<b>State</b>	<b>61st round</b> ratio of non-farm to farm wage	<b>66th round</b> ratio of non-farm to farm wage	<b>68th round</b> ratio of non-farm to farm wage
<b>Jammu &amp; Kashmir</b>	0.914	1.003	0.984
<b>Himachal Pradesh</b>	0.978	1.103	1.146
<b>Punjab</b>	1.075	1.023	1.010
<b>Chandigarh</b>	0	2.272	0
<b>Uttarakhand</b>	1.206	1.177	1.268
<b>Haryana</b>	1.102	1.378	1.156
<b>Delhi</b>	0.606	0	0

<b>Rajasthan</b>	1.019	1.164	1.195
<b>Uttar Pradesh</b>	1.219	1.185	1.281
<b>Bihar</b>	1.318	1.253	1.384
<b>Sikkim</b>	1.162	1.706	1.995
<b>Arunachal Pradesh</b>	1.779	1.776	1.768
<b>Nagaland</b>	0.809	5.583	1.914
<b>Manipur</b>	1.327	0.837	1.163
<b>Mizoram</b>	1.261	2.059	1.622
<b>Tripura</b>	1.016	1.096	1.074
<b>Meghalaya</b>	1.507	1.533	1.386
<b>Assam</b>	1.086	1.207	1.440
<b>West Bengal</b>	1.179	1.033	1.097
<b>Jharkhand</b>	1.278	1.611	1.575
<b>Orissa</b>	1.272	1.331	1.346
<b>Chhattisgarh</b>	1.486	1.439	1.310
<b>Madhya Pradesh</b>	1.474	1.436	1.315
<b>Gujarat</b>	1.503	1.469	1.480
<b>Daman &amp; Diu</b>	1.037	0.981	2.105
<b>Dadra &amp; Nagar Haveli</b>	1.251	1.285	1.120
<b>Maharashtra</b>	1.506	1.529	1.511
<b>Andhra Pradesh</b>	1.504	1.464	1.510
<b>Karnataka</b>	1.660	1.486	1.544
<b>Goa</b>	0.901	1.007	1.028
<b>Lakshadweep</b>	1.349	1.709	1.843
<b>Kerala</b>	1.026	1.120	1.227
<b>Tamil Nadu</b>	1.487	1.542	1.542
<b>Puducherry</b>	1.266	1.536	1.380
<b>A &amp; N island</b>	1.144	1.090	1.066
<b>All India</b>	1.468	1.449	1.443

*Source: computed from NSSO EUS data.*

Another indicator of the productivity gap between agriculture and non-agriculture sector is the wage gap that exists between them and narrowing this wage gap would indicate an

improvement in productivity between sectors which would contribute to lower wage inequality (Reddy, 2015). Although overall wage gaps have narrowed down there are state-wise variations (ibid). Table 6.5 depicts the ratio of non-agricultural wages to agricultural wages for the three time periods for each state. Wage gaps have narrowed down between 2004–05 and 2011–12 for states like Punjab, Uttarakhand, Chandigarh, West Bengal, Madhya Pradesh, Gujarat and Karnataka. Among the north-eastern states, wage gaps have reduced for Arunachal Pradesh, Manipur and Meghalaya. On the contrary, states where wage gaps have widened include Jammu & Kashmir, Himachal Pradesh, Haryana, Rajasthan, Uttar Pradesh, Bihar, Orissa, Maharashtra and other north-eastern states between 2004–05 and 2011–12. It is also observed that wage gaps are more in low-wage rate states like Maharashtra, Madhya Pradesh and Bihar, while it is low among the developed states. Again, comparing these wage gaps with the all-India figure, it is seen that developed states like Kerala, Punjab, Haryana and Jammu and Kashmir have lower wage gaps between farm and non-farm sectors. Reddy (2015) also found wage gap to be the least in Kerala, Punjab and Haryana while it is highest in Gujarat followed by Tamil Nadu.

The reasons behind low wage gap between agriculture and non-agriculture sector in high-wage rate states are attributed to inclusive growth where a higher level of urbanization and expansion of the non-farm sector in both GDP and employment have favourably affected rural wages. In other words, growth has not remained concentrated in urban areas but has trickled down to rural regions resulting in low rural-urban differences (Reddy, 2015; Jose, 2013). Again, the non-inclusive nature of growth in low-wage rate states has led to larger wage gaps between farm and non-farm sector. These states are also characterized by low agricultural productivity and huge dependence of labor force in agriculture. Therefore, growth of the non-farm sector has to occur substantially to absorb the surplus labor force, raise rural wages and reduce poverty (Reddy, 2015). It is thus observed that no such specific pattern of wage convergence has occurred for states over these three time periods as is pointed out by some literatures.

## **6.2. Methodology**

### **6.2.1. Data source**

We use the wage data available at employment-unemployment data of National Sample Survey Organization (NSSO) for 61<sup>st</sup> round (2004-05), 66<sup>th</sup> round (2009-10) and 68<sup>th</sup> round (2011-12). Wages are determined at NSSO state-region level. State-regions of the NSSO are group of districts that have similar geographical and demographic characteristics. Analysis is done at this level because it is the representative unit of analysis at the aggregate level. District level

analysis is not possible since the unit level data consists of central sample only while the state sample is not incorporated. As such many districts report zero sample units which is not an issue if the analysis is done at the state-region level. There are 78 state-region in 61<sup>st</sup> round while for 66<sup>th</sup> and 68<sup>th</sup> round, the number of state-regions increased to 88. Therefore, a panel data is formed which consists of 254 observations. Wage information is taken from block 6.3 of the data set which contains the current daily and current weekly activity status of the workers. The study utilized the wage data of casual laborers in the farm and non-farm sector pertaining to the activity status code 51. We have not included the wages of regular/salaried workers as they not only form a distinct group in terms of returns but also enjoy better social security benefits (Singhari & Madheswaran, 2017). Unlike the casual laborers, income of this section of the workers is less likely to be affected by wages prevailing in other sectors or there may be rigidities in the responsiveness of wages to changes in demand and supply conditions.

Average daily wage for each state region is obtained by first aggregating the number of days worked in a week by each worker and the total earning received by each worker belonging to that particular region. Then this aggregated weekly wage is divided by the aggregated total number of days worked in a week to get the average daily wage rate for each state region. Nominal wage of farm workers is deflated using consumer price index (CPI) for agricultural laborers and real non-farm wage is achieved by deflating nominal non-farm wages with CPI for industrial workers taking 2011–12 as the base year. The information on agricultural yield, irrigation intensity and cropping intensity are obtained from the Land Use Statistics (LUS) data source of the Directorate of Economics and Statistics, Government of India. These data are available at the district level and to obtain the estimates at the state-region level, simple average of the variables is estimated. These values were then aggregated at the state-region level. Further, the rainfall data is taken from the India Meteorological Department (IMD) of the Government of India.

### **Explanation of the various determinants used for analysis**

The dependent variables are the “real average daily casual farm wage” and “real average daily casual non-farm wage”. The independent/explanatory variables are elaborated below-

**Percentage share of ST, SC and OBC workers:** Workers belonging to Schedule Caste (SC), Schedule Tribe (ST) or Other Backward caste (OBC) mostly constitute the economically weaker section of the society (Das & Dutta, 2007). They are also endowed with a low level of human capital and have lesser access to land which contributes to their poor financial condition

and lower bargaining strength (Roy, 2020). They even constitute the majority of wage workers in rural India (Dutta, 2004). Therefore, the presence of larger number of caste-based workers is hypothesized to have a negative impact on wage rates in both markets.

**Percentage share of casual farm wage workers:** Share of casual farm wage workers can be regarded as a demand side determinant for farm wage rate as it reflects the actual amount of workers who are demanded in the labor market, given the presence of a surplus labor force. Moreover, Papola and Mishra (1980), demonstrate that in the presence of alternative employment opportunities like that in the non-farm sector, employment figures can be considered as a demand factor. Again, Bardhan (1973) also pointed out that the more the labor market is flooded with landless and marginal workers on one hand and the concentration of land in the hands of few farmers on the other, the stronger will be their monopsonistic power and more depressed will be the wages. Again, an increased concentration of workers in agriculture would mean a scarcity of labor in the rural non-agriculture sector and this might have a push effect on non-farm wages to attract workers out of agriculture. Therefore, for rural non-agricultural wages, this variable is expected to have a positive impact.

**Percentage share of illiterate, below primary and primary educated wage workers:** These are other supply-side determinants. Greater the share of illiterate workers among the daily wage earners, lower will be the returns as they are less endowed with a higher level of human capital and hence have lower bargaining power to raise wages in their favor. But if they are educated then their options increase leading to higher bargaining power and in turn higher wages.

**Percentage share of workers with higher secondary and above level of education:** This variable is incorporated in the non-farm wage equation. In addition to low educated workers, non-farm employment is also pursued by highly educated individuals. Also, being educated makes them capable of engaging in non-farm pursuits thereby lowering their dependence on agriculture (Roy, 2020). Therefore, higher the level of education, higher should be their bargaining ability which makes them capable of earning more income. Therefore, it is hypothesized that this variable would have a favorable impact on non-farm wages.

**Percentage share of landless, marginal and small land-owning households:** The size of land ownership is a major driver of occupational choice in rural regions (Bezu & Holden, 2014). The share of more landless households implies the presence of a greater share of wage workers which is expected to adversely affect wages in both markets. Moreover, participation

in both farm and non-farm labor markets is also high among workers belonging to landless, marginal and small land-owning households (Nagaraj et al, 2016).

**Percentage share of large landowning households:** In the absence of well-functioning land and credit markets (Vyas & Mathai, 1978; Abdulai & CroleRees, 2001), large land-owning households are more likely to focus on agriculture rather than utilizing their land for investing in non-agricultural activities. Therefore, the presence of large land-owning households would have a direct impact on demand for agricultural laborers which is expected to have a positive impact on wages of farm workers.

**Unemployment rate:** This variable is expected to have a negative impact on wages as regions with higher share of unemployment indicate the presence of surplus labor looking for work without any corresponding jobs.

**Average yield:** This variable is an important demand side determinant that is expected to augment farm wages directly. If a rise in agricultural yield is realized through greater use of labor-intensive techniques of production, then it is expected to augment wages of farm workers. But, if farm productivity is increased through the use of more modern techniques, then it may adversely affect wages. However, in this study, it is not possible to examine the relative strength of labor input versus mechanization due to the paucity of data. Furthermore, the influence of this variable on non-farm wages can occur indirectly by changing the overall labor availability in this sector.

**Cropping intensity:** Cropping intensity is a significant demand-side determinant that is hypothesized to have a positive influence on real wages. Higher the level of cropping intensity, more will be the demand for farm laborers which will have a favorable impact on wages. However, it is also pointed out by extant studies that if greater use of labor-saving techniques is implemented or if permanent workers are needed more compared to casual workers then demand for wage laborers would fall and hence would have a negative impact on wages (Himanshu & Kundu, 2016; Bardhan, 1973). Therefore, its impact on wages cannot be established a-priori. Also, this variable might act as an indirect demand side factor for non-farm wages resulting in a rise in wages in this sector as well. This will occur when an expansion in cropping results in a higher demand for not only farm laborers but also machines and inputs that need to be supplied by the non-farm sector. This might augment demand for more non-farm laborers who would be engaged in the production of farm inputs.

**Irrigation intensity:** This variable is another significant parameter that shifts both the demand for and supply of farm labor (Bardhan, 1973). Hence, a rise in irrigation intensity is hypothesized to have a direct and positive impact on farm wages.

**Percentage share of rural population:** The percentage share of rural population in a state-region is an indicator of the demographic pressure of population on land which is anticipated to have a dampening impact on both farm and non-farm wages.

**Percentage share of male wage workers:** This variable represents the share of male wage workers to total workers in a state-region. As male workers mostly dominate the rural labor market and also earn higher wages than female workers (Singhari & Madheswaran, 2018; Roy, 2020), the presence of more male workers is expected to have a favorable impact on rural wages.

**Rainfall deviation:** It is well known that agriculture forms a major source of livelihood in rural regions of developing countries, but it is also a sector that is vulnerable to weather variability. Since agriculture in India is mostly rain-fed, rainfall variability has a major role to play in farm production and income. Favourable weather conditions would significantly improve farm output whereas, adverse weather conditions might have a dampening impact on output and income. Further, in the absence of well-functioning markets for insurance, credit and other agricultural services, farm households tend to shift to other non-farm activities in order to cope up with the shock. A negative rainfall deviation would not only lower the wages and income of farm workers due to a fall in production but will even push them to shift to other non-farm activities. As a result of this shift of workers towards the non-farm sector, wages here would also likely to fall due to excess supply of labor. On the contrary, a positive rainfall deviation would attract more workers as well as push up the wages because more workers will be required on land now. Due to a greater shift of workers towards agriculture, wages in the non-farm sector will start increasing as a response to prevent workers from further shifting towards the former sector. Hence weather condition, measured through rainfall deviation is an important channel through which farm and non-farm wages can be linked. Extant studies (Demeke & Zeller, 2012; Rose, 2001; Kijima et al, 2006) have also measured weather variability in terms of rainfall deviation from the long-run average. To arrive at the deviation of rainfall for each survey round from its long-term mean, we first estimated the weighted average rainfall for ten years preceding the survey rounds and calculated the deviation of rainfall for each survey round from their long-term average rainfall values. Following Mahajan

(2017), we constructed a categorical variable representing rainfall shock from the rainfall deviation variable where it equals one if the rainfall deviation is above 80 percent, minus one if it is below 20 percent and zero if it lies between 20 to 80 percent. This variable indicates that any rise or fall in rural farm and non-farm wages is due to a positive or negative rainfall shock compared to normal deviation.

**Year dummy:** The year dummies are included to examine the time effect on wages.

**Table 6. 6 Description of dependent and independent variables used for analysis**

<b>Variables</b>	<b>Description</b>	<b>mean</b>	<b>SD</b>
<b>Dependent variables</b>			
<b>Real rural farm wage</b>	Real average daily farm wage	114.49	44.952
<b>Real rural nonfarm wage</b>	Real average daily non- farm wage	147.92	49.850
<b>Explanatory variables</b>			
<b>Percent ST</b>	Percent share of ST wage workers	22.711	28.292
<b>Percent SC</b>	Percent share of SC wage workers	28.741	19.991
<b>Percent OBC</b>	Percent share of OBC wage workers	31.255	21.178
<b>Percent illiterate</b>	Percent share of illiterate workers	39.590	18.798
<b>Percent BP &amp; P</b>	Percent share of workers with below primary & primary education	32.189	14.254
<b>Percent HS &amp; above</b>	Percent share of workers with HS and above education level	3.276	4.162
<b>Percent landless</b>	Percentage of landless households	6.757	8.673
<b>Percent marginal</b>	Percentage share of marginal landowning households	73.609	18.903
<b>Percent small</b>	Percentage share of small land-owning household	10.215	7.614
<b>Percent large</b>	Percentage of large landowning household	0.312	0.667
<b>Percent farm workers</b>	Percentage share of farm wage workers to total rural wage workers	56.139	28.992
<b>Unemployment rate</b>	Share of unemployed persons to total labour force per 1000	83.039	56.244

<b>Percent rural population</b>	Percent share of rural population to total population in a state-region	72.153	17.457
<b>Average yield</b>	Average agricultural yield	538.15	1497.61
<b>Cropping intensity</b>	It is obtained by dividing gross cropped area by net sown area	1.166	0.565
<b>Irrigation intensity</b>	It is obtained by dividing gross irrigated area by the gross cropped area.	0.305	0.283
<b>Percent male worker</b>	Percentage share of male wage workers	70.476	17.955
<b>Rainfall deviation</b>	Average rainfall deviation of survey years from its long run (10 years) mean.	11.289	289.207

### 6.2.2. Econometric model

The link between farm and non-farm wages can occur through a direct and an indirect channel. The direct relationship may establish when an increase (decrease) in farm wages, lowers (raises) the supply of workers in the non-farm sector, resulting in a rise (fall) in non-farm wages. Similarly, if non-farm wage increases (decreases), it will put pressure on the supply of farm workers resulting in a rise (fall) in farm wages as well. Again, farm and non-farm wages can be related indirectly also. For instance, positive rainfall shocks lead to an increase in demand for farm labor leading to a rise in farm wages. This increase in farm labor demand will also increase non-farm wages. Further, if there is a negative rainfall shock, it will reduce demand for farm labor resulting in a fall in farm wages. As farm wage decreases, it will also have a dampening impact on non-farm wages as more labor will shift towards the latter sector creating a situation of surplus labor force. This demonstrates the indirect effect of rainfall on farm and non-farm wages. We look for evidence of these two paths. First, we analyze the indirect channel. To estimate this linkage, we focus on the role of rainfall shock as our variable of interest and it explains the pathway through which wages in both markets are related. Another variable of interest is the “share of farm wage worker” variable which shows how much farm wage workers are on demand in the labor market and which is also a crucial factor that affects both farm and non-farm wages. First, we estimate the effect of rainfall deviation on real farm wages controlling for other determinants. Secondly, we again estimate the effect of rainfall shock on real non-farm wages, keeping other factors constant. Thirdly, we further regress the effect of rainfall deviation on the share of farm wage workers to see whether rainfall

has any direct impact on the demand for wage workers in agriculture. A positive and significant impact of rainfall deviation on farm wage and share of farm wage workers would establish that in good rainfall years, demand for agricultural labor also increases which leads to a rise in farm wages. Again, a positive and significant impact of rainfall deviation on non-farm wages would indicate that increased farm labor demand results in a simultaneous wage increase for the non-farm workers to keep them from leaving the latter for the former. However, a negative and significant result would indicate that adverse weather situation lowers the demand for wage workers which leads to a fall in wages of both farm and non-farm workers.

The three regression equations are given below.

### Equation 6.1

Real Farm – wage

$$\begin{aligned}
 &= \alpha_0 + \alpha_1 \text{Share of ST workers} + \alpha_2 \text{Share of SC workers} \\
 &+ \alpha_3 \text{Share of OBC workers} + \alpha_4 \text{share of illiterate workers} \\
 &+ \alpha_5 \text{share of workers with below primary and primary education} \\
 &+ \alpha_6 \text{percentage share of farm wage workers} \\
 &+ \alpha_7 \text{percentage share of male wage workers} \\
 &+ \alpha_8 \text{percentage of landless households} \\
 &+ \alpha_9 \text{percentage of marginal landowning households} \\
 &+ \alpha_{10} \text{Percentage of small landowning households} \\
 &+ \alpha_{11} \text{percentage of large landowning households} \\
 &+ \alpha_{12} \text{unemployment rate} + \alpha_{13} \text{average yield} + \alpha_{14} \text{cropping intensity} \\
 &+ \alpha_{15} \text{irrigation intensity} + \alpha_{16} \text{percentage of rural population} \\
 &+ \alpha_{17} \text{rainfall deviation} + \alpha_{18} \text{year dummy} + \varepsilon
 \end{aligned}$$

### Equation 6.2

Real non – farm wage

$$\begin{aligned} &= \beta_0 + \beta_1 \text{Share of ST workers} + \beta_2 \text{Share of SC workers} \\ &+ \beta_3 \text{Share of OBC workers} + \beta_4 \text{share of illiterate workers} \\ &+ \beta_5 \text{share of workers with below primary and primary education} \\ &+ \beta_6 \text{share of workers with HS and above level of education} \\ &+ \beta_7 \text{percentage share of farm wage workers} \\ &+ \beta_8 \text{percentage share of male wage workers} \\ &+ \beta_9 \text{share of landless households} \\ &+ \beta_{10} \text{share of marginal landowning households} \\ &+ \beta_{11} \text{share of small landowning households} + \beta_{12} \text{cropping intensity} \\ &+ \beta_{13} \text{average yield} + \beta_{14} \text{unemployment rate} \\ &+ \beta_{15} \text{Percentage of rural population} + \beta_{16} \text{rainfall deviation} + \beta_{17} \\ &+ \text{year dummy} + \varepsilon \end{aligned}$$

### Equation 6.3

Share of farm wage workers

$$\begin{aligned} &= \gamma_0 + \gamma_1 \text{rainfall deviation} + \gamma_2 \text{Share of ST workers} \\ &+ \gamma_3 \text{Share of SC workers} + \gamma_4 \text{Share of OBC workers} \\ &+ \gamma_5 \text{share of illiterate workers} \\ &+ \gamma_6 \text{share of workers with below primary and primary education} \\ &+ \gamma_7 \text{percentage of landless households} \\ &+ \gamma_8 \text{percentage of marginal landowning households} \\ &+ \gamma_9 \text{Percentage of small landowning households} \\ &+ \gamma_{10} \text{percentage of large landowning households} \\ &+ \gamma_{11} \text{percentage of rural population} + \gamma_{12} \text{unemployment rate} \\ &+ \gamma_{13} \text{average yield} + \gamma_{14} \text{cropping intensity} + \gamma_{15} \text{irrigation intensity} + \varepsilon \end{aligned}$$

### 6.3. Empirical findings

We first ran a Hausman test to choose between fixed effect or random effect model and the test suggested that fixed effect estimation is suitable for our analysis compared to random effect estimation. The result is shown below-

$H_0$  = There is no covariance between the unobserved time-invariant effects and the time-varying explanatory variables, i.e. random effect is suitable than fixed effect.

$H_1$  = Fixed effect is suitable than random effect

**For real rural farm wage**

**Chi2(18) = 94.08** Probability>chi2= 0.0000

**For real rural non-farm wage**

**Chi2(19) = 166.10** Probability>chi2= 0.0000

The significant P-values indicate rejection of the null hypothesis which implies the suitability of fixed effect estimation.

Now, tables 6.7 and 6.8 below provide the findings of the effect of rainfall deviation on real farm and non-farm wages and the share of farm wage workers.

**Table 6. 7 Regression estimates of real rural average daily farm wage and non-farm wage**

Model 1		Model 2	
Variables		Variables	
<b>Dependent variable: Real farm wage</b>		<b>Dependent variable: Real non-farm wage</b>	
Rainfall deviation category	-5.375*** (2.741)	Rainfall deviation category	-3.820*** (2.261)
Percent ST	0.714** (0.289)	Percent ST	-0.146 (0.327)
Percent SC	0.452 (0.307)	Percent SC	0.322 (0.254)
Percent OBC	0.109 (0.202)	Percent OBC	-0.309 (0.254)
Percent illiterate	0.283 (0.175)	Percent illiterate	0.687** (0.272)
Percent BP & P	0.589*** (0.342)	Percent BP & P	1.097* (0.273)
Percent HS & above	-	Percent HS & above	1.136** (0.438)
Percent landless	-1.007 (0.613)	Percent landless	0.115 (0.547)
Percent marginal	-0.701 (0.572)	Percent marginal	-0.148 (0.262)
Percent small	-1.642*** (0.971)	Percent small	0.049 (0.355)
Percent large	-0.930 (5.541)	Percent large	-
Percent rural population	0.090 (0.277)	Percent rural population	-0.180 (0.379)
Unemployment rate	-0.185* (0.066)	Unemployment rate	-0.124** (0.048)
Percent farm workers	0.519* (0.192)	Percent farm workers	0.312** (0.155)

Percent male workers	0.796* (0.268)	Percent male workers	-0.171 (0.204)
Average yield	-0.001 (0.002)	Average yield	-0.002 (0.003)
Cropping intensity	-26.850* (8.883)	Cropping intensity	10.26 (6.807)
Irrigation intensity	97.773* (27.303)	Irrigation intensity	-
Year (2004–05= base year)		Year (2004–05= base year)	
2009	17.165* (3.824)	2009	33.898* (4.917)
2011	33.807* (6.264)	2011	67.898* (7.405)
Constant	34.161 (58.085)	Constant	66.706 (49.094)
Number of observations	249	Number of observations	253
Number of groups	88	Number of groups	88
R-squared		R-squared	
Within	0.6339	Within	0.7263
Between	0.0712	Between	0.2464
Overall	0.0001	Overall	0.0147
F (19,87)	14.66	F (18,87)	26.45
Probability> F	0.0000	Probability> F	0.0000

Notes: Figures in parenthesis are robust standard errors. \*, \*\* and \*\*\* indicates significance at 1%, 5% and 10% level.

**Table 6. 8 Effect of rainfall deviation on the share of farm wage workers**

Dependent variable: Share of farm wage workers <sup>13</sup>	Coefficient	Robust Standard Error
<b>Variables</b>		
<b>Rainfall deviation category</b>	-1.153	2.019
Percent ST	0.069	0.121
Percent SC	0.193***	0.098
Percent OBC	0.380*	0.137
Percent illiterate	-0.074	0.178
Percent BP & P	0.056	0.135
Percent landless	-0.102	0.195
Percent marginal	0.039	0.156
Percent small	0.065	0.383
Percent large	-1.112	1.666
Percent rural population	0.193	0.16
Unemployment rate	-0.019	0.029
Average yield	-0.001	0.001

<sup>13</sup> We have even estimated the above-mentioned three regression equations with rainfall deviation and its square term. Also segregated the rainfall deviation into positive and negative rainfall deviation variables but we could not statistically establish the effect of these different aspects of rainfall deviation values on the demand for farm wage workers, which is the dependent variable. The results are attached in the appendix of this chapter.

Cropping intensity	5.932	5.697
Irrigation intensity	-28.510	19.633
Year (2004–05= base year)		
2009	-8.964*	2.24
2011	-15.189*	3.752
Constant	34.027*	12.466
Number of observations	254	
Number of groups	88	
R-squared		
Within	0.3491	
Between	0.0261	
Overall	0.0573	
F (19,87)	9.90	
Probability> F	0.0000	

Notes: \*, \*\* and \*\*\* indicate significance at 1%, 5% and 10% levels.

We observe from Models 1 and 2 in table 6.7 that a negative rainfall shock adversely affects both rural farm and non-farm wages. This indicates that during periods of adverse weather conditions, agriculture experiences a fall in production which also lowers the demand for wage workers. Low demand for wage workers results in a fall in wages which in turn pushes farm laborers to move towards non-farm employment opportunities. This, in turn, lowers the wages of non-farm laborers as more workers are now available compared to what is demanded. Also, we did not find a positive impact of rainfall deviation on farm and non-farm wages. This might be due to the presence of a high unemployment rate which implies that even if there is an increase in the demand for wage workers, availability of surplus labor would not result in a significant increase in wages.

However, the findings from table 6.8 do not imply that adverse weather conditions also affect the demand for farm wage workers as rainfall shock has no significant impact on the share of farm wage worker's variable. From this, we can state that the impact of rainfall on both farm and non-farm wages is not through its effect on the demand for wage workers. Therefore, the channel through which adverse weather conditions can affect farm and non-farm wages by influencing the demand for labor cannot be established in our analysis. Further, we observed that the variable demand for farm wage workers has a positive and significant impact on both real farm and non-farm wages. This variable also represents a demand side indicator when alternative employment opportunities are available (Papola & Mishra, 1980). The results show that a one percent increase in the share of farm laborers increases farm and non-farm wages by rupees 0.519 and 0.312 respectively.

Among other covariates of real farm wages, we observe that as the ‘share of male wage workers’ increases by 1 percent, farm wage also increases by rupees 0.796. This suggests that when the share of male wage workers is higher, it also increases the average farm wage rate. Further, workers having an education below primary and primary level have a positive and significant impact on farm wages. Wage increases by 0.589 rupees with a 1 percent increase in the share of educated workers indicating that those who have education can bargain for better returns. Another determinant that exhibits a positive and significant influence on farm wage is the share of ST wage workers. The share of SC and OBC workers is also positive but their effect is insignificant. One argument is that low-caste workers have historically been a major source of labor supply on land since upper-caste households were traditionally the owners of land (Lanjouw & Shariff, 2004; Misra, 2014; Mishra & Singh, 2019). As they are the major source of labor in agriculture, they can collectively bargain for a rise in wages as their share increases which might have been depicted in our findings. Further, real farm wage decreases when there is a rise in the share of small land-owning households. Since, a major share of rural wage laborers come from landless, marginal and small land-owning households, therefore, a rise in the share of small land-owned households implies a higher flow of wage workers which is likely to have a dampening impact on wages.

Among the variables considered as demand-side determinants, irrigation intensity tends to push up wages and its impact is found to be highest among all the other determinants. Irrigation being an important shift parameter leads to an upward movement of both demand and supply of labor due to higher yields and hence raises the returns to labor (Bardhan, 1973). A one-unit increase in irrigation intensity raises farm wages by rupees 97.77. On the other hand, cropping intensity is found to have a negative impact on the wages of casual farm workers. Himanshu and Kundu (2016) also found an adverse impact of cropping intensity on agricultural wages, but the result was not statistically significant. In our analysis, a negative influence of this variable on wages can be attributed to either increased use of labour-saving production techniques, which has reduced demand for temporary farm labourers. Or it may also happen that as cropping intensity increases, permanent workers are more in demand as they need to be available on land for a major part of the year which might adversely affect the demand for casual workers. The unemployment rate also has an adverse impact on wages. Year dummies show a continuous rise in real farm wages during 2009–10 and 2011–12. Farm wage increases from rupees 17 to rupees 33 during this period.

Now, factors that affect rural non-farm wages apart from rainfall deviation and the share of farm wage workers include the share of illiterate workers, workers who are educated till primary level, HS and beyond. Among them, the effect on wages is highest for those with HS and above level of education. This demonstrates that education not only increases employment options but also makes him/her capable of earning higher returns. Unemployment rate as expected has a negative impact on wages depicting a situation where the supply of workers is more than what is needed resulting in a fall in wage rates. Year dummies also reflect a significant rise in the wages of non-farm casual workers over time. Non-farm wages increase from rupees 33 to rupees 67 during 2009–10 and 2011–12 respectively and this increase in non-farm wages is higher than that of farm wages.

Now, we examine whether farm and non-farm wages have any direct influence on each other through the demand for farm wage workers. To do this, we include farm wage as a determinant in the non-farm wage equation and non-farm wage as a determinant in the farm wage equation along with other covariates. The regression equations are given below-

#### Equation 6.4.

$$\begin{aligned}
 \text{Real Farm – wage} &= \alpha_0 + \alpha_1 \text{ Real Non – farm wage} + \alpha_2 \text{ Share of ST workers} \\
 &+ \alpha_3 \text{ Share of SC workers} + \alpha_4 \text{ Share of OBC workers} \\
 &+ \alpha_5 \text{ share of illiterate workers} \\
 &+ \alpha_6 \text{ share of workers with below primary and primary education} \\
 &+ \alpha_7 \text{ percentage share of farm wage workers} \\
 &+ \alpha_8 \text{ percentage share of male wage workers} \\
 &+ \alpha_9 \text{ percentage of landless households} \\
 &+ \alpha_{10} \text{ percentage of marginal landowning households} \\
 &+ \alpha_{11} \text{ Percentage of small landowning households} \\
 &+ \alpha_{12} \text{ percentage of large landowning households} \\
 &+ \alpha_{13} \text{ unemployment rate} + \alpha_{14} \text{ average yield} + \alpha_{15} \text{ cropping intensity} \\
 &+ \alpha_{16} \text{ irrigation intensity}^{14} + \alpha_{17} \text{ percentage of rural population} \\
 &+ \alpha_{18} \text{ rainfall deviation} + \alpha_{19} \text{ year dummy} + \varepsilon
 \end{aligned}$$

<sup>14</sup> Irrigation intensity is considered as an IV for real farm wage.

## Equation 6.2

Real non – farm wage

$$\begin{aligned}
 &= \beta_0 + \beta_1 \mathbf{Real\ farm\ wage} + \beta_2 \text{Share of ST workers} \\
 &+ \beta_3 \text{Share of SC workers} + \beta_4 \text{Share of OBC workers} \\
 &+ \beta_5 \text{share of illiterate workers} \\
 &+ \beta_6 \text{share of workers with below primary and primary education} \\
 &+ \beta_7 \mathbf{share\ of\ workers\ with\ HS\ and\ above\ level\ of\ education}^{15} \\
 &+ \beta_8 \text{percentage share of farm wage workers} \\
 &+ \beta_9 \text{percentage share of male wage workers} \\
 &+ \beta_{10} \text{share of landless households} \\
 &+ \beta_{11} \text{share of marginal landowning households} \\
 &+ \beta_{12} \text{share of small landowning households} + \beta_{13} \text{cropping intensity} \\
 &+ \beta_{14} \text{average yield} + \beta_{15} \text{unemployment rate} \\
 &+ \beta_{16} \text{Percentage of rural population} + \beta_{17} \text{rainfall deviation} + \beta_{18} \\
 &+ \text{year dummy} + \varepsilon
 \end{aligned}$$

The regression results are given below in table 6.9 and 6.10.

**Table 6. 9 Determinants of real farm wage**

Variables	Coefficients	Robust S. E <sup>16</sup>
<b>Real non-farm wage</b>	<b>0.220*</b>	<b>0.068</b>
Percent ST	0.725*	0.270
Percent SC	0.460	0.305
Percent OBC	0.214	0.194
Percent illiterate	0.177	0.184
Percent BP & P	0.414	0.355
Percent landless	-0.975	0.611
Percent marginal	-0.675	0.558
Percent small	-1.657***	0.958
Percent large	-1.389	5.403
Percent rural population	0.080	0.246
Unemployment rate	-0.157**	0.067
Percent farm workers	0.436**	0.193
Percent male workers	0.829*	0.292
Average yield	-0.0002	0.001
Cropping intensity	-26.035*	8.758

<sup>15</sup> share of workers with HS and above level of education is taken as an IV for real non-farm wage.

<sup>16</sup> S.E. stands for Standard Errors

Irrigation intensity	87.396*	26.518
Rainfall deviation category	-4.228	2.586
Year (2004-05= base year)		
2009	9.557***	4.817
2011	18.467**	8.235
Constant	16.818	52.51
Number of observations	249	
Number of groups	88	
R-squared		
Within	0.6522	
Between	0.000	
Overall	0.0561	
F (21,87)	21.32	
Probability> F	0.000	

Notes: Figures in parenthesis are robust standard errors. \*, \*\* and \*\*\* indicates significance at 1%, 5% and 10% level.

The findings show that real non-farm wages have a significant positive impact on real farm wages. A one-rupee increase in non-farm wages result in a 0.220 rupee increase in farm wages. Also, the result is highly significant at 1 percent level. This indicates that any rise in non-farm wage acts as a pull factor for daily wage workers in agriculture which results in a shift of workforce from farm to non-farm sector. This shift of workers creates a situation of labor scarcity in agriculture resulting in an increase in farm wages as well. As pointed out by Bardhan (1973), wages prevailing in sectors outside agriculture is an important supply-side determinant, especially for landless and marginal farm workers. The favourable impact of a rise in non-farm wage on farm wage can also be attributed in part to the implementation of MGNREGA post-2005, which forms a major part of the rural non-farm sector. Several studies (Narayanamoorthy & Bhattarai, 2013; Gulati, 2014) found positive growth in real agricultural wages of both males and females in the post-MGNREGA period compared to the pre-MGNREGA period. By devoting more than 51 percent of the work to water conservation, irrigation, drought proofing and flood control under MGNREGA, farm production conditions have improved which might have resulted in a rise in demand for farm workers and thus on wages. Gulati (2014) even points out that this employment guarantee scheme has set a base price for workers and has improved their bargaining power. Wages also experienced a high growth rate even in states having fewer irrigation facilities (Narayanamoorthy & Bhattarai, 2013). Another significant parameter can be ascribed to the expansion of the construction sector as the sector registered quadrupled growth in employment from 3.1 percent in 1993–94 to 9.6 percent in 2009–10 (Gulati et al, 2014).

Here, we observe that with the inclusion of real non-farm wage variable, the effect of other crucial determinants has remained unchanged, except for the variable ‘percentage share of workers with below primary and primary level’ and rainfall deviation which became insignificant.

**Table 6. 10 Determinants of real non-farm wage**

<b>Variables</b>	<b>Coefficients</b>	<b>Robust S.E</b>
<b>Real farm wage</b>	<b>0.243*</b>	<b>0.087</b>
Percent ST	-0.194	0.349
Percent SC	-0.123	0.296
Percent OBC	-0.459	0.297
Percent illiterate	0.461	0.315
Percent BP & P	0.767**	0.360
Percent HS & above	0.644***	0.361
Percent landless	-0.014	0.529
Percent marginal	-0.043	0.239
Percent small	0.369	0.368
Percent rural population	-0.037	0.353
Unemployment rate	-0.076	0.053
Percent farm workers	0.235	0.156
Percent male workers	-0.362	0.321
Average yield	-0.001	0.003
Cropping intensity	9.197	6.671
Rainfall deviation category	-3.607***	2.069
Year (2004-05= base year)		
2009	29.201*	5.379
2011	60.277*	8.042
Constant	76.441	66.026
Number of observations	249	
Number of groups	88	
R-squared		
Within	0.7503	
Between	0.0003	
Overall	0.1862	
F (21,87)	26.25	
Probability> F	0.000	

*Notes: Figures in parenthesis are robust standard errors. \*, \*\* and \*\*\* indicates significance at 1%, 5% and 10% level.*

We found that with the inclusion of real farm wage, the effect of the variables- share of farm wage workers, the share of illiterate workers and the unemployment rate became insignificant although the effect of other determinants remains unchanged. However, real non-farm wage responds positively to a rise in farm wages and a rise in farm wage itself reflects a growing demand for wage workers due to which inclusion of the farm wage variable resulted in an insignificant impact of the farm wage worker variable. The results show that a one rupee rise

in farm wages increases non-farm wages by rupees 0.243. This can be attributed to an overall revival in the agrarian sector after experiencing severe distress in the early 2000s (Gulati et al, 2014). Rainfall deviation also has a positive influence on non-farm wages. What we observe from this analysis is that the linkage between rural farm and non-farm wages is direct. The direct relation is established when a rise in farm wage increases the demand for farm wage workers and this creates a situation of labor shortages in the non-farm sector. To prevent workers from moving towards agriculture, wages in the non-farm sector also rises. The indirect channel through which farm and non-farm wages can be related is through factors that affect the demand for farm labourers such as rainfall deviation leading to changes in farm and non-farm wages. However, this indirect relationship could not be established.

Again, as pointed out by Bardhan (1973), there may be the issue of endogeneity. The endogeneity issue may arise due to the omission of some possible paths through which farm and non-farm wages are related which are absent in the present model. To test whether farm and non-farm wages are endogenous, we have taken irrigation intensity as an instrumental variable (IV) for real farm wages and the share of workers with HS and above education level as an instrumental variable for real non-farm wages.

The strength of the IVs is shown in the appendix of this chapter with the help of a falsification test. From the falsification test, we see that irrigation intensity has a significant impact on real farm wages while it has no impact on real non-farm wages when we control for other covariates. Similarly, the share of higher secondary and above-educated workers has a positive and significant impact on real non-farm wages without having any impact on real farm wages.

Now, we followed the regression-based test provided by Hausman and given in Wooldridge (2015) to identify the presence of endogeneity in the model. The test is a two-stage procedure where one of the dependent variables, say, farm wage is regressed on all the exogenous variables (known as the reduced form equation) and from this, the predicted residual value is obtained. Now, in the second stage, this predicted residual is included as an explanatory variable in the non-farm wage equation along with other determinants and also incorporates the farm wage rate variable. The significance of this error variable implies that farm wage is endogenous and it is exogenous when the coefficient of the error term is insignificant. Similar steps are being followed for testing the endogeneity of non-farm wages. From our findings in table 6.9, we found that the fitted residual values are not significant implying that both farm and non-farm wages are exogenous. The test is given below.

Model 1 shows whether real farm wage is endogenous or not and Model 2 shows whether real non-farm wage is endogenous or not.

**Table 6. 11 Endogeneity test of real rural average daily farm and non-farm wage**

Model 1		Model 2	
Variables		Variables	
<b>Dependent variable: Real non-farm wage</b>		<b>Dependent variable: Real farm wage</b>	
<b>Real farm wage</b>	0.456** (0.23)	Real non-farm wage	1.095*** (0.597)
<b>Farm wage residual</b>	-0.241 (0.245)	<b>Non-farm wage residual</b>	-0.889 (0.601)
Percent ST	-0.381 (0.337)	Percent ST	0.899* (0.293)
Percent SC	-0.239 (0.309)	Percent SC	0.201 (0.328)
Percent OBC	-0.507*** (0.264)	Percent OBC	0.552 (0.343)
Percent illiterate	0.387 (0.255)	Percent illiterate	-0.364 (0.438)
Percent BP & P	0.582** (0.292)	Percent BP & P	-0.358 (0.557)
Percent HS & above	0.373 (0.672)	Percent HS & above	-
Percent landless	0.200 (0.421)	Percent landless	-1.178* (0.397)
Percent marginal	0.106 (0.304)	Percent marginal	-0.626** (0.28)
Percent small	0.699 (0.578)	Percent small	-1.765* (0.471)
Percent large	-	Percent large	-2.999 (3.647)
Percent rural population	-0.012 (0.305)	Percent rural population	0.123 (0.299)
Unemployment rate	-0.037 (0.068)	Unemployment rate	-0.042 (0.094)
Percent farm workers	0.139 (0.172)	Percent farm workers	0.130 (0.25)
Percent male workers	-0.534** (0.257)	Percent male workers	0.948* (0.191)
Average yield	-0.001 (0.002)	Average yield	0.002 (0.002)
Cropping intensity	9.867 (6.346)	Cropping intensity	-23.705* (7.909)
Irrigation intensity	-	Irrigation intensity	43.700 (36.645)
Rainfall deviation category	-2.909 (2.891)	Rainfall deviation category	-0.144 (3.948)
Year (2004-05= base year)		Year (2004-05= base year)	
2009	26.304*	2009	-22.194

	(5.498)		(22.087)
2011	53.712*	2011	-42.955
	(9.499)		(42.343)
Constant	70.193	Constant	-36.157
	(47.919)		(60.294)
Number of observations	249	Number of observations	249
Number of groups	88	Number of groups	88
R-squared		R-squared	
Within	0.7520	Within	0.6575
Between	0.0025	Between	0.0007
Overall	0.1565	Overall	0.0531
F (21,87)	21.38	F (21,140)	12.80
Probability> F	0.000	Probability> F	0.000

Notes: Figures in parenthesis are robust standard errors. \*, \*\* and \*\*\* indicates significance at 1%, 5% and 10% level.

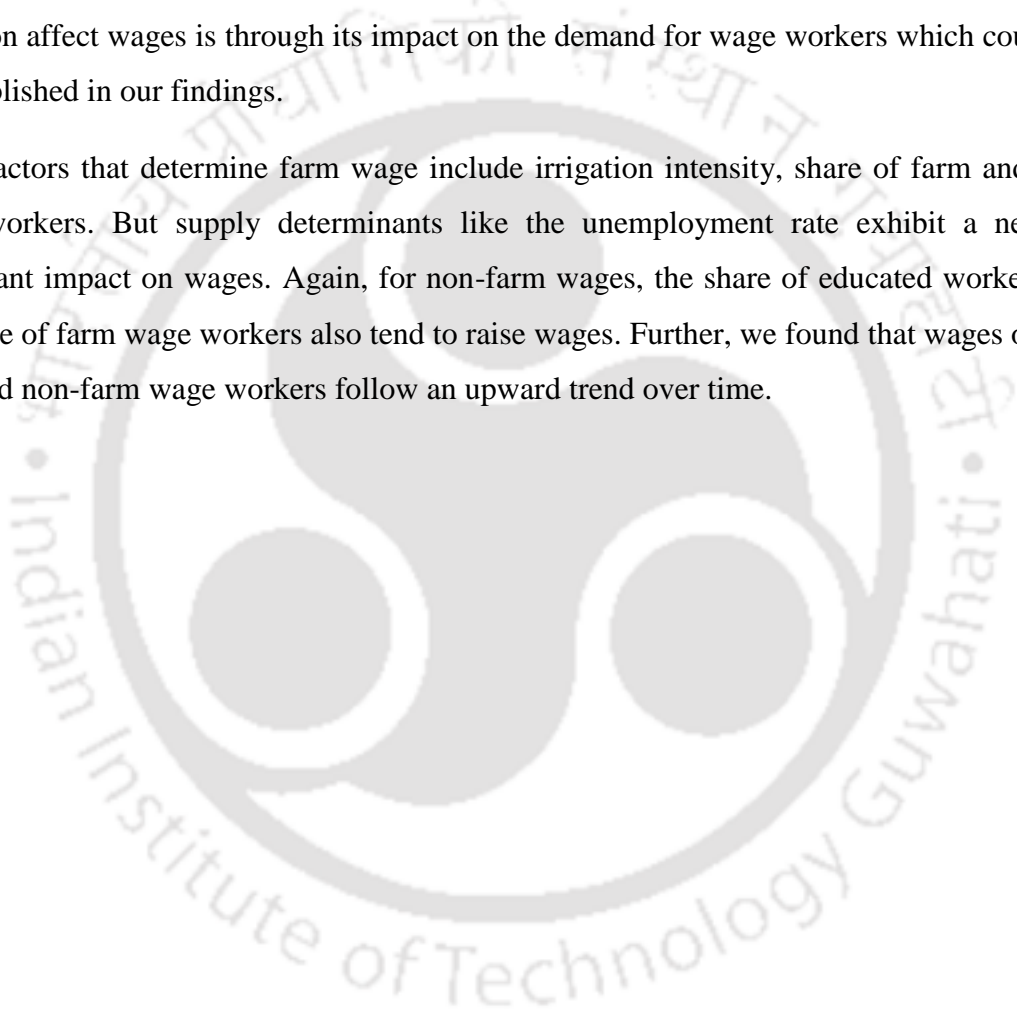
From Model 1 and Model 2 of table 6.11, it is found that the fitted residual values of farm wage and non-farm wage obtained from the reduced form equation have no significant impact on the dependent variables. Therefore, it is evident that both farm and non-farm wages are not endogenous which implies that increase in farm wage raises the demand for farm labor which in turn also increases the wages of non-farm labor. Similarly, a rise in non-farm wages adversely affects the supply of labor in agriculture thereby raising the farm wages as well.

#### 6.4. Summing up

This chapter attempted to empirically examine the nature of the interlinkage between farm and non-farm labor markets through their influence on wages. Due to a gradual decline in agricultural productivity and a shortfall of employment opportunities in the urban formal sector, several studies (Vyas & Mathai, 1978) have claimed the necessity of an expansion of rural non-farm employment to absorb surplus labor force leading to a tightening of the rural labor market and hence affecting wages. Therefore, some studies (Narayanamoorthy & Bhattarai, 2013, Kumar et al, 2020) have found a rise in farm wages due to the expansion of non-farm employment opportunities, particularly in the construction sector. Other studies like that of Gulati et al (2014), however, contend that growth-induced factors such as construction GDP and agriculture GDP are more favorable for increasing farm wages. However, these studies have not taken into account the fact that non-farm wages may be determined by existing farm wages in regions where surplus labor is available. Wages in the non-farm sector will then be as low as wages in the farm sector in this case. Our findings demonstrate a direct positive relation between rural farm and non-farm wages where a rise in farm wage also significantly

raises the non-farm wage. Also, when farm wage is controlled for in the non-farm wage equation, the share of farm wage workers is not significant which implies that factors affecting the demand for farm wage workers have no impact on non-farm wage when farm wage is controlled. Similarly, an increase in non-farm wages also positively affects farm wages because with a rise in non-farm wage, workers tend to shift from farm to non-farm which lowers the supply of workers in agriculture. Hence, farm wages also increase so as to prevent workers from moving away from agriculture. Further, we also observe that rainfall deviation had an adverse impact on both farm and non-farm wages. However, the channel through which rainfall deviation affect wages is through its impact on the demand for wage workers which could not be established in our findings.

Other factors that determine farm wage include irrigation intensity, share of farm and male wage workers. But supply determinants like the unemployment rate exhibit a negative significant impact on wages. Again, for non-farm wages, the share of educated workers and the share of farm wage workers also tend to raise wages. Further, we found that wages of both farm and non-farm wage workers follow an upward trend over time.



## Appendix 6A

**Table 6A. 1 Effect of rainfall deviation and rainfall deviation square on real farm wage, real non-farm wage**

Variables	Dependent variable: Real farm wage		Dependent variable: Real non-farm wage	
	Model 1	Model 2	Model 3	Model 4
<b>Rainfall deviation</b>	<b>-0.015*</b> (0.005)	<b>-0.014*</b> (0.005)	<b>-0.009**</b> (0.004)	<b>-0.008***</b> (0.005)
<b>Rainfall deviation square</b>	-	<b>0.0001**</b> (0)	-	<b>0.0000</b> (0)
<b>Percent ST</b>	0.715** (0.287)	0.739** (0.286)	-0.149 (0.328)	-0.144 (0.33)
<b>Percent SC</b>	0.419 (0.304)	0.445 (0.3)	0.316 (0.257)	0.316 (0.256)
<b>Percent OBC</b>	0.085 (0.202)	0.116 (0.197)	-0.316 (0.256)	-0.306 (0.261)
<b>Percent illiterate</b>	0.248 (0.176)	0.255 (0.174)	0.684** (0.271)	0.683** (0.268)
<b>Percent BP &amp; P</b>	0.614*** (0.345)	0.622*** (0.344)	1.109* (0.274)	1.114* (0.274)
<b>Percent HS &amp; above</b>	-	-	1.158* (0.431)	1.174* (0.438)
<b>Percent landless</b>	-0.979 (0.601)	-0.988 (0.595)	0.159 (0.539)	0.162 (0.54)
<b>Percent marginal</b>	-0.625 (0.552)	-0.663 (0.553)	-0.098 (0.255)	-0.103 (0.254)
<b>Percent small</b>	-1.543 (0.954)	-1.54 (0.941)	0.131 (0.353)	0.141 (0.355)
<b>Percent large</b>	-1.309 (5.547)	-2.03 (5.799)	-	-
<b>Percent rural population</b>	0.113 (0.278)	0.099 (0.28)	-0.194 (0.375)	-0.201 (0.384)
<b>Unemployment rate</b>	-0.177* (0.065)	-0.179* (0.064)	-0.119** (0.048)	-0.120** (0.048)
<b>Percent farm workers</b>	0.521* (0.188)	0.522* (0.188)	0.317** (0.152)	0.318** (0.152)
<b>Percent male workers</b>	0.802* (0.27)	0.829* (0.27)	-0.161 (0.204)	-0.153 (0.205)
<b>Average yield</b>	-0.001 (0.002)	-0.001 (0.002)	-0.002 (0.003)	-0.002 (0.003)
<b>Cropping intensity</b>	-27.158* (8.869)	-27.307* (8.996)	9.949 (6.561)	9.806 (6.555)
<b>Irrigation intensity</b>	96.693* (26.601)	96.178* (26.675)	-	-
<b>Year (2004–05= base year)</b>				
<b>2009</b>	17.169* (3.709)	17.314* (3.793)	34.165* (4.884)	34.188* (4.929)
<b>2011</b>	33.151* (6.096)	32.813* (6.233)	67.951* (7.381)	67.757* (7.421)

<b>Constant</b>	28.013 (56.607)	26.859 (56.117)	61.797 (48.896)	61.29 (48.939)
<b>Number of observations</b>	249	249	253	253
<b>Number of groups</b>	88	88	88	88
<b>R-squared</b>				
<b>Within</b>	0.6400	0.6449	0.7276	0.7273
<b>Between</b>	0.0658	0.0677	0.2411	0.2382
<b>Overall</b>	0.0000	0.0000	0.0168	0.0176
<b>F (18,87)</b>	13.68	14.67	26.08	24.70
<b>Probability &gt; F</b>	0.0000	0.0000	0.000	0.0000

Notes: Figures in parenthesis are robust standard errors. \*, \*\* and \*\*\* indicates significance at 1%, 5% and 10% level.

**Table 6A. 2 Effect of rainfall deviation and rainfall deviation square on share of farm wage workers.**

Dependent variable: Share of farm wage workers		
Variables	Model 1	Model 2
<b>Rainfall deviation</b>	<b>-0.002</b> <b>(0.004)</b>	<b>-0.002</b> <b>(0.004)</b>
<b>Rainfall deviation square</b>	<b>-</b>	<b>0.0000</b> <b>(0)</b>
<b>Percent ST</b>	0.067 (0.121)	0.069 (0.121)
<b>Percent SC</b>	0.191*** (0.098)	0.192*** (0.098)
<b>Percent OBC</b>	0.377* (0.136)	0.379* (0.135)
<b>Percent illiterate</b>	-0.077 (0.177)	-0.077 (0.178)
<b>Percent BP &amp; P</b>	0.057 (0.135)	0.057 (0.135)
<b>Percent landless</b>	-0.094 (0.192)	-0.095 (0.193)
<b>Percent marginal</b>	0.047 (0.154)	0.045 (0.156)
<b>Percent small</b>	0.083 (0.38)	0.083 (0.381)
<b>Percent large</b>	-1.161 (1.664)	-1.207 (1.699)
<b>Percent rural population</b>	0.184 (0.158)	0.184 (0.158)
<b>Unemployment rate</b>	-0.018 (0.03)	-0.018 (0.03)
<b>Average yield</b>	-0.001 (0.001)	-0.001 (0.001)
<b>Cropping intensity</b>	5.927 (5.627)	5.898 (5.663)
<b>Irrigation intensity</b>	-29.096	-29.107

	(18.907)	(18.934)
<b>Year (2004–05= base year)</b>		
<b>2009</b>	-8.875* (2.236)	-8.860* (2.244)
<b>2011</b>	-15.126* (3.66)	-15.146* (3.669)
<b>Constant</b>	34.185* (12.007)	34.237* (12.045)
<b>Number of observations</b>	254	249
<b>Number of groups</b>	88	88
<b>R-squared</b>		
<b>Within</b>	0.3489	0.3579
<b>Between</b>	0.0234	0.0662
<b>Overall</b>	0.0537	0.0978
<b>F (19,87)</b>	9.21	8.88
<b>Probability&gt; F</b>	0.000	0.000

Notes: Figures in parenthesis are robust standard errors. \*, \*\* and \*\*\* indicates significance at 1%, 5% and 10% level.

**Table 6A. 3 Effect of positive and negative rainfall deviation on real farm and non-farm wages.**

Variables	Dependent variable: Real farm wage		Dependent variable: Real non-farm wage	
	Model 1	Model 2	Model 3	Model 4
<b>Positive rainfall deviation</b>	<b>-0.012</b> (0.008)	-	<b>-0.007</b> (0.008)	-
<b>Negative rainfall deviation</b>	-	<b>-0.028*</b> (0.008)	-	<b>-0.017***</b> (0.009)
<b>Percent ST</b>	0.690** (0.302)	0.746** (0.288)	-0.172 (0.326)	-0.135 (0.333)
<b>Percent SC</b>	0.432 (0.317)	0.451 (0.293)	0.303 (0.259)	0.326 (0.256)
<b>Percent OBC</b>	0.061 (0.207)	0.136 (0.193)	-0.353 (0.256)	-0.286 (0.269)
<b>Percent illiterate</b>	0.316*** (0.177)	0.229 (0.177)	0.709** (0.276)	0.671** (0.264)
<b>Percent BP &amp; P</b>	0.591*** (0.342)	0.591*** (0.343)	1.087* (0.27)	1.105* (0.274)
<b>Percent HS &amp; above</b>	-	-	1.122** (0.436)	1.193* (0.449)
<b>Percent landless</b>	-0.960 (0.611)	-0.982 (0.592)	0.142 (0.547)	0.156 (0.535)
<b>Percent marginal</b>	-0.643 (0.568)	-0.674 (0.549)	-0.123 (0.261)	-0.118 (0.253)
<b>Percent small</b>	-1.525 (0.971)	-1.553 (0.948)	0.121 (0.359)	0.126 (0.353)
<b>Percent large</b>	-0.599	-1.633	-	-

	(5.426)	(5.512)		
<b>Percent rural population</b>	0.022 (0.259)	0.104 (0.288)	-0.231 (0.368)	-0.195 (0.394)
<b>Unemployment rate</b>	-0.179* (0.066)	-0.179* (0.064)	-0.120** (0.048)	-0.119** (0.047)
<b>Percent farm workers</b>	0.532* (0.19)	0.518* (0.189)	0.323** (0.154)	0.317** (0.152)
<b>Percent male workers</b>	0.804* (0.269)	0.827* (0.27)	-0.173 (0.204)	-0.149 (0.203)
<b>Average yield</b>	-0.0002 (0.002)	-0.001 (0.002)	-0.002 (0.003)	-0.002 (0.003)
<b>Cropping intensity</b>	-26.208* (9.106)	-27.679* (9.238)	9.818 (6.36)	9.585 (6.474)
<b>Irrigation intensity</b>	93.199* (26.989)	95.862* (26.569)	-	-
<b>Year (2004–05= base year)</b>				
<b>2009</b>	18.202* (3.701)	17.043* (3.809)	34.785* (4.919)	34.036* (4.961)
<b>2011</b>	35.492* (6.012)	32.558* (6.231)	69.281* (7.421)	67.462* (7.44)
<b>Constant</b>	33.505 (57.355)	27.619 (56.5)	69.061 (48.542)	60.615 (49.635)
<b>Number of observations</b>	249	249	253	253
<b>Number of groups</b>	88	88	88	88
<b>R-squared</b>				
<b>Within</b>	0.6287	0.6435	0.7240	0.7278
<b>Between</b>	0.0713	0.0683	0.2404	0.2391
<b>Overall</b>	0.000	0.000	0.0153	0.0186
<b>F (19,87)</b>	13.54	15.61	26.38	25.55
<b>Probability&gt; F</b>	0.000	0.000	0.000	0.000

Notes: Figures in parenthesis are robust standard errors. \*, \*\* and \*\*\* indicates significance at 1%, 5% and 10% level.

**Table 6A. 4 Effect of positive and negative rainfall deviation on share of farm wage workers.**

<b>Dependent variable: Share of farm wage workers</b>		
<b>Variables</b>	<b>Model 1</b>	<b>Model 2</b>
<b>Positive rainfall deviation</b>	<b>-0.002</b> (0.005)	-
<b>Negative rainfall deviation</b>	-	<b>-0.005</b> (0.006)
<b>Percent ST</b>	0.063 (0.121)	0.073 (0.119)
<b>Percent SC</b>	0.188*** (0.096)	0.196*** (0.099)
<b>Percent OBC</b>	0.369* (0.13)	0.386* (0.139)

<b>Percent illiterate</b>	-0.068 (0.179)	-0.082 (0.178)
<b>Percent BP &amp; P</b>	0.053 (0.134)	0.054 (0.134)
<b>Percent landless</b>	-0.092 (0.192)	-0.097 (0.193)
<b>Percent marginal</b>	0.047 (0.157)	0.040 (0.156)
<b>Percent small</b>	0.090 (0.38)	0.078 (0.383)
<b>Percent large</b>	-1.031 (1.668)	-1.234 (1.664)
<b>Percent rural population</b>	0.174 (0.157)	0.186 (0.158)
<b>Unemployment rate</b>	-0.018 (0.029)	-0.018 (0.03)
<b>Average yield</b>	-0.001 (0.001)	-0.001 (0.001)
<b>Cropping intensity</b>	6.058 (5.567)	5.787 (5.612)
<b>Irrigation intensity</b>	-29.79 (18.813)	-29.068 (18.627)
<b>Year (2004–05= base year)</b>		
<b>2009</b>	-8.740* (2.199)	-8.890* (2.266)
<b>2011</b>	-14.813* (3.552)	-15.253* (3.676)
<b>Constant</b>	35.009* (12.273)	34.203* (11.852)
<b>Number of observations</b>	254	254
<b>Number of groups</b>	88	88
<b>R-squared</b>		
<b>Within</b>	0.3474	0.3497
<b>Between</b>	0.0246	0.0258
<b>Overall</b>	0.0550	0.0567
<b>F (17,87)</b>	9.17	9.45
<b>Probability&gt; F</b>	0.000	0.000

Notes: Figures in parenthesis are robust standard errors. \*, \*\* and \*\*\* indicates significance at 1%, 5% and 10% level.

**Table 6A. 5 Falsification test of irrigation intensity taken as an identifying variable for farm wage**

<b>Variables</b>	<b>Real farm wage</b>	<b>Variables</b>	<b>Real non-farm wage</b>
<b>Irrigation intensity</b>	87.396* (26.518)	<b>Irrigation intensity</b>	24.237 (18.361)
<b>Percent ST</b>	0.725* (0.270)	<b>Percent ST</b>	-0.202 (0.347)
<b>Percent SC</b>	0.460	<b>Percent SC</b>	-0.125

	(0.305)		(0.298)
<b>Percent OBC</b>	0.214 (0.194)	<b>Percent OBC</b>	-0.469 (0.300)
<b>Percent illiterate</b>	0.177 (0.184)	<b>Percent illiterate</b>	0.468 (0.319)
<b>Percent BP &amp; P</b>	0.414 (0.355)	<b>Percent BP &amp; P</b>	0.768** (0.363)
<b>Percent HS &amp; above</b>	-	<b>Percent HS &amp; above</b>	0.624*** (0.362)
<b>Percent landless</b>	-0.975 (0.611)	<b>Percent landless</b>	-0.044 (0.528)
<b>Percent marginal</b>	-0.675 (0.558)	<b>Percent marginal</b>	-0.067 (0.240)
<b>Percent small</b>	-1.657*** (0.958)	<b>Percent small</b>	0.293 (0.369)
<b>Percent large</b>	-1.389 (5.403)	<b>Percent large</b>	-
<b>Percent rural population</b>	0.080 (0.246)	<b>Percent rural population</b>	-0.006 (0.365)
<b>Unemployment rate</b>	-0.157** (0.067)	<b>Unemployment rate</b>	-0.079 (0.052)
<b>Percent farm workers</b>	0.436** (0.193)	<b>Percent farm workers</b>	0.271*** (0.153)
<b>Percent male workers</b>	0.829* (0.292)	<b>Percent male workers</b>	-0.351 (0.324)
<b>Average yield</b>	-0.0002 (0.001)	<b>Average yield</b>	-0.002 (0.003)
<b>Cropping intensity</b>	-26.035* (8.758)	<b>Cropping intensity</b>	3.633 (7.795)
<b>Rainfall deviation category</b>	-4.228 (2.586)	<b>Rainfall deviation category</b>	-4.246** (2.117)
<b>Non-farm wage</b>	0.220* (0.068)	<b>Farm wage</b>	0.213** (0.086)
<b>Year (2004–05= base year)</b>			
<b>2009</b>	9.557*** (4.817)	<b>2009</b>	30.227* (5.476)
<b>2011</b>	18.467** (8.235)	<b>2011</b>	61.672* (8.087)
<b>Constant</b>	16.818 (52.510)	<b>Constant</b>	76.380 (67.086)
<b>Number of observations</b>	249	<b>Number of observations</b>	249
<b>Number of groups</b>	88	<b>Number of groups</b>	88
<b>R-squared</b>		<b>R-squared</b>	
<b>Within</b>	0.6522	<b>Within</b>	0.7522
<b>Between</b>	0.000	<b>Between</b>	0.0027
<b>Overall</b>	0.0561	<b>Overall</b>	0.1548
<b>F (21,87)</b>	21.32	<b>F (20,87)</b>	25.79
<b>Probability&gt; F</b>	0.000		0.000

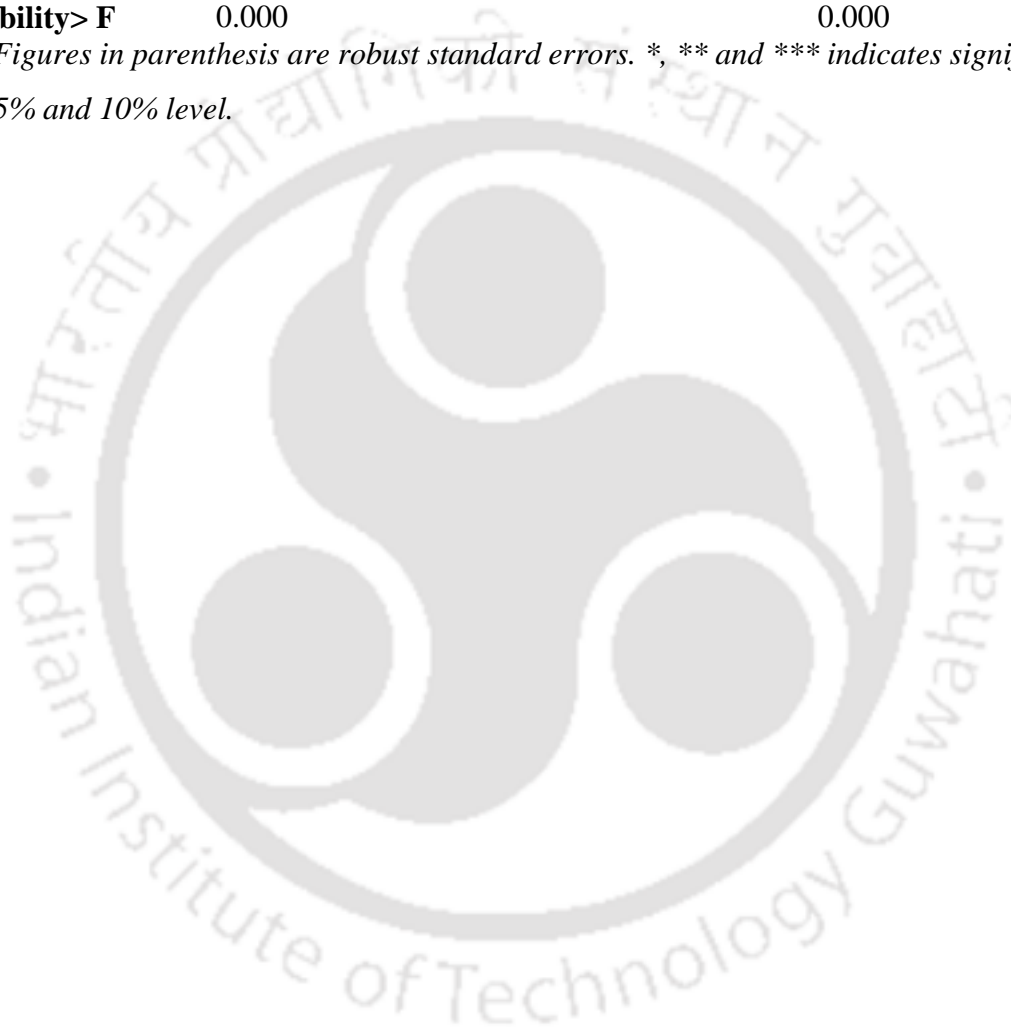
Notes: Figures in parenthesis are robust standard errors. \*, \*\* and \*\*\* indicates significance at 1%, 5% and 10% level.

**Table 6A. 6 Falsification test of percent share of workers with HS and above education level taken as an identifying variable for non-farm wage**

Variables	Real farm wage	Variables	Real non-farm wage
Percent HS & above	0.891 (0.759)	Percent HS & above	0.644*** (0.361)
Percent ST	0.741* (0.266)	Percent ST	-0.194 (0.349)
Percent SC	0.472 (0.306)	Percent SC	-0.123 (0.296)
Percent OBC	0.254 (0.194)	Percent OBC	-0.459 (0.297)
Percent illiterate	0.232 (0.199)	Percent illiterate	0.461 (0.315)
Percent BP & P	0.578*** (0.326)	Percent BP & P	0.767** (0.360)
Percent landless	-1.022 (0.643)	Percent landless	-0.014 (0.529)
Percent marginal	-0.720 (0.598)	Percent marginal	-0.043 (0.239)
Percent small	-1.720*** (0.991)	Percent small	0.369 (0.368)
Percent large	-1.685 -5.649	Percent large	-
Percent rural population	0.023 (0.244)	Percent rural population	-0.037 (0.353)
Unemployment rate	-0.149** (0.064)	Unemployment rate	-0.076 (0.053)
Percent farm workers	0.453** (0.184)	Percent farm workers	0.235 (0.156)
Percent male workers	0.791* (0.273)	Percent male workers	-0.362 (0.321)
Average yield	-0.0004 (0.001)	Average yield	-0.001 (0.003)
Cropping intensity	-24.004* (7.885)	Cropping intensity	9.197 (6.671)
Irrigation intensity	85.262* (25.651)	Irrigation intensity	-
Rainfall deviation category	-4.379*** (2.592)	Rainfall deviation category	-3.607*** (2.069)
Non-farm wage	0.207* (0.073)	farm wage	0.243* (0.087)
<b>Year (2004–05= base year)</b>			
2009	9.044*** (4.735)	2009	29.201* (5.379)
2011	18.371**	2011	60.277*

	(7.708)		(8.042)
<b>Constant</b>	14.547	<b>Constant</b>	76.441
	(54.508)		(66.026)
<b>Number of observations</b>	249	<b>Number of observations</b>	249
<b>Number of groups</b>	88	<b>Number of groups</b>	88
<b>R-squared</b>		<b>R-squared</b>	
<b>Within</b>	0.6575	<b>Within</b>	0.7503
<b>Between</b>	0.0007	<b>Between</b>	0.0003
<b>Overall</b>	0.0531	<b>Overall</b>	0.1862
<b>F (21,87)</b>	21.10	<b>F (21,87)</b>	26.25
<b>Probability&gt; F</b>	0.000	<b>Probability&gt; F</b>	0.000

Notes: Figures in parenthesis are robust standard errors. \*, \*\* and \*\*\* indicates significance at 1%, 5% and 10% level.



## Chapter 7

### Summary of findings, conclusion and policy suggestions

The present study is motivated by the various discussions and debates revolving around the role of RNFS as a source of livelihood. We focused on the nature and characteristics of workers who are engaged in different rural non-farm activities and the benefits they derive from such a diversification strategy. We further investigate how non-farm sector is linked with the farm sector through its effect on wages where wage income forms an important component of livelihood for 70 million rural workers. Wage workers, especially farm laborers are at the lower end of the income strata and any increase in rural agricultural wages due to a rise in non-farm wages would lead to an upliftment of their financial condition. Before discussing the conclusion and policy implications, we briefly elaborate on the major findings of this study which are summarised in the following section.

#### 7.1. Major Findings

##### 7.1.1. Determinants of occupational choice in rural India

During the period of this study, i.e. between 2004–05 to 2011–12, a gradual decline in employment share in agriculture can be witnessed for both male and female rural workers. However, women still represent 74.94 % of workers in agriculture. In case of employment in RNFS, male workers represent 40.64% while the share of females is 25.06% during 2011–12.

Examining the sectoral composition of rural non-farm employment, it is observed that for rural females, manufacturing has been the major employment generating sector throughout the study period. On the contrary, manufacturing was the dominant sector for rural males as well, but after 2009–10, it was the construction sector that provided jobs to most of the rural male workers. Again, among the tertiary sector employment, trade, hotel and restaurant provided the highest jobs to males while services sector generated most of the jobs for rural females.

From descriptive statistics, it is observed that diversification to non-farm employment is taking place for workers of the age group 30 to 59 and their participation declines beyond this age. Regarding educational qualification, the majority of male non-farm workers have an education of middle and secondary level. Also, the share of illiterate male workers is low in non-farm compared to farm sector. For the female workers, illiteracy is high in both farm and non-farm sectors but among the educated group, their participation is high if they are primary, middle and secondary educated. Participation in non-farm is also high among workers of marginal

land-owning households as more than 80% of them are engaged in this sector. Diversification is also high among SC households whose share has witnessed a sharp rise between 2004–05 and 2011–12 followed by upper caste households, OBC and STs.

To empirically analyze the determinants of occupational choice, we applied a multinomial logistic regression model for the 61<sup>st</sup> (2004–05), 66<sup>th</sup> (2009–10) and 68<sup>th</sup> (2011–12) rounds by pooling the data for these periods. First, we examined the role of individual, household and locational factors in determining the choice of rural non-farm employment over agriculture. We further analyzed how gender, education, caste and land ownership affects diversification probability over time. From table 3.13, we found that with an increase in age, individuals are more likely to join mining and quarrying, trade, transport and service activities but less likely to join manufacturing and construction implying a lesser probability to engage in physically demanding activities as people become older. Diversification to any of the non-farm occupations is high among males whereas females are more likely to engage in agriculture and allied activities. Again, with a rise in education and vocational training, the probability of diversification also increases except for construction where workers with an education of below primary and primary level are mostly employed.

Land ownership and household size have a significant negative impact on diversification. With a rise in household size, working members are more likely to focus on agriculture but as the number of dependents increases, diversification towards non-farm also increases. This shows that as the dependency ratio increases, working members tend to diversify more in order to cope with the rising expenses. Similarly, land being an important income-earning asset exhibits an adverse impact on diversification for rural workers.

Urbanization rate has a favorable impact on diversification towards mining and manufacturing while it negatively impacts diversification in construction and trade activities. This might indicate that regions which are characterized by a greater degree of urbanization, rural workers might migrate to urban areas for non-farm employment rather than working in rural non-farm sectors. Average distance to urban centers also favorably impacts diversification towards mining, manufacturing and construction employment although the coefficient value is very small. One reason can be the implementation of MGNREGA in the most backward districts at the first phase of its inception.

Now, the effect of gender, education, caste and land ownership on occupational choice over time provided in tables 3.14 to 3.17 demonstrate a changing pattern of rural non-farm

employment between males and females over time. Although diversification was higher among males compared to females, but by 2009–10 and 2011–12, we observed that females have started shifting towards construction, trade and transport related activities. Males' participation has increased in mining, manufacturing and services. Similarly, the preferences of educated individuals towards non-farm employment have changed over time. Although with a rise in the educational level, individuals were more likely to join manufacturing, trade and services and less likely to engage in construction and mining, yet in later periods, their participation in mining and quarrying activities also increased.

Furthermore, we also observe that occupational choice is significantly impacted by the prevalence of caste system in rural India. We found a gradual shift of low-caste ST and SC workers towards rural non-farm activities like manufacturing, trade and services. Diversification towards construction and trade is also high among OBC workers during 2009–10. Our findings are consistent with existing studies where low-caste workers mostly get employed in construction and factory jobs (Lanjouw and Shariff, 2004; Mishra, 2014; Mishra and Singh, 2019; Nakajima et al, 2018; Gang *et al*, 2017). Therefore, diversification is found to be high among ST, SC and OBC households compared to upper caste households.

Again, consistent with extant literature, we found an adverse impact of land ownership size on occupational diversification for all time periods implying that households owning land specialize in cultivation. Also, because of a lack of well-functioning land and credit markets, these land-owning households are stuck in agriculture.

We also examined the role of education, land ownership and caste on occupational choice of rural male and female workers by interacting these variables with gender. We observed that during 2009–10 and 2011–12, males with a higher secondary and above education favoured services employment. They are also more likely to join trade related activities if they have education above middle and secondary level. While for females, participation increased in manufacturing and construction for those having education of below primary and primary and middle and secondary level. Deshpande and Singh (2021) also found a decline in female employment by 25% in education sector where they have a comparative advantage. Further, when we interacted education and gender with land ownership size, we found that even after belonging to land-owning households, educated females not only diversify to trade and service activities but also to manufacturing and construction which might reflect a lack of suitable employment opportunities for educated rural women. Again, it is observed that women

belonging to affluent households are employed in high-return activities like services. But service sector jobs being less labor intensive and skill-based indicate that women can access service sector jobs only when they are not only educated but also belong to medium and large land-owning households.

Furthermore, interacting gender and caste categories reveal that low-caste ST, SC and OBC females have started diversifying to construction and manufacturing between 2009–10 and 2011–12. Their increasing participation in construction is due to the expansion of construction related activities through the implementation of MGNREGA after 2005.

### **7.1.2. Determinants of employment diversification or specialization in rural India**

Here we examine the role of various individual, household and locational characteristics that determine whether an individual would specialize in either farm or non-farm activities or combine both. Utilising the concept of principal and subsidiary activity status from NSSO's employment and unemployment data, we have classified individuals as specialized when he/she is engaged in only one economic activity in either principal or subsidiary status or both. Again, a worker is recognised as diversified when he/she is engaged in more than one economic activity. Here, we also identify the direction of this diversification strategy which can be either from farm to non-farm or from non-farm to farm. An individual is diversified from farm to non-farm activities when he/she is principally engaged in agriculture but also works in non-farm sector as a subsidiary worker. Similar concept is used to identify workers who diversify from non-farm to farm activities.

We applied a binary logistic regression model to estimate the determinants of diversification or specialization separately for farm and non-farm workers. The dependent variable being a dummy variable takes a value of 1 if the individual is engaged in multiple economic activities and 0 if he/she specialises. Here also, we have pooled the observations for all the three period of time, i.e. 61<sup>st</sup> (2004–05), 66<sup>th</sup> (2009–10) and 68<sup>th</sup> (2011–12) rounds. We also interacted gender, caste, education and land ownership with year dummies to investigate any change in the effect of these determinants over time.

From the regression estimates, we observe that factors such as gender, education, vocational training, caste, household size, dependency ratio and region level indicators have a uniform impact on diversification decision of both farm and non-farm workers while factors like age and land ownership size affect the diversification probabilities differently. The results show

that older people are less likely to diversify from farm to non-farm but for non-farm workers, age positively affects their chances of additionally working in farming. Diversification regardless of the sector is higher among males than females. In other words, males are more likely to combine multiple activities compared to females. It is interesting to note that education increases the chance of a worker to specialize in either sector rather than do multiple activities. In other words, with a rise in the level of human capital, individuals utilize their skills in one economic activity and by specializing they are capable of earning higher returns which lessens their requirements to engage in multiple pursuits.

Further we found that workers belonging to land-owning households are more likely to specialize in cultivation while those engaged in non-farm activities tend to diversify to farm sector employment with a rise in land ownership size. Again, household size has a negative impact on diversification whereas dependency ratio has a positive impact in either sector. Households with more dependent members tend to combine both farm and non-farm activities preferably to maintain their level of expenditure. On the other hand, they tend to specialize with a rise in the household size, implying that an additional member is more likely to follow the occupational path of other household members.

Among the region level determinants, we observe a negative impact of urbanization rate on diversification from non-farm to farm employment only. This shows that individuals residing in areas with a high level of urbanization are more likely to prefer working in non-farm activities alone as residing in the vicinity of urban areas increases their chance of earning high returns from non-farm activities. Average distance has a positive impact on diversification.

Now, from the interaction of gender, education, caste and land ownership with time dummies, we found that by 2009–10 and 2011–12, diversification from farm to non-farm employment has increased for rural female workers while males are more likely to diversify from non-farm to farm employment. Inheritance of land mostly by male members might increase their chances of working in the field. Again, the effect of education demonstrates that although educated workers were more likely to specialize, but in the later periods, we observe that diversification by non-farm workers towards agriculture has increased but for farm workers, diversification to non-farm activities increased only among those with primary level of education.

We also found a greater participation of low caste workers in non-farm activities during 2009–10 and 2011–12. The diversification of ST, SC and OBC workers from farm to non-farm activities were positive and significant in later years compared to base period. They are also

more likely to specialize in non-farm employment. This can be attributed to their low level of land ownership as well as low educational qualification. The effect of land ownership remained unchanged over time. Workers belonging to land-owning households specialize in agriculture rather than dividing their labour between farm and non-farm activities. Similarly, individuals primarily engaged in non-farm activities diversify to agriculture with a rise in landowning size compared to landless households.

### **7.1.3. Impact of diversification on household consumption expenditure**

We compare the food and non-food consumption expenditure of households who have diversified compared to those who have not in order to determine whether diversification results in an increase in income leading to higher consumption of food and non-food. We estimate it through Propensity Score Matching (PSM) method which applies matching indicators to compare diversified and non-diversified households based on observed characteristics. Once the sample units are matched, the difference in their outcome is attributed to the treatment effect. Treatment in our study refers to whether a household has diversified or not. Non-diversified households form the control group. The outcome is the household's food and non-food consumption expenditure and their shares. We have adopted a broader definition of diversification where diversification implies both a situation when at least one member of a household is employed in an activity other than the household's principal occupation as well as those households who have completely shifted from one economic activity to another. For instance, self-employed farm households completely moving towards self-employed non-farm activities.

The primary outcome of interest is the Average Treatment Effect on the Treated (ATT) which examines the effect of treatment and which forms the primary focus of our analysis. Examining first the effect of diversification on household's food and non-food consumption expenditure, we found that not only casual farm households but even cultivator households are able to increase their spending on food and non-food items if they combine non-farm activities. We also observe that the magnitude of food expenditure by diversified casual farm households has increased over time from rupees 131 in 2004–05 to rupees 276 in 2011–12. Similarly, non-food spending increased from rupees 205 to 593 during the same time period. For self-employed non-farm households, diversification towards farm employment only significantly increases food expenditure without having any impact on their non-food expenditure.

Benefits in terms of higher consumption expenditure are also accrued to casual farm households who completely moved towards casual non-farm activities. On the contrary, the level of household spending falls when cultivator households completely shift to self-employed non-farm activities. Their level of consumption expenditure was reduced as a result of this shift. This suggests that cultivator households would be better off specializing in agriculture rather than switching completely to non-farm pursuits. However, when casual farm households either diversify or shift towards non-agricultural activities, their wellbeing improves indicating that they are the most marginalized group and any shift away from agriculture would significantly enhance their economic well-being.

Findings of ATT for food and non-food expenditure share show that cultivator households spend a higher share on non-food and a lesser share on food due to both diversification and occupational shift during 2004–05 and 2009–10 but in 2011–12, no significant impact on food and non-food expenditure share is observed. For casual farm and casual non-farm households, diversification significantly reduces their food expenditure share without having any impact on non-food share. On the contrary, diversification by self-employed non-farm households towards agriculture augments their food expenditure share while reducing their share of non-food expenditure which might imply that they are already earning very low income from non-farm and as such their earnings from agriculture are spent entirely to meet food expenditure needs.

The ATE and ATU which demonstrate the impact of treatment on the entire sample and the untreated group respectively show similar signs and magnitude of the treatment effect on the outcome variables as that of the ATT. Examining the ATE results, we found that diversified farm and non-farm households are better off in terms of consumption spending compared to non-diversified households. Again, for cultivator households, those who did not shift are better off than those who switched to non-farm occupations as it resulted in a fall in their consumption spending. On the contrary, diversification is always a better option for casual farm workers compared to non-diversification as diversified casual farm households could spend rupees 207 and 249 more on food and non-food respectively (68<sup>th</sup> round).

The ATU, which depicts the benefits accruing to non-diversified households had they actually participated, is another key matching estimator. By comparing the ATU values with the ATT values, one can compare whether the non-diversified households would have benefitted had they received the treatment. Our findings reveal that non-diversified cultivator households

could have accrued greater benefits had they participated in non-farm activities. The magnitude of food and non-food expenditure for them is rupees 187.69 and 597.92 which is higher than the ATT values of rupees 89 and 329 respectively. But for casual farm households, diversification would have lowered the consumption expenditure of the non-diversified households if they had diversified. That is, non-diversified casual farm households could spend only rupees 197.92 on food had they participated in non-farm employment whereas those who actually diversified could increase food spending by rupees 276.67. Again, for the control group of self-employed and casual non-farm households, diversification would have raised their consumption expenditure. For instance, non-participant casual farm households could spend rupees 169 more on food through participation and this is higher than the ATT value of rupees 134.

#### **7.1.4. Determinants and linkage between farm and rural non-farm wages**

We estimate here the determinants and linkage between farm and non-farm wages of casual workers in rural India at the NSSO state-region level and estimated the relationship using fixed effects model forming panel data for the period 2004–05, 2009–10 and 2011–12. Our findings demonstrate a direct positive relation between rural farm and non-farm wages where a rise in farm wage also significantly raises the non-farm wage. Also, when farm wage is controlled for in the non-farm wage equation, the share of farm wage workers is not significant which implies that factors affecting the demand for farm wage workers have no impact on non-farm wage when farm wage is controlled. Similarly, an increase in non-farm wages also positively affects farm wages because with a rise in non-farm wages, workers tend to shift from farm to non-farm which lowers the supply of workers in agriculture. Hence, farm wages also increase so as to prevent workers from moving away from agriculture. Further, we also observe that rainfall deviation had an adverse impact on both farm and non-farm wages. However, the channel through which rainfall deviation affects wages is through its impact on the demand for wage workers which could not be established in our findings.

Other factors that determine farm wage include irrigation intensity, share of farm and male wage workers. But supply determinants like the unemployment rate exhibit a negative significant impact on wages. Again, for non-farm wages, the share of educated workers and the share of farm wage workers also tend to raise wages. Further, we found that wages of both farm and non-farm wage workers follow an upward trend over time.

## 7.2. Conclusion

From our study, we observe that several factors are operational in determining whether an individual should choose non-farm employment over farm employment and whether he/she should specialize in one economic activity or combine both. The various individual, household and locational factors that affect diversification probabilities can be classified as those having a favourable impact on diversification and those that represent distress level determinants. The study of these determinants has shown that education and vocational training enable workers to choose non-farm occupations. Education even facilitates individuals to specialize in either farm or non-farm activities rather than combining both. This demonstrates that educated individuals not only prefer non-farm employment but they are also capable of earning high returns from agriculture.

Even females were found to diversify towards non-farm sectors if they had education and belonged to land-owning households. But their engagement in manufacturing and construction implies non-availability of suitable jobs outside agriculture. Non-farm employment options are also favoured by marginalized individuals from ST, SC and OBC households who are deprived of both human and physical capital. But because non-farm wages are generally higher than farm wages, it is a better option for them to engage in non-farm pursuits. These low-caste workers also specialize in non-farm activities and even when they are principally engaged in cultivation, they diversify to non-farm activities for a lesser period of time. Furthermore, we also found that non-farm employment is mostly preferred by landless households while land-owning households focus on agriculture. Even, marginal and small land-owning households prefer farming which might be a result of a lack of a well-functioning land market that leave households with no other option but to utilise land for cultivation. Also, non-farm workers diversify to agriculture as a subsidiary activity when they belong to land-owning households.

Some of the factors that might act as a push factor of diversification include dependency ratio and unemployment rate. Both these factors increase the likelihood of joining non-farm employment. Also, with a rise in the dependency ratio, rural labour force combines both farm and non-farm activities which indicates that working age members engage in multiple economic activities to maintain household expenses.

Furthermore, we observe that as a result of the implementation of this diversification strategy, both rural farm and non-farm households are in a better position in terms of consumption expenditure. However, the benefits also depend on the household type and the nature of

diversification strategy implemented, that is, whether households combine farm with non-farm activities or they completely shift from the former to the latter. We found that although cultivator households could afford to spend more on food and non-food items and a greater share of income can be devoted to non-food goods yet a complete shift from self-employed farm activities to self-employed non-farm employment reduces their welfare through a decline in their expenditure. On the contrary, the findings demonstrate the low economic status of casual farm households which can be improved either through combining farm with non-farm activities or by completely shifting towards casual non-farm work. The findings even reveal that not only farm households but non-farm households, particularly casual households are better off through diversification. These households by combining non-farm with farm activities can significantly increase their spending on food and non-food. Their capacity to spend more on non-food items like health, education and other durable goods is also feasible through diversification. But in case of self-employed non-farm households, diversification to agriculture activities enhances only their food expenditure while lowering their spending on non-food expenditure share. This might imply that self-employed non-farm households are already earning very low income and the amount earned from farm activities is spent entirely to meet food needs.

Again, one of the major sources of income of rural casual workers is wages which can be obtained from either agriculture or non-farm activities. As such, any rise in the wage rates indicates an increase in the income level of these workers. Therefore, we studied the linkage between farm and rural non-farm wages and found a significant positive relation between them indicating a close association between these two markets. A rise in non-farm wages results in the labor movement from agriculture to the non-farm sector which generates a situation of labor scarcity in agriculture. This results in a rise in real farm wages in order to keep the supply of farm labor intact. Similarly, a rise in farm wages also leads to an increase in non-farm wages. Some other factors that raise wages in both markets include irrigation ratio and share of agricultural wage workers whereas unemployment rate has an adverse impact on wages.

### **7.3. Policy implications**

We observe from our study that human capital factors play a crucial role for rural workers to engage in non-farm activities and it particularly favours rural females to compete for jobs outside agriculture. Therefore, the first policy suggestion would be to facilitate workers in achieving education and vocational training facilities. Provision of skill training programs for

rural workers would help them to compete for various employment opportunities. Also, pro-women policies should focus on easy transferability of resources, especially ownership rights of land to women. Moreover, mechanisms through which credit facilities can be conveniently accessed by women should also be developed.

Secondly, expansion of infrastructure facilities like all-weather roads, electricity, and telecommunications and even a well-functioning financial market would better serve the diverse employment requirements of the people.

Thirdly, to address the heterogeneous nature of the RNFS, policies should be formulated keeping in mind the local requirements through a decentralized process to enable the people to actively participate in the decision-making. This would facilitate more efficient use of resources and development of physical assets and social capital as per local requirements.

Further, we observe that non-farm activities are undertaken by farm workers for a lesser time period when the overall income level falls due to non-availability of regular work or due to an increase in the number of dependent members. This signifies that neither agriculture is remunerative enough nor working in non-farm activities for a lesser time period guarantees decent returns. Hence, the focus should be on raising not only farm productivity but also on generating employment opportunities in manufacturing and services like education and health.

But when non-farm occupations become the principal income-earning source for members of cultivator households, then they are found to be highly benefited in terms of higher spending on food and non-food items. Casual farm households have especially benefitted from this process. As such, for non-farm activities to offer a pathway out of poverty, policies should focus on investment in education and health of rural people in order to improve the stock of human capital.

Our findings also show a positive linkage between rural farm and non-farm sectors not only through its favourable effect on household consumption expenditure but also through wages. Therefore, as pointed out by Haggblade et al (2010), agriculture still plays a significant role in influencing the structure and size of the rural non-farm sector. As such focus should be on strengthening the growth linkage between these two sectors. Investments in irrigation facilities and rural infrastructure along with provision for subsidized credit facilities would enable farmers to finance agriculture. Similarly, development of transport and communication networks and electrification would encourage development of non-farm businesses.

#### **7.4. Limitations of the study and scope for future research**

Some of the limitations of the study recognized by the researcher during the course of the study period include the following.

The first limitation of the study is that it is confined to the year 2011–12 and analysis based on recent data sets on employment and unemployment could not be extended. Some of the limitations of the latest employment data set by PLFS have already been pointed out in the introduction chapter of this thesis. Therefore, NSSO and PLFS data are not compatible. However, future research by using PLFS data will be an important contribution to the existing work.

Furthermore, we applied propensity score matching (PSM) method for studying the impact evaluation of diversification on household's consumption expenditure. Although PSM is a widely applied method but one of the major limitations of this method is its inability to take account of unobserved heterogeneity that may affect treatment and outcome simultaneously. Application of other methods such as Endogenous Switching Regression (ESR) can address this selection bias issue but paucity of appropriate instrumental variables (IV) required in ESR and any such other methods have prevented us from applying them.

Finally, the study only focused on the industrial classification of rural non-farm sector and did not focus on the occupational classification of this sector. However, future research can be undertaken using this aspect of occupations.

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## **Publication:**

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**Das, K., & Mahanta, A.** (2023). Rural non-farm employment diversification in India: The role of gender, education, caste and land ownership. *International Journal of Social Economics*, 50 (6), 741–765. DOI [10.1108/IJSE-06-2022-0429](https://doi.org/10.1108/IJSE-06-2022-0429).

### **Abstracts in Scientific Meetings**

**Das, K.** Determinants of Occupational choice in India: An empirical analysis, *conference of Achieving Sustainable Development Goals in North Eastern Region of India*, 21<sup>st</sup> Annual Conference of North Eastern Economic Association (NEEA), Manipur University, Manipur, 14–15<sup>th</sup> February, 2020.

**Das, K & Mahanta, A.** Rural non-farm employment diversification and farm household welfare: Evidence from rural India. *22<sup>nd</sup> Annual Conference of North Eastern Economic Association (NEEA)*, Rajiv Gandhi University, Arunachal Pradesh, 14–15<sup>th</sup> December, 2021.

**Das, K. & Mahanta, A.** Implications of rural employment diversification on farm household's consumption expenditure in India. *62<sup>nd</sup> Annual Conference of the Indian Society of Labour Economics*, Indian Institute of technology Roorkee, Uttarakhand, India, 11–13<sup>th</sup> April, 2022.

**Das, K., & Mahanta, A.** Impact of employment diversification on household's pattern of consumption expenditure in rural India. *57<sup>th</sup> Annual Conference of the Indian Econometric Society*, University of Hyderabad, Hyderabad, 4–6<sup>th</sup> January, 2023.