MEASURING HOUSEHOLD VULNERABILITY TO POVERTY AND ASSESSING IMPACT OF WELFARE PROGRAMS ON VULNERABILITY TO POVERTY: AN EMPIRICAL STUDY IN ODISHA

Thesis

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by

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DECLARATION

by the Ph.D. Research Scholar

I hereby declare that the Research Thesis entitled, **'MEASURING HOUSEHOLD VULNERABILITY TO POVERTY AND ASSESSING IMPACT OF WELFARE PROGRAMS ON VULNERABILITY TO POVERTY: AN EMPIRICAL STUDY IN ODISHA'** which is being submitted to the National Institute of Technology Karnataka, Surathkal in partial fulfillment of the requirements for the award of the **Degree of Doctor of Philosophy in Economics** is a *bonafide report of the research work carried out by me.* The material contained in this Thesis has not been submitted to any University or Institution for the award of any degree.

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CERTIFICATE

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ABSTRACT

Households are not only poor but also vulnerable, which means that poor households may remain poor while non-poor households may fall into poverty as a result of different covariate and idiosyncratic shocks and lack of coping measures. An understanding of households vulnerable to future poverty will be crucial for sustainable growth and development. This study examines three inherently interconnected issues: changes in poverty status, household vulnerability to future poverty, and the role of the welfare program in reducing vulnerability. Using panel data of 1353 households and a survey dataset of 479 households in rural Odisha, the study addresses three objectives: First, to estimate the changes in poverty status and the factors determine it. Second, to measure household vulnerability to poverty using both the monetary and multidimensional approaches. Third, to assess the impact of welfare program on household vulnerability to monetary and multidimensional poverty.

The panel dataset used in the study was derived from the India Human Development Survey (IHDS) with a state representative sample of 1353 rural households from Odisha. The second data comes from the household survey of 479 households from three districts of the southern region of Odisha. For the purpose of estimating changes in poverty status and the factors that influence it, the study used a spells approach and a multinomial logistic regression model. The findings demonstrate that over time, households move in and out of poverty. In particular, it is observed that 25.26% of the households have been chronically poor, 45.24% of the households have been transient poor, and the remaining 29.50% of households have been non-poor. It has also been found out that households are less likely to remain as ‘chronic poor’ if they have access to higher education, asset, engaged in the non-farm sector, participate in social capital, and ownership of land.

The second objective was analyzed in two steps. Firstly, conventional and counting approaches were used to estimate monetary and multidimensional poverty rates. Secondly, the vulnerability was modelled as expected poverty using the Feasible Generalized Least Squares (FGLS) econometric approach to measure the monetary and multidimensional vulnerability to poverty. The results show that about 35% of households in Odisha are vulnerable to monetary poverty and 55% of households are vulnerable to multidimensional poverty. This is significantly higher than the observed poverty level of about 28% and 47%, respectively. Among the districts analyzed, the proportion of households that are at high risk of falling into poverty is highest in the Koraput district, followed by Kandhamal and Nabarangpur districts. Further, households engaged in farming are observed to be most vulnerable, followed by those engaged in wages in non-farm and self-employed in non-farm sectors.

The impact of the welfare program (rural livelihoods program) on both the monetary and multidimensional vulnerability to poverty was analyzed using Propensity Score Matching (PSM) and Endogenous Switching Regression (ESR) models. The findings demonstrate that welfare program has a positive impact on reducing monetary vulnerability to poverty. More specifically, the household's vulnerability to poverty is reduced by 3% for the households who participated in the welfare program. The main policy implications are that poverty reduction efforts in rural Odisha would be more effective if they include not only the poor but also the vulnerable.

Keywords: Poverty dynamics; Multidimensional poverty; Vulnerability to poverty; Impact evaluation; Odisha; India

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ABBREVIATIONS

2SLS	Two-Stage Least Squares
AAY	Antyodaya Anna Yojana
AB-PMJAY	Ayushman Bharat Pradhan Mantri Jan Arogya Yojana
AIR	American Institutes for Research
ATT	Average Treatment Effect on the Treated
ATU	Average Treatment Effect on the Untreated
BISP	Benazir Income Support Program
BPL	Below Poverty Line
CBI	Community-Based Health Insurance
CCT	Conditional Cash Transfer
CHE	Catastrophic Health Expenditures
CHIP	China Household Income Project
CLP	Chars Livelihoods Program
CRED	Center for Research on Epidemiology of Disaster
CRPR	Chronic Poverty Research Centre
CT-OVC	Cash Transfer Program for Orphans and Vulnerable Children
DFID	Department for International Development
DID	Difference in Difference
ENSANUT	National Health and Nutrition Survey
ESR	Endogenous Switching Regression
FFW	Food for Work
FGLS	Feasible Generalized Least Squares
FGT	Foster–Greer–Thorbecke
FIES	Family Income and Expenditure Survey
FSP	Food Security Package
GDI	Gender Development Index
GoI	Government of India
GoO	Government of Odisha
HDI	Human Development Index

HIV	Human Immunodeficiency Virus
HYVs	High-yielding Varieties
IAY	Indira Awas Yojana
ICRISAT	International Crops Research Institute for Semi-Arid Tropics
IEG	Independent Evaluation Group
IFAD	International Food for Agricultural Development
IFAD	International Food for Agricultural Development
IFPRI	International Food Policy Research Institute
IHDS	India Human Development Survey
IMF	International Monetary Fund
IPCC	The Intergovernmental Panel on Climate Change
IV	Instrumental Variable
NRLP	National Rural Livelihood Mission
KBK	Koraput Balangir Kalahandi
LP	Livelihoods Program
LSMS-ISA	Living Standard Measurement Study-Integrated Survey on Agriculture
MDGs	Millennium Development Goals
MDP	Multidimensional Poverty
MDS	Midday Meal Scheme
MGNREGA	Mahatma Gandhi National Rural Employment Guarantee Act
MPI	Multidimensional Poverty Index
NCAER	National Council of Applied Economic Research
NDDP	Net District Domestic Product
NGOs	Non-Governmental Organizations
NHIS	National Health Insurance Scheme
NITI	National Institution for Transforming India
NSS	National Sample Survey
NSSO	National Sample Survey Office
OCTMP	Odisha Community Tank Management Project
OOPE	Out-Of-Pocket Expenditure

OPHDI	Oxford Poverty and Human Development Initiative
OTELP	Odisha Tribal Empowerment and Livelihoods Program
PDS	Public Distribution System
PMAY	Pradhan Mantri Awas Yojana
PM-JAY	Pradhan Mantri Jan Arogya Yojana
PSM	Propensity Score Matching
PSNP	Productive Safety Net Program
QR	Quantile Regression
RCT	Randomized Control Trial
RD	Regression Discontinuity
RPW	Rural Public Works
RSBY	Rashtriya Swasthya Bima Yojana
SC	Scheduled Castes
SDGs	Sustainable Development Goals
SGSY	Swarna Jayanti Gram Sahari Yojana
SHG	Self-Help Group
SNP	Special Nutrition Program
SP	Social Protection
ST	Scheduled Tribes
TPDS	Targeted Public Distribution System
TREE	Training for Rural Economic Empowerment
TRIPTI	Targeted Rural Initiative for Poverty Termination and Infrastructure
UCT	Unconditional Cash Transfer
UN	United Nations
UNDP	United Nations Development Program
UNHCR	United Nations High Commissioner for Refugees
VEP	Vulnerability as Expected Poverty
VER	Vulnerability as Uninsured Exposure to Risk
VEU	Vulnerability as Expected Low Utility
VGD	Vulnerable Group Development

VMDP	Vulnerability to Multidimensional Poverty
VtP	Vulnerability to Poverty
WB	World Bank
WFP	World Food Program
WORLP	Western Odisha Rural Livelihoods Program

CHAPTER 1

INTRODUCTION AND BACKGROUND TO THE STUDY

1.1 Overview

Several efforts have been made over the past three decades to eradicate poverty throughout the world. Among the global commitments, which started in 1990, the Millennium Development Goals (MDGs) put a specific target and have successfully achieved reduction in the poverty rate by half by 2015. More specifically, the population living in extreme poverty has decreased from 1.9 billion in 1990 to 836 million in 2015 (United Nations, 2015). The post-2015 global development agenda is known as Sustainable Development Goals (SDGs), which targets zero poverty in the world by 2030. International organisations such as World Bank, United Nations Development Program (UNDP), Department for International Development (DFID), World Food Program (WFP), and International Food for Agricultural Development (IFAD) have been supporting the least developed and developing countries to run wide-ranging anti-poverty programs such as fostering education, job creation, and asset building to support the poor and vulnerable (World Bank, 2016).

As a result of these efforts and the country's poverty alleviation strategies, there is a significant poverty reduction, despite that, countries like Sub-Saharan Africa and other underdeveloped areas of many parts of the world endure high poverty rates (United Nations, 2015a). For instance, the poverty rate in Sub-Saharan Africa is 41%, for South Asia it is 17%, and 14% of them live in extreme poverty in developing regions (United Nations, 2015a). In addition, the SDGs report reveals that globally 1 in 8 people live below the poverty line (United Nations, 2016). Specifically, the statistics about extreme poverty indicate that more than 1.2 billion (22%) people live below the poverty line of $1.25 per day (United Nations, 2016). Further, increasing the poverty line from $1.25 per day to $2.50 per day will increase the proportion of poor to 2.7 billion (UNDP, 2014, p. 19). More importantly, the recent COVID-19 pandemic has disrupted livelihoods and pushed millions of households into poverty (United Nations, 2020). Because of the global pandemic, the SDGs target of poverty elimination may take longer to achieve than initially estimated. This suggests that more attention is required for poverty eradication.

The central objective of the SDGs is to end poverty in all forms, such as zero hunger, good health, quality education, gender equality, clean water, and sanitation. Recently, poverty estimation has also been extended to 'Multidimensional Poverty (MDP)' analysis using different household well-being indicators. It was first highlighted in the 1997 Human Development Report (UNDP, 1997) and 2000/01 world development report made further progress on multidimensional poverty index (MPI) (World Bank, 2001). UNDP (2010) estimated MPI for the first time using three dimensions, namely education, health, and living standards for the 104 countries. According to UNDP (2014) report, 1.5 billion people from 91 countries are living in multidimensional poverty, wherein 2.2 billion people are very close to or at the risk of falling into poverty. It was also reported that poor people are structurally vulnerable, and about 12% of people suffer from chronic hunger. Further, the MDP rate is found to be highest in the less developing countries (UNDP, 2014), and out of the total MDP, 84.3% live in Sub-Saharan Africa and South Asia (UNDP, 2020). This suggests that it is equally important to focus on multidimensional indicators to end poverty in every form.

Over the past three decades, several studies on poverty eradication have been conducted, and they have identified various causes of poverty in order to address the problem effectively. Recently, studies from different countries have suggested that persistent poverty is due to the risks and shocks that households cannot overcome. In this context, studies suggest that eradicating poverty is not just about getting zero; it is also about staying there (UNDP, 2014). This indicates that households move in and out of poverty over the period. For instance, as reported by the UNDP (2014), 75% of poor households around the world live in rural areas, and those areas are exposed to various risks and shocks. The theoretical and empirical literature reviewed in chapter 2 demonstrates that rural households are more likely to move into poverty due to the risks, shocks, and lack of coping measures. The adverse events impact the households in several ways, for example, losing a job, the death of the household breadwinner, natural disasters that reduce the agricultural productivity, an accident that makes permanent income loss, which leads a household to fall into or remain in poverty (Chaudhuri et al., 2002; Carter and Barrette, 2006). Understanding the dominant risks and shocks, coping measures of the households, and their impact on household livelihood helps design appropriate policies in order to eradicate poverty. Therefore, the estimation of vulnerability to poverty (VtP) has received attention in recent years quite evidently by the theoretical and empirical studies (Gunther and Harttgen, 2009; Chaudhuri et al., 2002; Azeem et al., 2019; Dutta and Kumar, 2016).

The empirical studies on VtP demonstrate that knowledge on the characteristics of poor and vulnerable is important because it is essential to uproot poverty. However, it is also equally important to understand the impact of policies on poverty as well as on vulnerability. Empirical evidence indicates that another factor contributing to uneven poverty reduction progress is inter-country disparities in social protection measures available to vulnerable households. More importantly, in addition to the lack of coping measures, the lack of social protection measures makes it difficult for households to cushion against idiosyncratic (e.g., job loss, death of breadwinner) and covariate (e.g., natural disasters) shocks that increase the prevalence of poverty and VtP. Therefore, given the target of social protection for both the poor and vulnerable, analysing the impact of social protection on VtP helps design effective policies to enhance both poor and vulnerable households' risk reduction capacity. It is worth mentioning that social protection and vulnerability assessment were not included in the MDGs (Elkins, 2014).

After 15 years of the MDGs period, the governments worldwide are now focusing on SDGs. This new period in international development has shifted the strategies to end poverty by focusing on VtP groups. Therefore, the first SDG emphasizes minimizing vulnerability to various shocks and attaining long-term social protection (SP) coverage for the poor and vulnerable by 2030. The united focus on eradicating multiple deprivations, VtP, and social protection are the SDGs' essential elements (United Nations, 2016). This is particularly important for countries in South-Asia and Africa that are lagging behind achieving MDGs and prone to vulnerability due to poor economic activities such as the absence of credit market, lack of insurance support, and high unemployment rate (Azeem et al., 2019).

More specifically, India is one such country from Asia where poverty alleviation is the top priority in the government’s national development planning, as is the case in many developing countries. The statistics about poverty indicate that the proportion of poor has declined to 29.8% in 2010 from 54.88% in 1974 (GoO, 2012). Further, at the global level, India’s Human Development Index (HDI) rank has improved from 135 in 2011 to 131 in 2019 (out of 189 countries) (UNDP, 2020). These improvements in the living standard are highly encouraging because they demonstrate that poverty can be overcome and reduced. However, the fight is far from the end as the country's poverty remains widespread. While specifically comparing consumption/income poverty to multidimensional poverty, the country ranks 62 among the 107 countries in the case of multidimensional poverty. According to the UNDP (2020) report, 27.91% of households are multidimensionally poor, where 23.4% are educationally poor, 31.9% are health poor, and 44.8% live in a poor standard of living. This implies that more research is needed to tackle poverty. Further, adopting the SDGs strategy of understanding VtP and analysis of policy impact on VtP will assist the government in effectively eradicating poverty.

The official statistics show that poverty alleviation is still the main challenge of many parts of the country despite the various anti-poverty policies. In this scenario, as per the census 2011, Bihar and Odisha are the top poverty states among the Indian states, and this study focuses on the state of Odisha for the analysis.

1.2 Statement of the Problem

During the last few decades, new methodologies for measuring poverty have emerged as a result of flourishing studies in the area of poverty research. However, the majority of empirical research continues to be dominated by the conventional approach, which uses cross-sectional data and one-dimensional approach to measure poverty. The reason for criticizing the one-dimensional approach is that households move in and out of poverty over time and this approach fails to capture the changes in household wellbeing. Using the poverty dynamics approach, previous literature on poverty found that poor households are coming out of poverty, but at the same time, non-poor households are falling into poverty (Krishna, 2007; Ward, 2016). It was also observed that the poverty rate remains large because policies are being targeted to the current poor but neglect the households who are in danger of falling into poverty in the near future (Krishna, 2010). The common findings from previous literature have shown that households that are likely to fall into poverty comprise a larger share of overall poverty (Carter and Barrette, 2006; Ward, 2016; Azeem et al., 2018). Therefore, it is better to go beyond the merely observed poverty than to address the needs of a relatively large population that is at risk of becoming poor (Pritchette et al., 2000, Grimm et al., 2016, Deersa, 2013).

The empirical literature reviewed in chapter 2 revealed that households frequently move in and out of poverty. Identifying the key factors influencing households to move in and out of poverty helps design appropriate policies to alleviate poverty. The first objective of our study estimated poverty dynamics (falling into and escaping poverty) using panel data from the India Human Development Survey (IHDS) for 2004-05 and 2011-12. The findings demonstrate that 25% of households are chronically poor and about 8% of households have fallen into poverty (Khosla and Jena, 2020). As also observed from past studies, a significant proportion of households fall into poverty and the literature defines them as vulnerable to poverty (Kristjanson et al., 2010). Although the various factors associated with poverty dynamics are largely identified, it is observed that households fall into poverty due to various shocks and lack of coping strategies (Gunther and Harttgen, 2009). Poverty literature has segregated the reason for falling into poverty under two categories: idiosyncratic and covariate shocks (Azeem et al., 2016; Gunther and Harttgen, 2009). The former affects the individual or household, and the latter affects the village, community, state, or nation (Chaudhuri et al., 2002; Carter and Barrette, 2006).

Because the covariate and idiosyncratic factors are bound to have a significant negative impact on household wellbeing, it is necessary to identify the vulnerable households to enhance their coping strategy. Generally, this estimation of the impact of negative adverse events on household wellbeing is called vulnerability to poverty. Knowing the limitation of popular poverty measures failing to identify VtP households, various approaches are developed, such as forward-looking or ex-ante poverty approaches to estimate the household that is likely to fall into poverty. In the last two decades, the ex-ante approach has gained attention to identify the VtP households, and this application is considered the main strategy of poverty reduction in the SDGs (United Nations, 2016). However, given the absence of panel data and lack of information on household experienced shocks and coping measures, the majority of the VtP estimation used proxy for the shocks and coping strategy and relied on cross-sectional data. The limitation of those findings can be overcome by including the households that have experienced shocks and adopted coping measures in the VtP estimation (Gunther and Harttgen, 2009; Gloede et al., 2013). Recently, literature is accommodating more studies to measure households vulnerable to multidimensional poverty in order to achieve the goal of ending poverty in every form (Feeny and McDonald, 2016). Our second objective aids to better understand VtP by including shocks and coping strategies in relation to monetary and multidimensional measures.

It is established in the literature that households are vulnerable because of adverse events and a lack of coping mechanisms. One way of reducing vulnerability to poverty is enhancing the coping strategies of households through social protection (SP). Identifying vulnerable households and enhancing their resilience capacity through social protection is the key to ending poverty. In other words, social protection policies are designed to enhance households' resilience capacity through different ways, like training, insurance, and cash transfer (Mendola, 2017; Devereux and Sabates-wheeler, 2004, p.9). Knowing that social protection enhances households' resilience capacity, the government needs to be well informed to design an evidence-based policy framework. While social protection's potential to reduce ex-post poverty is theoretically and empirically supported, empirical evidence supporting its effectiveness in reducing ex-ante vulnerability is mainly absent (Azeem et al., 2019; Vo and Van, 2019; Bronfmon and Floro, 2014). Therefore, more research is required in order to understand the potential of SP on reducing VtP. Assessing the impact of social protection on reducing vulnerability to poverty is the aim of the research. Our third objective contributes to the VtP literature by assessing the impact of social protection on household VtP for both monetary and multidimensional measures using rigorous impact evaluation approaches.

1.3 Research Objectives

The overall objective of the study is to measure household VtP and assess the impact of welfare program on the household VtP in rural Odisha. Specifically, the study has the following objectives:

1. To estimate the changes in poverty status and the factors determine it.
2. To measure household vulnerability to poverty using both the monetary and multidimensional approaches.
3. To assess the impact of the welfare program on household vulnerability to monetary and multidimensional poverty.

1.4 Significance of the Research

This thesis significantly contributes to the development economics literature by (i) measuring the vulnerability to poverty in two different dimensions: monetary measure and multidimensional measure, and (ii) assessing the impact of welfare program on household vulnerability to both monetary and multidimensional poverty. Firstly, the majority of the existing poverty assessments focus exclusively on the prevalence of poverty and its annual percentage changes, i.e. an ex-post outcome of poverty. In contrast, this study provides both the ex-post and ex-ante outcomes of monetary poverty and multidimensional poverty. Furthermore, most of the previous studies have estimated the determining factors of poverty using cross-sectional data. In contrast, this study uses panel data to map changes in the well-being of the dynamic poverty groups and their various livelihood strategies. Specifically, the study contributed to the literature by examining the role of livelihood diversification and social capital on poverty dynamics.

Secondly, in the case of India, very few studies have estimated vulnerability using both monetary and multidimensional measures. Poverty and vulnerability are not the same, but they are closely related and share some similar characteristics. Therefore, being able to identify the key determinants of vulnerability, particularly the risks and shocks, that are significant in both contexts would assist the government in implementing policies that could effectively reduce poverty and also mitigate shocks at the same time.

Finally, this study provides a more in-depth analysis of the economic impact of rural livelihoods program (LP) on vulnerability to poverty by categorizing households into monetary vulnerable groups and multidimensional vulnerable groups. It would be greatly beneficial for policymakers to know if a policy can reduce both monetary as well as multidimensional VtP. The study used detailed household survey data using a comprehensive questionnaire during 2018-19. The findings suggest that monetary VtP households that participated in LP are able to mitigate the negative events than their counterfactuals. Further, the impact assessment findings on multidimensional measures show that participation in LP has not reduced vulnerability. Therefore, from the VtP analysis and policy evaluation, it is suggested that policy design should target the multidimensional indicators of the population than improving the household income alone. This study is expected to assist the government in coming up with economic and development policies that are more appropriate and efficient in targeting the right groups of poor and vulnerable households so that poverty eradication would speed up.

1.5 Organization of the Thesis

The thesis comprises three empirical parts focusing on assessing changes in household poverty status; measuring household VtP for the monetary and multidimensional measures; and the impact of welfare program on household VtP, employing impact evaluation approaches for both monetary and multidimensional vulnerable households.

The thesis is structured into 7 Chapters. The significance of and motivation for doing this research are discussed in Chapter 1. Objectives, research significance, and thesis outline are also provided in this chapter. Chapter 2 exhibits the review of the literature, which includes various previous empirical studies and methods of measuring changes in poverty status, measuring household VtP, and impact evaluation of welfare programs. The chapter then goes on to summarize the research gaps addressed in the thesis. Chapter 3 named as "Study Context and Data Description", presents the data employed for the analysis. The chapter then explains the context of the study and the descriptive statistics of the data analyzed. Chapter 4 titled "To Estimate Changes in Poverty Status and the Factors Determine it", examines the changes in household wellbeing for the period between 2004-05 and 2011-12. It has sections such as introduction, analytical framework, results and discussion, and conclusion. Chapter 5 titled "To Measure Household Vulnerability to Poverty using both the Monetary and Multidimensional Approaches" estimates household VtP. The ex-ante econometric model is applied in both the monetary and multidimensional measures to estimate household VtP. Chapter 6 named as "To Assess the Impact of Welfare Program on Household Vulnerability to Monetary and Multidimensional Poverty", assesses the impact of welfare measures on household VtP. It has sections such as introduction, analytical framework, results and discussion, and conclusion. Chapter 7 includes an overview, summary of findings, concluding remarks and policy implications, and research limitations and future directions.

CHAPTER 2

REVIEW OF LITERATURE

2.1 Introduction

As mentioned earlier in chapter 1, the overall objective of this study is to measure household VtP and assess the impact of welfare program on VtP in Odisha, India. The analysis carried out in this study can be broadly classified into three categories: analyses of changes in poverty status, estimation of household VtP, and the investigation of the impact of welfare program on household VtP. This chapter describes the various methods and approaches employed to measure the changes in poverty status, vulnerability to poverty, and the impact of welfare programs on poverty and vulnerability to poverty. There is different vulnerability to poverty assessment approaches to estimate the households that are at a high risk of falling into poverty. There is scope for adopting the recent methodologies in the vulnerability assessment. Studies critically examining the impact of the adverse events would address the subsequent policy formulation for reducing the risk associated with poor and vulnerable households (Gallardo, 2018). This chapter critically reviews the results from past studies which have particularly focused on change in household wellbeing. Further, the chapter analyzes the effect of risks and shocks on household VtP, as it is defined as important to understand the intricate links between risks, shocks, and VtP (Chaudhuri, 2003).

Moreover, even though coping strategies of the households offset the effect of negative events to a certain extent, it has been observed that rural households in developing nations have limited coping mechanisms, and as a result, many are VtP (Gunther and Harttgen, 2009). In view of the prevalence of poverty and lack of coping mechanisms of rural households, it is also established in the literature that various social protections (safety net and targeted policies) have been implemented by the developed and developing nations to uplift the poor and vulnerable households. These programs are intended to enhance the coping capacity of the poor and vulnerable households in response to the risk they experience (Hidrobo et al., 2018). The assistance of social protection to the poor and vulnerable is reflected in the Sustainable Development Goals (SDGs) strategies which were missing in the Millennium Development Goals (MDGs) (United Nations, 2015; United Nations, 2016; Elkins, 2014). Given the prevalence of poverty across the nation and various social protections working against poverty, it would be really beneficial to quantify the impact of social protection not only on poverty but also on vulnerability to poverty.

2.2 Review of Literature on Measuring Household Poverty Dynamics

The majority of the literature on poverty analysis is based on static or cross-sectional quantitative analysis that can only be used to show net improvements in poverty incidence (Grootaert et al., 1995). There are two approaches, namely “money metric” and “multidimensional”, that are widely used to identify the poor and the poverty rate. The money metric approach applied to estimate the poverty rate is based on the single indicator of household income or consumption. In this approach, the individuals or households are identified as poor if their wellbeing – referred to as expenditure or income - is lower than a certain pre-specified threshold level, normally known as the poverty line. Generally, two poverty lines are used in order to measure the poverty rate: the government-defined poverty line and the international poverty line. The headcount (or incidence), poverty gap (or depth), and poverty gap squared (or severity) are the three key indicators commonly used to assess the aggregate issues of poverty. A variety of studies have looked at how to measure poverty, but Foster et al. (1984) study is the most classic and well-known. The second approach is a multidimensional one, in which poverty is analyzed from several perspectives. Recent studies have argued that uni-dimensional poverty measure is a static approach because it is unable to capture the multiple deprivations of human life that affect a person’s wellbeing (Dehury and Mohanty, 2015; Alkire and Seth, 2015). Further, Vijaya et al. (2014) have argued that poverty might persist because poor people are deprived of basic needs, namely education, health, and living standards, and are not suffering from low income alone. In terms of multidimensional poverty measurement, recently, there has been growing interest in using the approach devised by Alkire and Foster (2011a, 2011b). For instance, using Alkire and Foster (2011a, 2011b), UNDP (2014) estimated Multidimensional Poverty Index (MPI) for developed and developing nations, and revealed that worldwide 1.5 billion people live multidimensional poverty.

Neither an increase in poverty rates nor a decline in poverty rates indicates how many people have escaped poverty or how many new poor have joined the existing poor. Additionally, they are unable to explain the mechanism of poverty dynamics, as well as the process by which people move into and out of poverty over time (CRPR, 2004). In order to achieve the objective of ending poverty by 2030, it is crucial to understand the movement of changes in poverty status. Identifying the key influencing factors for household wellbeing change would be beneficial for the government to design strategies that are appropriate for poverty reduction. Investigation of the changes in poverty status helps understand the factors responsible for the movement of change in household wellbeing. It is well recognized that poverty is dynamic and can change over time (UNDP, 2014). The fact that some of the poor are not always poor is a central theme in the literature on poverty dynamics. Furthermore, not all poor people are born poor; they can enter and exit poverty at any time (Yaqub, 2000; Addison et al., 2008; Baulch and Hoddinott, 2000; Krishna, 2011).

Almost half of the world population in rural areas live with fewer coping measures (World Bank, 2015; Lowder et al., 2016), enhancing household capacity to improve household wellbeing is necessary (Mendola, 2017). Past studies from different countries have observed different factors are responsible for households escaping or falling into poverty. Focusing on those factors and understanding the factors helping escape poverty can result in poverty reduction (Krishna, 2010). Similarly, identifying factors responsible for the household falling into poverty and enhancing household capacity in advance to remain non-poor results in reducing poverty. Therefore, understanding both the processes of escaping and falling into poverty is important to design effective anti-poverty policies. Thus, for escaping from the poverty trap, the literature suggests two different sets of policies: one is for the households that are likely to fall into poverty and the other one for those that are chronically poor (Jalan and Ravallion, 1999, 2000; Gaiha and Deolacilar, 1993; Krishna, 2003; Thorat et al., 2017; Boulch and McCulloch, 2002; Kristjanson et al., 2007; Chiwaula et al., 2011). The factors responsible for falling into and escaping poverty cannot be identified using the static approach of poverty measurement.

To formulate such a different effective set of policies, it is important to recognize the households that need programs to help them overcome poverty and those that need programs to help them develop resilience so that they are less likely to fall into poverty. In order to identify and target the different households that need support, the household poverty level is categorized into different poverty categories. The categories of poverty are basically distinguished into chronic poverty and transient poverty (Bauch and Hodinott, 2000; Bauch, 2011; Jalan and Ravallion, 2000). These categories of poverty are important from a policy point of view (Hulme and Sheperd, 2003; Radeny et al., 2012). Estimating different poverty categories of poverty is called 'the dynamics of poverty', which is estimated using panel data and a dynamic approach. It is observed that households stay poor for several years; however, many households frequently move out and fall into poverty (Baulch and Hoddinott, 2000; Duncan et al., 1993; Jha et al., 2010; Chaudhuri et al., 2002). The households that continue to live in poverty for a long time are called the 'chronic nature of poverty' (Chronic poverty report, 2004-05). The households that move in and out are called 'transient poverty' (McKay and Lawson, 2003).

The estimation of poverty dynamics has been increasing in recent years. Due to the absence of long panel data, most of the studies use two-three waves of survey data. Past studies on poverty dynamics in developing countries have used two main methods, namely 'the spells approach' and 'the component approach', to identify patterns of changes in household wellbeing (Mckay and Lawson, 2003; Baulch and Hoddinott, 2000). Generally, the former approach counts the length of the household's wellbeing below the poverty line. The term used in estimating poverty dynamics is broadly classified into 'chronic poverty', 'transient poverty', and 'non-poor'. According to the spells approach, a household is considered chronic poor if the household remains poor for all periods. The transient poor are those who experience poverty during at least one period of the study. If a household has not experienced poverty in all periods, it is called 'non-poor' (CRPR, 2004). Generally, two-year panel data is used in this approach, and therefore, a large number of literature has employed this approach due to the lack of lengthy panel data. The spells approach's utilization is widely seen (see, for instance, Justino et al., 2008; Lawson et al., 2006; Baulch and Masset, 2003; Sen, 2003; Baulch and McCulloch, 2002; Hossain and Nargis, 2009; Lohano, 2011). On the other hand, the components approach focuses on both transitory and permanent components of household welfare. The approach assumes that income has both permanent and fluctuating components. According to this approach, households are considered chronic poor if the permanent component is below the poverty line (Haddad and Ahmed, 2003; Jalan and Ravillion, 2000). According to the method, estimating poverty dynamics requires a minimum of three waves of panel data (Baulch and Hoddinott, 2000).

By reviewing the empirical studies based on panel data, Yaqub (2000) explained that the poverty dynamics approach is better than the poverty incidence (cross-sectional study) for the development intervention. Baulch and Hoddinott (2000) reviewed 13-panel studies in 10 different countries. Their review showed a higher percentage of transient households than the households characterized as chronically poor. Among the early contributions, Grootaert et al. (1997) examined the determinants of welfare changes over time based on the panel data collected from cote D'ivoire living standard surveys between 1985 and 1988. Their results from the first difference model reveal that poverty is a temporary condition. For urban areas, human capital is the most influencing factor that pulls out the chronic poor, whereas landholding and farm equipment are the most influencing factors for the rural areas. The study has also observed that the socio-economic factors of the households had an impact on the changes in household welfare. A study by Mcculloch and Baulch (2002) estimated chronic and transient poor, using 5years of longitudinal data from the International Food Policy Research Institute (IFPRI), which covers 686 households in rural Pakistan. The authors use a conventional income-based and robust semi-parametric approach to categorize households into chronic and transient poor. The study found that income poverty incidence was high, varying between 20% and 33% of households below the poverty line for any year. However, at the end of five years, only 3% remained chronic poor. The multinomial logit and ordered logit model show that less livestock, less land,

and larger household size are the determinants of the chronically poor.

After the MDGs framework was proposed, the chronic poverty report (2004-05) provided guidelines to end poverty from everywhere by analyzing poverty research from different countries. The study categorized different poverty groups into three economic groups: chronically poor, transient poor, and always non-poor. Chronically poor are the categories of households for which the wellbeing remains below the poverty line for each period. The transient poor are those who experienced poverty for some period but not for all periods. The non-poor households are those of which wellbeing remains above the poverty line in each period. Following the chronic poverty report (2004-05), Arif and Bilquees (2007) used the panel data from Pakistan Socio-Economic Survey (PSES). The study found that 11.9% of households were chronically and 22% of households were transient poor. The findings show that a significant proportion of rural households are more chronically and transiently poor than are those in urban areas. The study concluded that while interventions are required to reduce chronic poverty, the factors that need to be considered include broad-based education, improvement of rural infrastructure, health and credit policies in rural areas. Krishna et al. (2004) investigated the factors influencing escape and falling into poverty in 36 villages in Uganda. Using a community-based approach, the study categorized households into four groups: chronically poor (poor in last 25years ago and today), households that escaped poverty (poor 25years ago, but not so today), households that became poor (non-poor in 25years, but are poor today), and non-poor (non-poor both in 25years and at present). The study observed that 24% of the households escaped poverty but 15% have moved into poverty. The study also highlighted that falling into poverty is associated with multiple factors such as crop disease, ill health, huge health care costs, large family size, land division, and expenditure on marriages; but a single set of factors like land improvement, income diversification, and small business is enough to escape poverty, which differs from region to region as well. The study concluded that a significant proportion of households that moved into poverty caused a slowdown of poverty reduction in Uganda.

Using both quantitative (1800 households' panel data) and qualitative (116 focused group discussion) data, Davis (2007) examined the poverty dynamics in rural Bangladesh. The study observed that dowry, ill-health, large household size are the main factors for the chronic poor, whereas flooding, business loss, less land, and debt cause a decline in poverty. The factors such as improvement in agriculture, business activities, salaried jobs, microfinance loan, and migration were the most important causes for wellbeing improvement. The findings suggest that development intervention should be implemented based on the changing risk profile in Bangladesh. Radeny et al. (2012) contributed to poverty dynamics literature by measuring wellbeing changes using an asset-based approach. The study employed panel data of 1500 rural Kenya households over a period of 2000-09 in order to examine the poverty dynamics in rural Kenya. The study found that households falling into poverty rate (66%) were higher than those escaping poverty rate (35%). The findings also highlighted that covariate shocks are the most important factors for the structural poverty transitions. Further, Thomas and Gaspart (2015) introduced a panel data model to measure the change in household wellbeing. The study applied the Markovian transition, random effect, and endogenous switching probit models. Specifically, the study analyzed the factors for the persistently high poverty in rural Malagasy based on the panel data collected by Reseau des Observatories Ruraux (ROR) from 1996 to 2006. The findings show that poverty itself is creating a vicious circle and leading to a poverty trap. The study suggested policies that include providing a safety net, cash transfer, cash for work, and short-term credit to poor households to overcome persistent poverty.

In India's case, due to the absence of panel data, most of the studies apply the few available panel data sets from the National Council of Applied Economic Research (NCAER) and the International Crops Research Institute for Semi-Arid Tropics (ICRISAT). Gaiha (1988) analyzed the income mobility in rural India based on the panel data from 1968-69 to 1970-71 carried out by NCAER, covering 4118 rural households. The study found that 50% of the households were poor during the study period, 12% became poorer, and 36% of households remained poor. Among the non-poor, more than 75% remained non-poor, whereas the remaining 25% moved into poverty. The study also observed that accessing modern technology and expanding the cultivated land helped the poor escape poverty. Bhide and Mehta (2004) estimated chronic poverty in rural India by using panel data from NCAER for the period from 1970/71 to 1981/82. The study found that 57% of households moved out of poverty but at the same time, 25% of households moved into poverty. It was also observed that ownership of the house, ownership of livestock, infrastructure, education were the factors that helped the poor household to escape poverty. On the other side, the study found that households' demographic composition is the determinant of the possibility of falling into poverty. At the state level in India, using the stages-of-progress method in the 20 villages of Gujarat for a long period of 25 years, Krishna (2007) observed that 9.2% of households escaped poverty but at the same time, 7.3% of the households moved into poverty. The study concludes that different reasons account for escaping and falling into poverty. Studying the factors responsible for falling into poverty in the 36 villages in Andhra Pradesh, Krishna et al. (2004) find that 14% of households escaped poverty, while at the same time, 12% of households moved into poverty. The findings suggest that different sets of programs need to be implemented in the villages for effective poverty reduction.

Another empirical study is by Bhide and Mehta (2008), examined the impact of economic growth on poverty dynamics in rural India, based on the panel data collected by NCAER between 1995 and 1997. The study categorized household poverty level into different poverty groups. In particular, the study divided the poor into severe poor (below 25% of the poverty line) and moderate poor (below the poverty line but not less than 25%). The study concludes that growth alone is not sufficient to reduce poverty. The findings also highlighted that the factors that influenced the poor are the large household size, scheduled caste, scheduled tribe, and greater child dependency. Recently, a contribution by Thorat et al. (2017) confirmed that households from developing countries fall and escape from poverty. The study utilized panel data set for 2004-05 and 2011-12 from IHDS. The dynamic logit model results show that Dalits and Adivasis are more likely to fall into poverty and less likely to escape poverty than the other backward castes. The findings also highlighted that salaried jobs and education are the main factors that help to escape poverty. The contribution of the study highlights that factors that help escape poverty are different from the factors that push into poverty. Most recent research using panel data is adopting the advanced econometrics model to distinguish chronic and transient poverty. It uses an asset-based approach, mixed-method approach, and by assessing the impact of adverse events on household wellbeing, it categorizes households into structural poor, stochastic poor, structural non-poor, and stochastic non-poor (Liebenehm, 2018; Ward, 2016). The present study has followed CRPR (2004) categorization to study the poverty dynamics and the determining factors.

This section reviewed the empirical literature on the dynamics of poverty in developing countries. Due to the growing availability of panel datasets, there has been an increase in the number of poverty dynamics studies in developing countries over the last decade. However, comparatively, a few research studies in the literature on poverty dynamics in developing countries examined the factors that help escape poverty. Most available literature identified the determining factors related to household characteristics and neglect factors like if livelihood diversification and social capital play a role in escaping poverty. Additionally, the magnitude of poverty transitions is expected to vary significantly across countries and studies. There is still a need for additional panel studies in other countries to fill in the gaps in the empirical literature in order to better understand the patterns of poverty dynamics, particularly in developing nations. The study of poverty dynamics in rural Odisha, based on a panel survey tracking the same households over time, limited studies have been examined to the author's knowledge. This will result in a greater understanding of the complexity of poverty dynamics, both from the perspective of income and from the perspective of subjectivity. While the multinomial logit approach provides the outcomes of consumption poverty dynamic patterns, micro-level information about livelihood diversification and the role of social capital will add richness to understanding poverty and provide important additional insights into the processes and contextual factors that underpin poverty dynamics.

2.3 Review of Literature on Measuring Household Vulnerability to Poverty

Though the causes and determining factors of poverty are identified, the challenge of poverty occurrence is largely unsettled. The empirical findings show that households from developing countries are vulnerable to different covariate and idiosyncratic factors. As a result, households are likely to fall into poverty or remain poor (Gunther and Harttgen, 2009; Carter et al., 2007). The covariate factors affecting the household/community are drought, flood, cyclone, famine, tsunami, and economic crisis. The idiosyncratic factors include job loss, death of the breadwinner of households, severe health shocks, disability, accidents, and business loss (Hoddinott and Quisumbing, 2003). As these factors are expected to increase in the future, they are likely to affect households' livelihoods and lives (IPCC, 2012, 2014; Fang et al., 2016). Because the covariate and idiosyncratic factors are bound to have a significant negative impact on household wellbeing, it is expected that poverty eradication may remain a challenge in the future. Over the last two decades, investigating the welfare impact of these adverse events on vulnerability has become a major theme of applied research in development economics. Therefore, the concept of VtP has drawn the attention of researchers towards identifying those who are likely to fall into poverty and supporting them in advance in order to stop them from falling into poverty, as evident by the growing number of literature (Chaudhuri et al., 2002; Chiwaula et al., 2011; Azeem et al., 2019; Ward, 2016; Vo and Van, 2020). Researchers argue that identifying households with a chance of falling into poverty and including them in social protection results in ending poverty (Krishna, 2010; Chiwaula et al., 2011; Azeem et al., 2019; ward, 2016). Further, vulnerability research helps us understand why a few households, communities, and regions are vulnerable (or not vulnerable), emphasizing the dynamic and complex interactions between risk, shocks, coping strategies, and households. As a result, it draws upon a diverse and extensive body of intellectual results.

The term “vulnerability” is derived from the Latin word “vulnerare”, meaning “to wound”. Different disciplines, ranging from economics and anthropology to psychology and engineering, are investigating the concept of vulnerability (Fang et al., 2016). The study related to vulnerability estimation in economics and in the literature on “poverty” was conceptualized in the 1990s (Townsend, 1994, 1995; Udry, 1995), who were first to analyze household wellbeing and income fluctuation due to idiosyncratic shocks. The concept “space of vulnerability” was proposed by Watts and Bolhe (1993) to refer to “the locally and historically specific configuration of poverty, hunger, and famine”. The study of Morduch (1994) on “poverty and vulnerability” introduced the concept of “stochastic poverty” to describe a situation in which a household's consumption is below the poverty line even though the household has a permanent income above that threshold. In this spirit, by the early- to mid-2000s, a substantial amount of well-established literature focusing on vulnerability assessments had been compiled and published (Morduch, 2005; Christiaensen and Boisvert, 2000; Glewwe and Hall, 1998; Skoufias and Quisumbing, 2004; Dercon, 2003; Dercon and Krishnan, 2000; Jalan and Ravallion, 1999). Several international organisations and governments have recognised the significance of this assessment and have developed policies in response to it. For instance, SDGs added vulnerable groups to the poverty alleviation strategies - which was missing in MDGs - to speed up the eradication of the poverty rate by 2030 (Elkins, 2014; United Nations, 2016).

As explained above, vulnerability is associated with risks and shocks that a household experiences. It is essential to understand the vulnerability in the household wellbeing context. Economists define vulnerability as “exposure to negative shocks to welfare” (Glewwe and Hall, 1998; Cunningham and Maloney, 2000), or “the probability or risk today of being in poverty or of falling into deeper poverty in the future” (World Bank, 1990) or “the ex-ante risk that a household will, if currently non-poor, fall below the poverty line, or if currently poor, will remain in poverty” (Chaudhuri, 2003). “Vulnerability is the risk that a household will, if currently non-poor, fall below the poverty line, or if currently poor, will remain in poverty or fall deeper into poverty”. Thus, “vulnerability is synonymous with a high probability of becoming poor or poorer in the future” (Holzmann et al., 2003). “Vulnerability is a dynamic process, a continuous state that fluctuates in the biophysical and social environment that shapes a region's resilience to cope with the external risk possessed” (O'brien et al., 2007).

In the last two decades, researchers have conducted a number of studies on estimating household VtP. There are two major methodologies applied to estimate VtP: “indicator method” and “econometric method”. One of the most common ways to quantitatively assess vulnerability is to use the “indicator method”. This approach estimates vulnerability based on household wellbeing indicators, and it is estimated using three indicators: adaptive capacity, exposure, and sensitivity. Under each indicator, there are measures that collect information to assess household VtP (IPCC, 2012). The application of the indicator method is widely used in estimating the climatic impact on socio-economic VtP. However, in the case of indicator choice, there is significant debate among the research community. A number of criticisms have been leveled at the indicators used in the studies, claiming that they fail to capture the research's motivation and demonstrate an inability to address vulnerability (Ford et al., 2018). Since the VtP concept is related to future poverty, a forward-looking approach, “econometric method”, is suggested.

Under the “econometric method” there exist different approaches to estimate household VtP. Ligon and Schechter (2004) explain that there is no single best approach to estimate VtP. Past studies have argued that based on the nature of data (cross-sectional and panel data), different approaches are used to estimate household VtP (Ligon and Schechter, 2004; Klasen and Waibel, 2015; Gunther and Harrtgen, 2009; Azeem et al., 2019). According to the vulnerability-to-poverty literature, there are mainly three different approaches widely employed to estimate household vulnerability to poverty: vulnerability as expected low utility (VEU), vulnerability as expected poverty (VEP), and vulnerability as uninsured exposure to risk (VER) (Hoddinott and Quisumbing, 2003; Klasen and Waibel, 2015; Mahanta and Das, 2017). However, recently other VtP estimation approaches such as asset-based and multilevel modeling have been developed.

2.3.1. Vulnerability as Uninsured Exposure to Risk (VER)

Glewwe and Hall (1998) introduced the “vulnerability-as-uninsured-exposure-to-risk” approach to measuring the economic impact of adverse events on household wellbeing. The VER approach uses household consumption as the wellbeing indicator. The VER model is employed by various researchers in estimating risk exposure impact on household wellbeing (Tesliuc and Lindert, 2002; Skoufias and Quisumbing, 2004; Amin et al., 2003; Dercon and Krishnan, 2000). The pioneering work of Glewwe and Hall (1998) used the panel data from Peru, and estimated which groups of households are most affected by the macroeconomic shock, such as sharp drops in export prices and increased real interest rates. The study observed that a well-educated person is less vulnerable. Further, female-headed households are less vulnerable than male-headed households. A contribution by Dercon and Krishnan (2000) confirmed that risk plays a major role in the change of household wellbeing. The study examined the consumption variation due to rainfall and other climatic variables, livestock diseases, illnesses, crop pests and diseases, and health shocks among household members. Using panel data of 1450 households from Ethiopia, the study found substantial short-run movement in and out of poverty. The findings demonstrate the high volatility of consumption and poverty over the season in a year. The study found that idiosyncratic and common shocks, such as rainfall and household-specific crop failure, have an impact on consumption. More specifically, according to these findings, one-third of households escaped poverty, whereas the majority remained poor.

Tesliuc and Lindert (2002) studied vulnerability to poverty in Guatemala using both quantitative and qualitative analyses. The study used the living standards measurement survey module on risks and shocks to investigate the sources of vulnerability. The findings demonstrate that the impact of natural disasters and agricultural shocks are disproportionately higher on the poor than on the non-poor. The qualitative analysis shows that natural disasters have long-lasting negative effects on the welfare of the poor. The further analysis highlights that most vulnerable households are chronically vulnerable, and suggests building assets for the poor. Using the VER approach, Amin et al. (2003) examined vulnerability to poverty in northern Bangladesh using panel data for 1991-92 and 1995. The study found that vulnerability to poverty among micro-credit members is substantially higher than among the non-macro credit members. The result found a contradictory result that female-headed households are less vulnerable than male-headed households. In this framework, Skoufias and Quisumbing (2005) analyzed five IFPRI case studies and discussed vulnerability to poverty in five countries, namely Bangladesh, Ethiopia, Mali, Mexico, and Russia. The study used panel data from these five countries and found that food consumption is better insured than non-food consumption in all five countries.

The advantage of the VER models is the inclusion of the “risk exposure” factor than on “exposure poverty” of other vulnerability estimation models (Gallardo, 2018). This acts as an important feature in the modeling of household wellbeing impacts. Here the models can predict the consumption shift due to the idiosyncratic factors, and also the macroeconomic shocks such as price variation of the commodities, which the cross-sectional models fail to capture. Although the VEU approach has merit in consumption smoothing and insurance studies, this approach is criticized as not being an advanced vulnerability concept for forward-looking schemes. In addition, the approach also requires panel or pseudo panel data, which is rarely available in developing counties (Klasen and Weibel, 2016).

2.3.2 Vulnerability as Expected Low Utility (VEU)

The VEU approach developed by Ligon and Schechter (2003) is based on the individual utility framework. It distinguishes between vulnerability caused by poverty and vulnerability caused by uninsured risk. The risk part can be further divided into “poverty”, “idiosyncratic”, “covariate”, and “unexplained components”. There are several studies that have employed vulnerability as expected low utility approach in examining risk factors' impact on household wellbeing. The seminal work by Ligon and Schechter (2003) assessed vulnerability to poverty using panel data sets for 2284 households from Bulgaria. The outcome variable for the model was the consumption expenditure. The expected mean was estimated based on the utility framework as devised by Von Neumann and Morgenstern (1944). Covariate and idiosyncratic shocks are introduced in the model separately, collected from each household. The results indicated that aggregate shock has more impact on household wellbeing than idiosyncratic shocks.

Jha et al. (2010) used the VEU approach to analyze poverty and vulnerability in Tajikistan by using panel data for 2004 and 2005. The findings indicate that almost half of the non-poor households were vulnerable to poverty. In the segregation of covariate and idiosyncratic shocks, the study found out that idiosyncratic shock has more impact than covariate shocks. The results further showed that vulnerability differs in geographical locations. More specifically, the analysis indicates that rural households tend to be poorer and more vulnerable than urban households. The study also showed surprising results, such as household heads working in the service sector is more likely to fall into poverty than household head working in the farming sector. Further, Jha et al. (2011) adopted the VEU approach and panel data to study vulnerability and responses to risk in rural India. The results showed that vulnerability is mainly explained by poverty and idiosyncratic factors. The study further observed that social protection enhances households to cope with idiosyncratic risks. A recent contribution by Patnaik et al. (2017) employed the VEU approach to estimate VtP in rural coastal Odisha, India. The findings show that aggregate risk and poverty emerge as major sources of vulnerability, which contradicts Jha et al. (2011).

Despite the advantages of the VEU model of estimating vulnerability to poverty, there are shortcomings associated with the model. Although the model incorporates the sensitivity of risk to measure expected poverty, it does not support the probability threshold. The second shortcoming of the model is that the model looks at the 'risk exposure' as a symmetrical view, which is criticized because it is considered an asymmetric view (Povel, 2010; Dutta et al., 2011). Another drawback of this VEU model is the risk component's consideration based on the researchers' view of utility, as more concave means more risk, and assumes that the risk factor is equal for all individuals (Gallardo, 2018).

2.3.3 Vulnerability as Expected Poverty (VEP)

As mentioned in the above two approaches, VtP is measured using panel data. However, panel data are rarely available in developing nations (Chaudhuri et al., 2002; Gunther and Harttgen, 2009; Azeem et al., 2019). Chaudhuri et al. (2002) developed an approach to measure VtP using cross-sectional data, and the approach is called “vulnerability as expected poverty” (VEP). It is one of the most popular approaches in assessing household wellbeing change due to negative events, as it has the advantage of applying to cross-sectional data. The VEP model defines vulnerability “within the framework of poverty eradication, as the ex-ante risk that a household will, if currently non-poor, fall below the poverty line, or if currently poor, will remain in poverty” (Chaudhuri et al., 2002). In this VEP approach, the wellbeing indicator household consumption/income is the outcome variable, and household characteristics, including the community characteristics and adaptive capacities, are the control variables. The vulnerability to poverty is estimated based on the two major changes in household wellbeing. The changes in household wellbeing are observed based on the expected mean and variance of the household. If the expected consumption is lesser than the current poverty threshold, then the household is considered vulnerable to poverty. The expected mean consumption is calculated using the household characteristics, community characteristics, and the variance is calculated as a result of shocks. The VEP model has the advantage of estimating the household's future wellbeing based on the household's current wellbeing status.

This analysis requires data on the household characteristics (livelihoods and various capitals such as human capital, physical and social capital), coping strategies to overcome negative events (e.g., selling productive assets, borrowing from different sources, dropping children from school, and migration), and the risk and shocks households experience (e.g., drought, flood, cyclone, job loss, and death of breadwinner). Due to the lack of data that provides all this information, it is difficult to estimate VtP. Haughton and Khandker (2009) suggest that in the simplest case, three pieces of information and additional assumption are enough to measure a household's vulnerability to poverty. The required information is as follows: expected consumption, estimated variance, and the poverty line. Since the expected mean is unknown for each household, a model is used to predict the expected mean for the household. Further, a vulnerability threshold has to be specified to identify vulnerable and non-vulnerable households. Generally, the threshold is arbitrary and the most used threshold is 50% probability (Gunther and Harttgen, 2009). This indicates that a household is considered vulnerable if the household’s estimated wellbeing is greater than the 50% probability threshold. The underlying assumption of this method is that the structural economy is stable over time, idiosyncratic shocks are ideally and independently distributed, and consumption is log-normally distributed.

There are several studies that used the “vulnerability as expected poverty” approach aimed at understanding the impacts of adverse events on household wellbeing, using cross-sectional data. Chaudhuri et al. (2002) and Chaudhuri (2003) have employed the VEP method to the Philippian 1997 family income and expenditure survey (FIES) data. The significant findings show that 25% of Philippians were currently poor in 1997, but 40% of Philippians were transient poor (vulnerability to poverty). The same method was employed in Indonesia, and the data source used was mini-SUSENAS data. The finding shows 22% of Indonesians were currently poor in 1998, and 45% were vulnerable to poverty. The study argues that the expected poverty rate is higher than the currently classified poverty rate in both countries. Therefore, the suggestions from the findings were to focus on vulnerable households in order to reduce poverty. The pioneering work by Chaudhuri et al. (2002) argues why vulnerability to poverty assessment is important for policy interventions to eradicate poverty. Four major points are mentioned: “using a static-approach-measured poverty is limited to use for policy intervention to improve future wellbeing”. Second, “vulnerability assessment makes distinctions between ex-ante poverty prevention interventions and ex-post poverty alleviation interventions”. Third, “vulnerability assessment provides sources and forms of risks household experiences”. Fourth, “vulnerability is an intrinsic aspect, whereas the individual is risk-averse”.

An early contribution by Pritchett et al. (2000) estimated VtP in Indonesia. The study used a panel data set of both mini-SUSANAS and 100 village survey data. Using the poverty line approach, the study concluded that a small proportion of the population is chronically poor but a greater proportion is transient (future) poor. More specifically, the 20% population is currently poor, whereas 10-30% of households are transient. Following the VEP approach, a contribution by Christiansen and Subbarao (2005) empirically assessed the VtP using pseudo-panel data for rural Kenya. The study included historical information on risk in the model. A series of variables was added as a proxy for risk, and household coping capacity. The rainfall shock was the main proxy for the covariate, and health shock was used for idiosyncratic shocks. The study found out that in 1994, about 40% of rural households in Kenya were VtP, which was higher than the currently classified poverty rate of 36% in Kenya. Further, the study observed regional variation in vulnerability estimation. It was observed that the vulnerability to poverty was higher in arid areas due to the large volatility of rainfall, whereas due to health shock, non-arid areas were vulnerable. The findings also highlighted that livestock possession such as goat/sheep failed to smooth consumption against covariate shocks. The study suggests that specific policies for a particular issue such as health shock (Malaria), promoting adult literacy, and enhancing market accessibility should be enhanced to reduce vulnerability.

Another study using the VEP approach is by Sarris and Karfakis (2006) which estimated household vulnerability to poverty in rural Tanzania using time series data from 1961 to 2006. The study confirmed that household vulnerability to poverty is higher than the current poverty rate. The results indicated that rural households in the poorest region exhibited considerably higher vulnerability. The findings suggested that different policies should be designed for different regions. More specifically, appropriate safety nets are necessary for the vulnerable region of Tanzania. In Uganda, a study by Kasirye (2007) used a panel data set of 1309 households to measure vulnerability to poverty between 1992-93 and 1999-2000. By employing the VEP approach, the study observed that community infrastructure, education, and spatial characteristics were found to have an impact on household VtP. The major finding indicated that northern Uganda was about 60% more vulnerable compared to its counterparts in central Uganda.

In this context, Azam and Imai (2009) estimated VtP in Bangladesh. Using the VEP approach and survey data of 10080 households collected by the Bangladesh Bureau of Statistics, they found that 47.81% of households were VtP, which is higher than the currently classified poverty rate of 39%. Among the VtP categories, 23.55% of households were chronically poor, 15.01% were transient poor, and 9.25% were highly vulnerable to poverty. The study also observed that VtP is geographically diverse, with the coastal region being 4-5 times more vulnerable than Khulna divisions. The study suggested that enabling the coping mechanism of households by building productive assets and promoting financial service is important for poverty reduction. Then, Jamal (2009) assessed VtP in Pakistan using cross-sectional data and the VEP approach. The study estimated vulnerability to poverty for two separate years, 2001 and 2005. The findings indicated that the poverty rate over time declined; however, VtP rate increased. The results showed that 51.62% of households were VtP in Pakistan in the year 2005. The study confirmed that the household VtP rate was higher than Pakistan's currently classified poverty rate of 29.85%. The findings also showed that the rural VtP rate was higher than the urban VtP rate between urban and rural areas.

Jha and Dang (2009) examined VtP in central Asian countries. The study focused on four countries, namely Azerbaijan, Kazakhstan, Kyrgyzstan, and Tajikistan. Using the VEP approach, the analysis showed that the Tajikistan households were more vulnerable and Kazakhstan households were less vulnerable. As the findings revealed, when risk increases and the poverty rate increases, the adaptation/coping mechanism of the households becomes an important strategy. The study suggested that reform policy should consider vulnerable households alongside poverty. In the case of Ghana, a study by Novignon (2010) assessed vulnerability to poverty among households. The study adopted the VEP approach and cross-sectional data of 8687 households from the fifth-round Ghana living standard survey for the year 2005/06. The findings showed that households are more likely to fall into poverty than the current poverty rate of Ghana. In particular, the results showed that 56% more households were VtP than the poverty rate of 28%. Further, the VtP rate was observed to be varying for the geographical regions. The study suggested that educational attainment is an influential factor in reducing vulnerability to poverty.

Adepoju et al. (2011) also used the VEP approach to estimate the VtP of rural households in southwest Nigeria. The study analyzed the VtP using four different poverty lines, such as the international poverty line, the relative poverty line, 80% of the relative poverty line, and the NBS poverty line. The findings showed that by the international poverty line, 63.01% of households were VtP. Further, it was also observed that the relatively high poverty rate was associated with higher vulnerability and low poverty rates with lower vulnerability. The findings suggest reducing exposure to risk or enhancing the ex-post coping mechanism of vulnerable households that end poverty. Another study based on the VEP approach by Bogale (2012) used 277 randomly selected household data, and studied the vulnerability of smallholder rural households to food insecurity in Eastern Ethiopia. The study observed that households vulnerable to food insecurity are higher than the currently classified poverty rate. The findings suggest that the implementation of food security policies should include both the currently classified poor and the households who are likely to fall into poverty.

A support to this outcome is also observed in a study made in rural Oromia-Ethiopia. Deressa (2013) used secondary cross-sectional data and the VEP approach to estimate household vulnerability to poverty. Overall, the findings showed that 47.66% of households were VtP, which is higher than the current poverty rate of 37%. In the categories of VtP, 17.93% of households were non-poor but vulnerable to poverty. Besides, Muleta and Deressa (2014) analyzed vulnerability to expected poverty in rural Ethiopia, especially for female-headed households. The study further analyzed the determinants of VtP using a binary regression model. The major findings showed that 38% of households were VtP and the current poverty rate was 35.26%. Further, the study observed that 16.38% of non-poor were highly VtP, and large family size, small land holding, illiterate, less livestock ownership were the factors to increase the likelihood of falling into poverty.

A panel data analysis of rural China revealed results that were similar to these. Using VEP approach, Ward (2016) estimated transient poverty, poverty dynamics, and VtP in rural China. The study used balanced panel data for the period from 1991 to 2006. Further, based on the panel data, both fixed effect and random effect models were introduced. The result showed that the chronic poor declined over the period; however, the transient poor increased over time. The study concluded that household vulnerability was mostly due to high-income variability. The study further suggested incorporating household behavioral characteristics into the vulnerability to poverty estimation. Mahanta and Das (2017) also estimated the impact of the flood on household VtP in Assam, India. The study used the VEP approach and survey data of 476 households. The outcome variable in this study was the household wellbeing (consumption per capita), whereas the covariate impact mostly was the flood effect and another coping measure by the households. The estimates showed that 83% of households were VtP due to floods. The analysis suggested that community coping measures and the role of the local institution should be given attention to reducing VtP. Besides, using a nationally representative cross-sectional data set of 10311 households and a VEP approach, Demissie and Kasie (2017) studied rural households' vulnerability to poverty in Ethiopia. The study found out that 54% of households were vulnerable to poverty, which is higher than the currently classified poverty rate of 31%. Further, the study identified that household size, the gender of the household head, age of household head, literacy status, dependency ratio, marital status, and agroecology are the major determinants.

Recently, using three-wave panel data and the VEP approach, Vo (2018) studied household VtP in Vietnam. The study also used a multinomial logit model to estimate factors influencing poverty dynamics. Using the reference poverty line to estimate VtP was the unique contribution of the study. The findings demonstrated that the households with VtP rates of 16.51%, 12.74%, and 9.14% were likely to fall into poverty in 2002, 2004, and 2006 respectively. Further, in the case of poverty dynamics, 4% of non-poor households fell into poverty in 2002-2004, and 5% of non-poor households became poor in 2004-2006. The findings also observed that the poor are more likely to get trapped and households are that currently non-poor have more chances to fall into poverty. The suggestions are to design policies to ensure non-poor are prevented from falling into poverty, to saturate infrastructure development, and to integrate with migration policies in Vietnam. Similarly, using two-period panel data of 2010 and 2012, and the VEP approach, Vo and Van (2019) assessed the impact of health insurance on vulnerability in Vietnam. The findings demonstrated that vulnerability to poverty levels had increased over the years. The vulnerability decomposition shows that in 2010 the vulnerability rate was 13%, whereas it was 27% in 2012. The findings suggest that the policy meant to reduce vulnerability has a negative impact on vulnerability in Vietnam. More recently, Maganga et al. (2021) studied climate-induced vulnerability to poverty among smallholder farmers in Malawi. Using three-year survey data and the VEP approach, the study concludes that household vulnerability to poverty rate is higher than the currently classified poverty rate. The study further estimates determinants of VtP. The study has found out that the head's gender, household size, literacy status, age of household head, marital status, and dependency ratio are the major determinants.

2.3.4 Asset-Based Approach to Estimate Vulnerability to Poverty

The implication of the dynamic approach to estimate vulnerability to poverty has been increasing, and estimates have shown that transient poverty is higher than the current poverty rate (Pritchtt et al., 2000; Chaudhuri et al., 2002; Ward, 2016). Recent researchers criticized the money metric (consumption/income) approach by arguing that income or consumption might not be a good guide to understanding households' wellbeing. Carter and Barrett (2006) developed the dynamic asset-based poverty approach. The Household's accessible asset level is included because assets are considered as the income booster and risk manager. The study emphasizes the importance of assets in preventing households from the poverty trap. This study argues that households that start with very low-level asset ownerships are unable to escape long-term poverty. Households that are above this threshold but close enough to the threshold that unanticipated shocks can push them below it is similarly at danger of falling into long-term poverty in this manner. If social protection measures can lift these households to above the threshold, they can prevent falling into the poverty trap. The study categorized the approach into four categories: structural poor, structural non-poor, stochastic poor, stochastic non-poor. The structural poor are those that have both assets and consumption below the poverty line. Structural non-poor are those households that are above the poverty line in assets and income/consumption. Stochastic poor households are income non-poor but asset-poor, whereas stochastic non-poor households are income poor but asset non-poor.

This approach of measuring vulnerability to poverty is an expansion of the Foster–Greer–Thorbecke (FGT) approach. However, the estimation steps are followed using the VEP approach developed by Chaudhuri et al. (2002). Following the asset-based approach, Dutta and Kumar (2013) have analyzed poverty dynamics in rural India. Their study used secondary panel data and adopted a principal component analysis approach to estimate the asset threshold. The findings show that the transient poverty rate was higher than the currently classified poverty rate. More specifically, the findings show that 29% of households were asset poor, and 35% of households are vulnerable to poverty. Further, Dutta and Kumar (2015) used national and family, and health survey data for the period of 1992 and 2005 to estimate the poverty dynamics in rural India employing the asset-based approach. The study divided poverty into four parts: low-vulnerable non-poor, high-vulnerable non-poor, transient poor, and chronic poor. Further, the study has also employed the multinomial logistic model to find out the determining factors for the different categories of vulnerable households. The result indicated that more dependency ratio and low education are the main factors of vulnerability to poverty. Again, Dutta and Kumar (2016) applied the asset-based framework to analyze stochastic and structural poverty in the Indian context. The study assessed multiple equilibria using household asset data. The study used secondary data from the India human development survey (NCAER-IHDS). The major findings are that the majority of households are stochastically poor and Odisha remains the highest structurally poor state.

In this context, Mburu (2016) studied income and asset poverty among pastoralists in northern Kenya. The study used panel data and an asset-based approach to investigate pastoralists' households' assets and income poverty. The main findings showed that the majority of households remained structurally poor, whereas stochastic non-poor increased marginally. The policy implications for the study area suggest that livestock insurance and improving livestock markets are particularly important. In a related study, Chiwaula et al. (2011) assessed VtP in the small-scale fishing community in two countries, namely Cameroon and Nigeria. The study adopted an asset-based approach to cross-sectional data of 562 households, 295 from Cameroon and 267 from Nigeria. The estimated result showed that VtP is higher in Cameroon at 67% than in Nigeria at 59%. The analysis also decomposed the VtP into four parts: “structural chronic poor, structural transient poor, stochastic transient poor, and never poor.” The findings highlighted that structural chronic poverty was 45% and 30% for Cameroon and Nigeria, respectively. Further, the percentage of the structural transient poor was higher than the stochastic poor. The findings suggested that asset formation is necessary for long-term poverty reduction. Similarly, You (2014), using panel data and an asset-based approach in rural china, argued that future reform and policy should focus on asset building for households. Recently, You (2017) used the assets-based approach to poverty in the context of rural China. Using panel data for the period 1986-2000, the study observed that asset holding below the poverty threshold reproduces poverty.

2.3.5 Multilevel Modeling to Estimate Vulnerability to Poverty

Recent works have tended to employ multilevel modeling to estimate household VtP developed by Gunther and Harttgen (2009). This approach is an extension of the VEP approach devised by Chaudhuri et al. (2002). The important feature of this approach is that it distinguishes household VtP due to covariate shocks and idiosyncratic shocks. The advantage of this approach is that household VtP due to covariate and idiosyncratic shocks can be calculated without even the information on the shocks. Further, the model can be used in both panel and cross-sectional data. The pioneering work by Gunther and Harttgen (2009) used the cross-sectional data from Madagascar employed multilevel modeling, distinguished household VtP due to covariate and idiosyncratic shock. The investigation was done using a proxy for idiosyncratic and covariate shocks. The findings demonstrated that the vulnerability to poverty rate was 66% compared to the poverty rate of 49%. Further, idiosyncratic vulnerability (64%) was higher than covariate vulnerability (57%). The result showed that the impact of the negative adverse events varies based on geographical situations. More specifically, the findings revealed that covariate shocks had a greater impact on rural areas, but idiosyncratic shocks have a greater impact on urban areas.

Echevin (2013) estimated VtP in rural Haiti using cross-sectional data of 2000 households from 228 rural communities collected in the year 2007. Using a multilevel decomposing approach, the study observed that idiosyncratic shock, like health shocks, has more impact than covariate shocks. Also, Mina and Imai (2015) used longitudinal data from 2003 to 2009, and used a multilevel modeling approach to estimate VtP in the Philippines. The findings showed that one-third of the households are vulnerable to unobserved shocks that are higher than the current poverty rate. In distinguishing VtP due to covariate and idiosyncratic shocks, the analysis showed that households are more susceptible to idiosyncratic shocks than covariate shocks. Liebenehm (2017) studied risk attitude and the impact of adverse shocks on household VtP in Vietnam and Thailand using multilevel modeling. Using a panel data set of 2812 for 2008 and 2010, the study found out that the adverse impact differs from country to country. The findings show that the variability in risk attitude was observed to be a covariate in Vietnam, whereas it was idiosyncratic in Thailand. Following multilevel modeling, recently, Azeem et al. (2018) used cross-sectional data of 90,000 households to analyze VtP in Pakistan. The study observed that 15% of households were vulnerable due to covariate shocks and 14% due to idiosyncratic shocks. Further, the study also examined the social protection impact on reducing VtP using multilevel modeling and observed that idiosyncratic vulnerability was higher than covariate vulnerability (Azeem et al., 2019).

Recently, VtP has also shifted to vulnerability to multidimensional poverty. The pioneering work by Feeny and McDonald (2016) observed that vulnerability to poverty of 87% is higher than the current poverty rate of 43%. The study also highlighted that education plays a major role in enhancing the capacity to adapt to changing circumstances. At the national level, Azeem et al. (2018) have found out that a different estimation of VtP provides the same results in Pakistan. Further, they suggested education, health, and living standards should be given priority to help the affected people come out of the situation. Similarly, Tigre (2019) observed in Ethiopia that households are more likely to fall into multidimensional poverty.

This research review aims to understand different approaches used by the researchers on the VtP estimation and the gaps to be filled to contribute to the literature on VtP. Most of the research found was greater on the ex-ante poverty rate than on the current poverty rate. This is significant because shocks' impacts are severe, given the lack of coping strategies in rural areas, and often many fall into poverty. More research is required to better understand which groups of households are more VtP, which shocks are predominant, which group of households needs protection against what, the coping strategies used by the households, whether the poor fall into the poverty trap? In addition, because adverse events are such a serious challenge, given rural households' lack of coping mechanisms, it is important to reduce their impact on household well-being. However, research of this type is limited in terms of including the factors in the model because of a lack of data on negative adverse events. This problem might be able to overcome by including household reported shocks and coping measures, and exploring that possibility is the aim of this research. Though the above-stated models estimate the household vulnerability to poverty, each of the methods has its own merits and demerits. Despite the shortcomings of these approaches, one should work with one or more of these since there is no single best approach to estimate household vulnerability to poverty. Based on the data availability and nature of data, approaches are used to measure household VtP. The present study has adopted the VEP approach devised by Chaudhuri et al. (2002) to estimate household VtP in rural Odisha because the data used in the study is cross-sectional in nature.

2.4 Review of Literature on the Impact of Social Protections on Economic Outcomes

The concept of “social protection”, evolved out of the “social safety net” agenda of the 1980s and 1990s, initially addressed “shocks” but over time, came to include “chronic poverty”. There is a plethora of definitions of social protections (Mendola, 2017; Fiszbein et al., 2014). The broadly representative definition of social protection is “all public and private initiatives that provide income or consumption transfer to the poor, protect the vulnerable against the livelihood risks, and enhance the social status and rights of the marginalized; with the overall objective of reducing the economic and social vulnerability of the poor, vulnerable and marginalized groups” (Devereux and Sabates-wheeler, 2004, p.9). In other terms, “social protection is generally defined as a set of formal or informal mechanisms which enables households either to reduce vulnerability and risk or to cope with economic shocks” (Mendola, 2017).

Social protection is broadly classified into three components such as social assistance, social insurance, and labor market protection (Barrientos, 2017; World Bank, 2014, 2015).

The social assistance programs are known as non-contributory interventions such as cash transfer and in-kind transfer. The cash transfer programs are further divided into conditional transfer programs and unconditional cash transfer programs. The Conditional Cash Transfer (CCT) programs refer to the program that transfers cash to the targeted beneficiaries by requiring meeting some specified conditions. Examples of conditional cash transfer programs are Mexico's PROGRESA and Brazil's Bolsa Familia. On the other hand, Unconditional Cash Transfer (UCT) programs refer to the programs that distribute cash to the targeted beneficiaries without meeting any requirement. India's "Targeted Public Distribution System (TPDS)", a food price subsidy, Kenya's "Cash Transfer program for Orphans and Vulnerable Children (CT-OVC)", Lesotho's "child grand program", and South Africa's "child support grant" are the unconditional cash transfer programs. Further, public work programs are also referred to as conditional cash transfer programs as the beneficiaries have to work to create community assets. India's "Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA/NGEGS)", the world's largest anti-poverty employment program, and Ethiopia's "Productive Safety Net Program (PSNP)" are examples of conditional cash transfer programs. According to the World Bank report (2017), about 122 developing nations provide unconditional cash transfers, and 95 developing nations support conditional cash transfers.

The next component is "social insurance programs"; these programs are typically designed to protect poor households from risks by providing insurance facilities. Such programs are typically targeted at health shocks and crop losses. Finally, "labor market interventions" are typically designed to provide job training and focus on skill development. The goal of this protection is to enhance the capacity of beneficiaries for employability. It was observed that nearly one-third of the population from the developing world, that is, 2.1 billion people, have benefited from some form of social protection, whereas by 2013, nearly 1 billion people from all over the world have received some form of social protection benefits (Croppenstedt et al., 2018; Hidrobo et al., 2018).

There have been outstanding efforts to reduce poverty and vulnerability through social protection. The number of 'social protection programs' are increasing in underdeveloped and developing countries to enhance the resilience capacity of poor and vulnerable households. There is evidence that social protection has both positive and negative impacts on poverty (Hagen-Zanker et al., 2011; Hidorbo et al., 2018). However, understanding the impact of social protection on household VtP is of great relevance for public policy. This concern may make this concept more effective in policy interventions aimed at ending poverty, since it will make the concept more feasible in the application. Evidence-based evaluation helps the funding agencies modify the program or design another more appropriate program. In addition, government and donor agencies funding social protection programs want to know whether devoted funds meet projected outcomes (Gentilini, 2009). Over the years, there has been extensive literature on understanding the key challenges and impacts on the targeted objectives. The methods employed to estimate the impact of social protection on household wellbeing are broadly categorized into three categories: 1. Experimental design, 2. Quasi-experimental design, and 3. Non-parametric approach. The reviews of such strategies used by the researchers are presented below.

2.4.1 Experimental Design: Randomized Control Trial (RCT) Method

The experimental approach in program evaluation is known as a “Randomized Control Trial (RCT)”. In the impact evaluation study, the RCT approach is the gold standard for evaluating social protection programs. The approach randomly selects sample households for treatment and control groups and provides support to the treated group. After the specified period, this approach evaluates the impact of the program by estimating the difference of outcomes between treated and control groups. Worldwide, there are several studies that have estimated social protection impact using the RCT method. Since RCT cannot be applied in many cases, such as government-sponsored schemes that are not randomly distributed, and since the present study used a quasi-experimental design to evaluate the program, we have not presented the details of the literature review using RCT measure. We admit that the RCT approach is more reliable and robust than the quasi-experimental approach. However, we cannot measure the impact using RCT due to the lack of such randomized data. We have provided a brief description and research discussion of RCT.

The details of RCT measures and techniques can be found in Banerjee and Duflo (2009). Empirical studies have been undertaken using RCT methods for the impact of social protections on various economic outcomes. A number of studies were conducted using RCT in the context of microfinance (Crépon et al., 2015; Banerjee et al., 2019; Banerjee et al., 2018; Banerjee et al. al., 2015; Banerjee et al. 2014). The mixed findings of positive and negative impact on household wellbeing are observed in the context of cash transfer on poverty reduction (Banerjee et al., 2020; Bardou et al., 2017; Blattman et al., 2015). Several studies have undertaken the impact evaluation on food security (Aker et al., 2011; Fernald and Hidrobo, 2011; Hidrobo et al., 2012b; Merttens et al., 2013). In the case of employment, the following are the studies that have evaluated cash transfer impact on household wellbeing through employment support (American Institutes for Research (AIR), 2014; Asfaw et al., 2014; Attanasio et al., 2010; Barrera-Osorio et al., 2008; Barrera-Osorio et al., 2011; Benedetti et al., 2015). A number of studies were conducted using RCT in the case of saving, investment, and production (Evans et al., 2014; Gertler et al., 2012; Green et al., 2015; Maluccio, 2010; Pellerano et al., 2014). Past studies have found a positive impact of cash transfer in the context of empowerment (Siaplay, 2012; Stecklov et al., 2006; Stecklov et al., 2007; Baird et al., 2013). Several studies focus on the impact of welfare program on education, specifically on the outcomes of enrollment, improvement in grades, and test scores (Gertler and Fernald, 2004; Akresh et al., 2013).

2.4.2 Quasi-Experimental Approach

As explained above, randomized evaluations, on the other hand, may not always be feasible. In these instances, researchers then turn to so-called non-experimental methods. The basic problem with a non-experimental design or quasi-experimental approach is that, for the most part, individuals are not randomly assigned to programs, which results in selection bias when assessing the program impact. There are a number of non-experimental approaches that address this problem of selection bias, which are discussed here. Instrumental variable (IV) model, regression discontinuity (RD) approach, the difference in difference (DID), endogenous switching regression (ESR), and Propensity score matching (PSM) are different approaches in the quasi-experimental approach developed to assess the impact of social protection on household wellbeing. A reliable impact assessment's main challenge is to create a counterfactual outcome- that is, identifying what would have happened to the targeted beneficiary households that participated in social protection measures in the absence of social protection. In other words, the beneficiary households who actually participated or received a benefit from social protection would have had the outcome had they not received the benefit from social protection. A matching method like the PSM approach has been developed to help design and analyze non-randomized observational studies in order to mimic some of the features of a randomized control trial (Rosenbaum and Rubin, 1983). Further, other quasi-experimental approaches such as DID, IV, ESR, RD are widely used based on the nature of data in order to control selection bias and bias arising from unobserved variables.

a) A Literature Survey on the Impact of Social Protection on Household Wellbeing

Since 1990, several welfare programs are being implemented to reduce poverty and to improve household wellbeing by providing food security, health care support, investment and credit support, income and consumption improvement, and employment opportunities to the targeted households. Several studies have evaluated the impact of those programs using quasi-experimental approaches among developed and developing economies (Jena, 2019; Jena et al., 2012; Jena and Grote, 2017; Tesfaye et al., 2017). In this context, Hagen-Zanker et al. (2011) reviewed 37 experimental and non-experimental articles on employment generation and cash transfer to study the impact of social protection on poverty, income, and consumption. In this study, the reviewed paper reported that social protection reduces poverty and improves income and consumption of the participated households more than the counterfactuals do. Kabeer (2012) also systematically reviewed the economic impacts of conditional cash transfer programs using 46 experimental and quasi-experimental papers. The findings show strong evidence of conditional cash transfer, increased household consumption, increased investment in productive assets, reduced child labor, and increased school attendance. More importantly, the study shows that CCTs protect household consumption during a time of crisis. Further, Baird et al. (2013) reviewed the relative impact of conditional and unconditional cash transfers on educational performance in developing nations. The findings highlighted that both CCTs and UCTs improved enrolment and attendance in schools.

In addition, Kabeer and Waddington (2015) considered 46 randomized and quasi-experimental impact evaluation studies to conduct a systematic review of the impacts of CCT programs on household economic outcomes. The study adopted statistical meta-analysis and analysis of program mechanisms to examine the impacts for participants and non-participants. The findings concluded that CCT programs resulted in decreased child labor, increased household consumption smoothing, and improved investment. Another comprehensive review was done by Banks et al. (2017). The study considered 15 cash transfer grants for the period of 1990-2014, specifically for the outcome of poverty, employment, and health. The study concluded that the program had failed to impact the targeted outcome. The impact of cash transfers (both conditional and unconditional) on various economic outcomes was systematically reviewed by Bastagali et al. (2016). The study considered 201 studies for the analysis, and the findings showed that cash transfers impact is largely positive on reducing monetary poverty, improved educational outcome, improved health outcomes, positive effect on savings, investment, and production, but no significant impact on employment outcome. Recently, a comprehensive review by Hidorbo et al. (2018) adopted a meta-analysis tool to assess the impact of welfare program on household wellbeing. Papers that have used rigorous impact evaluation approaches (121 referred papers) were included for the analysis. The study found out that social protection policies positively impact economic outcomes such as poverty reduction, food security, and improvement in productive assets. More recently, McGuire et al. (2020) reviewed the impact of cash transfers on subjective wellbeing and mental health in low and middle-income countries using articles for the period of 2000-2020 and meta-analysis technique. Reviewing 37 studies, the findings conclude that a UCT has a larger impact than a CCT program.

More recently, in this direction of social protection and household wellbeing, Nawaz and Iqbal (2021) evaluated the effect of a cash transfer program, namely “Benazir Income Support Program (BISP)” on environmental poverty, using 9823 households across

Pakistan. Using the Alkire-Foster method, 57% environmental poverty index was estimated. The RD technique findings revealed that the BISP cash transfers program has a positive and significant impact on reducing environmental poverty. An impact evaluation study made in Pakistan confirms that unconditional cash transfer increases household wellbeing. Malhi (2020) used 6677 household data drawn from Pakistan Rural Household Panel Survey 2012-13 and adopted the PSM technique to estimate the impact of UCT on three dimensions such as consumption, assets, and social status. The results indicate that UCT positively impacts the targeted economic outcomes in rural Pakistan. In addition, using 3713 household panel data (8675 in 2011 and 11358 in 2016) and RD technique, Nawaz and Iqbal (2020) analyzed the impact of UCT-BISP on fuel choices among the ultra-poor in Pakistan. The research found that the BISP cash transfer program has a significant impact on inter-fuel substitution.

Contrastingly, a recent study by Saeed and Hayat (2020) used 24,238 observations from household integrated economic survey data 2015-16 and the PSM approach to estimate the impact of social cash transfer programs, namely BISP, on poverty in Pakistan. The findings demonstrated that there was no significant association between BISP transfer and poverty reduction. However, it was observed to be negative and insignificant when the bottom consumption quantiles were considered. A study by Gazeaud and Stephane (2020) applied DID approach to examine the impact of PSNP on agricultural productivity in Ethiopia, using a satellite-based indicator of agricultural productivity. The empirical findings show that the program is associated with limited changes in agricultural productivity. In the context of Colombia, Malerba (2020) studied the impact of the CCT program on poverty alleviation and local environmental degradation. The study used 5477 household data for 2002, 2003, and 2005-06 for both household and municipality level, and employed DID approach. The results of this study showed that participation in the CCT program is associated with an increase in land and energy-intensive goods but does not have a negative effect on environmental degradation. In the case of Vietnam, Duong et al. (2021) used 892 household panel data for the period 2002, 2008, and 2014 to examine the impact of off-farm employment programs on food security and poverty reduction in rural Vietnam. The study employed PSM and DID approaches and found that off-farm employment boosts income, assures food security, and helps to alleviate poverty in rural Ethiopia. In the Indian context, Bagavathinathan and Chaurey (2020) examined the impact of MGNREGA on female participation and the food consumption of children. The study used panel data for the period 1999–2007 from the National Sample Surveys and a DID strategy. The study concluded that MGNREGA positively impacts the household well-being of participants. Similarly, in Mexico, Kronebusch and Damon (2019) studied the impact of PROGRESA, a CT program, on the micronutrient and macronutrient consumption levels of program participants using 20469 households and DID approach. The findings showed that PROGRESA positively affects Vitamin consumption by 15% and mineral consumption by 7%. Again, Maity (2020) examined the effects of MGNREGA on expenditure patterns and food security. Using the IV technique, the study found that increasing the number of days worked increased the amount of money spent on food in the household. Deininger and Liu (2019) also studied the welfare effects of NREGS on direct beneficiaries using 4013-household panel data from Andhra Pradesh, India. The highlights reveal that there is a positive association between participation in the program and household wellbeing.

Teka and Lee (2019) used extensive panel data from Tigray's Eastern zone to assess the farm productivity impact of integrated agricultural package programs in Ethiopia. The study employed the fixed effect estimation model and the PSM technique. The fixed effect findings show that the programs positively and statistically significantly impact farm productivity in Tigray's Eastern zone. Further, the finding from PSM assures that the ATT for package participant smallholder farmers is positive and statistically significant. Another empirical study by Lachaud et al. (2018) evaluated Training for Rural Economic Empowerment (TREE) programs in Zimbabwe, using 2211 household panel data for two periods (2011 and 2014) and both PSM and DID approaches. The findings show that the program increased income, child welfare, and health expenditure of beneficiaries compared to non-beneficiaries. Besides, Berg et al. (2018) used monthly data on wage rates from the period 2000-2011 and DID approach to estimate the impact of NREGS on agricultural wages. The study found that the program boosted daily agricultural wages by 4.3% per year. In this framework, using data collected from 150 farmers and a PSM econometric technique, Beshir (2018) examined the impact of an irrigation project on poverty alleviation and its determinants on the use of water resources in South Wollo. The program intervention had a positive and statistically significant impact on participants regarding the outcomes of consumption expenditure and livestock holding. The logit result revealed that the household's food security was improved by irrigation program intervention in the study area. Another impact evaluation study by Yuya and Daba (2018) used the PSM technique to study the rural household livelihood strategies and their impact on livelihood outcomes in Eastern Oromia, Ethiopia. The finding draws from the data collected in 2016-17 for the 180 households. The study concludes that the choice of livelihood strategies is crucial in increasing the household's food security status and in reducing the poverty levels of farmers. The policy implication is that government policy should encourage rural livelihood diversification.

Another work by Do et al. (2017) undertook a study to evaluate the impact of livelihood production on rural poverty and perceived shocks in Vietnam. The study adopted PSM and DID approach and 8090 household data for 2007, 2008, 2010, and 2013 to estimate the poverty reduction effect. Further, dynamic econometric models were applied to study the determinants of livestock assets. The findings show that large livestock significantly reduces the depth of poverty and consumption inequality among the poor. In evidence of Ethiopia, Weldegebriel (2016) examined the role of the PSNP in reducing vulnerability to climate-related shocks and its impacts on household income diversification. The paper assessed vulnerability using an index-based approach and the impact of the program using DID combined with the PSM technique for a panel of 1,306 rural households from the Ethiopian Rural Household surveys for the years between 2004 and 2009. The highlights reveal that PSNP helps to decrease the vulnerability of households to climate-induced shocks.

Another empirical study on cash transfer is by Farooq (2014) evaluated the impact of the BISP on poverty using the Pakistan Panel Household Survey, 2010. The study employed the PSM technique and found no significant difference between participants and non-participant households in terms of poverty. An impact evaluation study by Charlery et al. (2016) used 177 household data and DID approach to estimate the impact of infrastructure on rural household wellbeing and inequality in Nepal. The study concludes that infrastructure improvement has a significant positive impact on household income. The study states that contrary to the expenditure, the findings did not show an increase in inequality. The study conclude that infrastructure has decreased income inequality compared to the counterfactual site. Further, Loschmann et al. (2015) assessed the impact of shelter assistance programs on poverty reduction in Afghanistan, using the PSM approach and 3715 household data from United Nations High Commissioner for Refugees (UNHCR). Using Alkire and Foster's (2011a, 2011b) method, the percentage of multidimensional poor is estimated. The study findings show that there is 3% points multidimensional poverty observed for the households that received shelter assistance program than their counterfactuals.

In this line of arguments, Ravi and Engler (2015) analyzed the impact of NREGS on food security, savings, and health outcomes of rural poor. The study used triple DID approach to the two-year panel data from Andhra Pradesh, 1,064 households from 198 villages. The study found a positive association between participating in the NREGS and the monthly per capita expenditure (both food and non-food goods) during the two-year period. Similar studies from India by Klonner and Oldiges (2014) employed the RD technique to estimate the effects of MGNREGA during the years 2007 and 2008 on household consumption and poverty rates in rural India. The study concludes that the employment program has a positive impact on consumption smoothing and poverty reduction. Similarly, Gebresilassie (2014) applied the PSM technique to evaluate the impact of the PSNP on poverty using primary data from randomly selected 600 households in Ethiopia's central zone. The study observed that the program has a positive and significant impact on protecting productive assets and poverty reduction. In addition, Tutor (2014) examined the impact of conditional cash transfer programs on consumption using the PSM approach in the Philippines. The study observed an impact for the bottom 20% of the income distribution. The study did not find any significant impact on overall per capita consumption. Also, Garroway (2013) examined the impact of social assistance programs on poverty among pension holders in India using the PSM approach and 2666 households from IHDS-2005 survey data. The findings showed that programs have reduced poverty among participants by about 2.7%. Again, Deininger and Liu (2013) analyzed the welfare effects of the NREGS on short and medium-term poverty using three wave panel data (4,000 households) from Andhra Pradesh. Triple difference estimates suggest that participation in the program significantly increases consumption in the short run, and accumulates more nonfinancial assets in the medium term. Another study in the Indian context by Azam (2012) employed the DID approach to study the impact of NREGS on labor market outcomes in India. The study used data for the 120000 households and 600000 individuals for the period of 1989-2000, 2004-05, and 2009-10 from NSSO. The study found a positive impact of NREGA on labor force participation, and the impact on wages of female casual workers increased by 8%.

Agostini and Brown (2011) estimated the impact of various government programs (cash transfers) on poverty in Chile. The study observed that transfers resulted in significant decline in headcount ratio at the county level in Chile. The study suggests that anti-poverty programs should be targeted at the micro level as it leads to greater success in poverty alleviation than targeting at the aggregate level. Another study by Nega et al. (2010) examined the impact of the food for work (FFW) and the food security package (FSP) programs on the dynamics of poverty. Using a three-year panel data set, the empirical findings demonstrate that the FSP program has reduced total and chronic poverty but did not reduce transient poverty in the rural Tigray region of northern Ethiopia.

Another empirical study in the case of India, by Jha et al. (2009), used household datasets for 1993-1994 and 2004- 2005 to analyze the impacts of access to Rural Public Works (RPW) and the PDS on consumption poverty, undernutrition, and vulnerability in India. The findings from treatment effect and PSM models show RPW and PDS programs reduced poverty, undernutrition, and vulnerability. Gilligan et al. (2009) assessed the impact of Ethiopia’s PSNP using the PSM technique. The study found that the program has little impact on participants. Olson (2007) observed that the livelihood program improved livelihood and food security, and reduced poverty in eastern Zambia. In Kenya, Gotor and Irungu (2010) observed the positive impact of the employment program on the household well-being of the women who participated in the employment program. Sparling and Gordon (2011) studied the impact of post-disaster livelihood programs on children in Indonesia and Sri Lanka and found a positive impact on household well-being. Shimizu et al. (2016) observed a positive impact of the employment program on the burden of depressive symptoms among people living with Human Immunodeficiency Virus (HIV) in Cambodia.

Given the dominant share of rural households and deriving livelihoods from the farming sector, various programs and technologies supported, through social protection, in improving household wellbeing and reducing poverty. In this scenario, Sinyolo (2020) employed PSM and Tobit model and 415 household survey data to study the impact of improved maize varieties on household food security among rural households in South Africa. The study found a positive and significant impact on household wellbeing. The study suggests promoting less costly improved seed varieties, targeting female farmers, improving access to information, and enhancing food security among poor South African households. Another impact evaluation study by Ahmed et al. (2017) assessed the impact of improved maize varieties on farm productivity and household welfare in Ethiopia's east Hararghe zone. The study used both PSM and ESR approaches and household survey data of 385 households. The study concludes that the adoption of improved maize varieties results in substantial increase in consumption expenditure. In this framework, Sahu and Das (2015) used cross-sectional household-level data from 270 households to examine the impact of agriculture-related technology adoption on poverty in rural India. In particular, the study used the PSM technique to assess the impact on expenditure and poverty reduction. The findings conclude that there is a positive and significant impact on expenditure and a negative and significant impact on poverty incidences among households in rural India. Similarly, Khonje et al. (2015) analyzed the impact of improved maize varieties in eastern Zambia. The study employed both PSM and ESR approaches, and the data obtained were from a cross-sectional 800 farm households. The empirical results show that improved maize adoption leads to significant gains in crop income, consumption expenditure, and food security. Using cross-sectional farm-level data from 3,164 rice-farming households in the Philippines, Villano et al. (2015) measured the impact of modern rice technologies on farm productivity. The analysis demonstrates that the use of certified seeds has a large and beneficial effect on rice farming production, efficiency, and net income.

Another study by Asfaw et al. (2012) used cross-sectional household survey data of 613 and both PSM and ESR approaches to evaluate the impact of improved pigeonpea technology on consumption expenditure and poverty status in rural Tanzania. The findings confirmed that adopting improved pigeonpea boosts consumption expenditure and reduces poverty significantly. The study suggests improving investment in agriculture research and access to seed market outlet improvement. Another work by Kassie et al. (2011) used the PSM technique to evaluate the impact of adopting improved groundnut varieties on household crop income and poverty reduction in rural Uganda. The study analysed cross-sectional data from 927 households collected in 2006. The study found that adopting improved technology results in considerable gains in agricultural income and poverty reduction. The literature shows overall positive impacts and suggests offering new technologies to improve household well-being and poverty reduction. Further, Wu et al. (2010) applied three wave panel data for 2000, 2002, and 2004 from 473 households in Yunnan and China to assess the impact of improved upland rice technology on farmers' well-being. The findings from the PSM technique indicate that improved upland rice technology adoption improved income levels and reduced the incidence of poverty. Another study made in South Africa by Asfaw and Shiferaw (2010) assessed the potential impact of the adoption of modern agricultural technologies on rural household welfare in rural Ethiopia and Tanzania using both PSM and ESR approaches. The study used 1313 farm households' data collected in 2007 (700 in Ethiopia and 613 in Tanzania). The ESR results confirm that the adoption of pigeonpea significantly impacts consumption expenditure per adult equivalent, although the result from the PSM method is not significant. In the case of Mexico, Becerril and Abdulai (2010) examined the impact of improved maize varieties on poverty in the country, using cross-sectional data of 325 farmers. The highlights reveal that the adoption of improved maize varieties has a positive and significant impact on per capita expenditure, and the poverty reduction observed is between 19% to 31%.

In a related study, in the case of the impact of certification on household wellbeing, Jena and Grote (2017) applied the PSM approach and 256 coffee farmer household survey data to analyze the impact of Fairtrade certification on small-scale coffee producers in a tribal community of India. The study observed that Fairtrade certification positively impacts farmers' income. Another empirical study by Jena et al. (2017) investigated the impact of Fairtrade and organic certification on smallholder coffee farmers' household income in the Jinotega Municipality of Nicaragua using primary data, which was obtained from a sample of 233 coffee farming households. The ESR and PSM approach results indicate that the overall impact of these certification standards on the total household income is statistically insignificant.

Health issue plays a critical role in pushing households into poverty. Due to lack of health insurance, the situation gets worse for poverty reduction. Developing countries have designed social health insurance policies to reduce the catastrophe cost and improve household wellbeing. It is observed from the findings that previous studies have mostly examined the impact of health policy on reducing out-of-pocket expenditure (OOPE), related to the implementation of the scheme and utilization, and are mainly related to ex-post poverty reduction (e.g., Boyanagari and Boyanagari, 2019; Singh and Kumar, 2017; Taneja and Taneja, 2016; Azam, 2018; Shahrawat and Rao, 2011). For instance, in China, Lei and Lin (2009) found no evidence of reducing OOPE for the insured. Similarly, Wagstaff (2007) showed no overall impact on the OOPE of the healthcare program in Vietnam. Atagubaa and Goudge (2012) observed that health insurance policy does not result in lower OOPE for the insured in South Africa. However, Wagstaff (2010) and Axelson et al. (2009) found that China's health insurance scheme does result in lower OOPE for the insured. Wagstaff and Yu (2007) observed that China's health insurance scheme reduced ex-post poverty. Galarraga et al. (2010) showed that health insurance reduced OOPE for poor households in Mexico. Aryeetey et al. (2016) found that health insurance reduced OOPE, catastrophic expenditure (CE), and poverty in Ghana. Trujillo et al. (2005) observed that health insurance greatly reduced OOEP and increased utilization in Colombia. Similarly, in South African countries, namely Burkina Faso, Niger, and Togo, Atake (2018) found a reduction in VtP and poverty. Based on a meta-analysis and systematic review, Habib et al. (2016) found out that health insurance reduced OOPE, borrowings, and poverty in the majority of cases.

To analyze in detail, in this context, Bonfrer et al. (2018) used the PSM approach and panel data collected in 2009 and 2011 from 3509 households to estimate the effects of introducing the Kwara State Health Insurance program in Nigeria. The empirical findings confirmed that the program increased health care utilization by 36% and reduced out-of-pocket expenditure by 63%. A study conducted by Karan et al. (2017) used household-level panel data for 1999/2000, 2004/05, and 2011/12 from NSSO to estimate the causal effects of RSBY on out-of-pocket expenditure. The DID approach indicated that RSBY was inefficient in reducing the burden of out-of-pocket spending for poor households. In addition, Sparrow et al. (2013) examined the impact of Indonesia's universal health insurance on poverty reduction using DID methods for 8582 households observed in 2005 and 2006. The study found that program-Askeskin has a positive impact on reducing catastrophe OOPE health payment. An impact evaluation study by Gao et al. (2015) examined the impact of urban China's primary poverty reduction program using data from the China Household Income Project (CHIP) in 2002 and 2007. The PSM model findings show that the program had significant poverty reduction effects in both years, and the effect was larger in 2007 than in 2002.

Food security is becoming an increasingly serious issue in the developing world. The ability to overcome this obstacle is crucial in the eradication of poverty. In this scenario, studies have evaluated the programs implemented to ensure food security in emerging countries. Among the studies, Savy et al. (2020) measured the impact of a food voucher distribution of the World Food Program, targeting vulnerable households in two cities of Senegal using both DID and PSM approaches and 2004 household data. The findings show that severe food insecurity decreased from 83.9% to 64.6%. A recent work of Rahman and

Mishra (2019) studied the impact of non-farm income on food security in India, using panel data for 2004-05 and 2011-12 from IHDS survey of 26012 households. It was discovered through the use of an IV model that engaging in non-agricultural livelihood has a positive impact on overall food expenditures. Another empirical study by Rahman (2016) used the DID approach and two-period panel data of 2004-05 and 2011-12 from NSSO to examine the impact of universal food security programs in the hunger-prone KBK (Koraput, Balangir, Kalahandi) districts of Odisha, India. The study concludes that PDS participation improved the calorie intake and diet quality for the participants compared to the counterfactuals. Using nationally representative 55,970 household data from the Household Budget Survey conducted in 2008–2009, Martins and Monteiro (2016) studied the impact of the Bolsa Família Program on food purchases of low-income households in Brazil. The findings showed that the beneficiary households had 6% higher food expenditure and 9.4% higher total energy availability. On the other hand, Kaushal and Muchomba (2015) also applied both the OLS and IV model and panel data for 1993-94, 19990-2000, 2004-05 from all major states to study the impact of PDS on household food security measured by intake of calories. The empirical findings show that the program has a negligible impact on the outcome variable. Another study by Kishore and Chakrabarti (2015) investigated the impact of PDS on household wellbeing in India by using panel data for 2004-05 and 2009-10 from selected states of India. The findings from DID approach indicate that the program has a positive impact on household wellbeing. Similarly, Kaul (2014) used 2002-2008 panel data from selected states and the OLS approach to estimate the wellbeing improvement effect of PDS in India. The findings show that PDS has a positive effect on overall calorie intake. In addition, Krishnamurthy et al. (2014a) employed DID approach and panel data for 1999-2000 and 2004-05 from Chhattisgarh to estimate the impact of PDS on food security. The findings show that PDS has increased the calorie intake of participants than that of non-participants.

Another comprehensive study by Jha et al. (2011) applied the IV model to estimate the NREGS and PDS impact on macronutrients and micronutrients in three states in India: Andhra Pradesh, Maharashtra, and Rajasthan. The study used cross-sectional data of 7124 individuals collected during 2007-08. It concludes that participation in social protection positively impacts the targeted economic outcomes. Support to this finding is also seen in a study made by Abebaw et al. (2010). The study evaluated integrated food security programs on household food consumption, using the PSM approach and 200 household data from the Ihinat district in Northern Eastern Ethiopia. The highlights reveal that the IFSP program has raised physical food calorie intake by 30% among the beneficiary households. Empirical evidence by Salinas-Rodríguez and Manrique-Espinoza (2013) estimated the effect of the Oportunidades on vaccination coverage for poor and rural older people in Mexico using the 2007 Oportunidades Evaluation Survey. The results from the PSM estimate show that the poverty alleviation program has increased vaccination rates in the population of older people. In contrast, Kochar (2005) used panel data for 1993-94, 1999-2000 from 17 major Indian states to evaluate the impact of PDS on food security. The study employed both OLS and IV models which said PDS subsidy had no impact on the intake of calories.

Several studies have been undertaken to understand the impact of cash transfers on improvement in investment, productive assets, and household wellbeing. Using a nationally representative cross-sectional data set of 3380 households from rural Nigeria, Shehu and Sidique (2014) examined the effect of participation in non-farm enterprises on household wellbeing. The study used the PSM approach and found a positive impact of the program on household wellbeing. Another study by Owusu et al. (2011) assessed the impact of non-farm work on food security and household income in Northern Ghana using the PSM approach. The findings revealed that non-farm work positively impacts households' income and security status.

In this context, Kumar et al. (2017) used large national farm household level 35200 data and IV as well as Two Stage Least Squares (2SLS) estimation approaches to examine the role of institutional farm credit on farm income and farm household consumption expenditures. Findings show that formal credit has a positive and significant impact on both net farm income and per capita monthly household expenditures of participants. Ghalib et al. (2012) examined whether household access to microfinance reduces poverty using 1,132 households of the province of Punjab in Pakistan. The findings from the PSM model suggest that despite producing some degree of positive impact, microfinance institutions still have to make sustained efforts to bring about a real difference to the livelihoods of the poor. Also, Shariar (2012) used the PSM approach to examine the impact of microfinance on seasonal hardship in Northern Bangladesh. The data for the study was collected from a cross-sectional survey of 293 households from Kurisgram district in Northern Bangladesh in the year 2006. The study found that the participants were 31% points less likely to be affected by acute food poverty than the counterfactuals. On average, fluctuation in daily income is reduced by 13 takas for the program participants. In a related study, Imai et al. (2010), using national household data from India, employed Tobit and PSM models to examine whether household access to microfinance reduces poverty. The study found that loans for productive purposes were found to be more important in rural areas than in urban areas for poverty reduction.

This section highlights the main findings for the impact of livelihood programs in developing countries. Diversification of livelihoods by increasing non-farm activities is seen as an essential mechanism for driving development, decreasing rural poverty, and increasing farm income across countries (Rahman and Mishra, 2019). Previous studies have found that livelihood programs are key drivers for improving the wellbeing of rural households in developing countries. For instance, In Kenya, Gotor and Irungu (2010) observed the positive impact of the livelihood program on women that have participated. Empirical evidence by Sparling and Gordon (2011) used a mix-method approach to investigate the impact of livelihood programs on children's wellbeing in Indonesia and Sri Lanka. The quantitative findings from the study found no significant impact on the different outcomes of the children's wellbeing. However, the qualitative analysis corroborates the quantitative findings, but it also supported that the program positively impacts children's wellbeing in both countries.

In this line of argument, Yager et al. (2011) studied the impact of livelihood programs in Uganda. The study adopted qualitative data from 21 key informants who worked on the livelihood programs implemented in Uganda. The study suggested that programs targeting the epidemic of HIV and food security should integrate HIV care, food supplementations, and livelihood activities. Also, Barrett et al. (2014) examined the impact of Chars livelihoods program (CLP) on the disaster resilience of Chars communities. Using a mixed-method approach, the study found that livelihoods program improved the overall disaster resilience of Chars communities.

In the case of India, Datta (2015) investigated the impact of the livelihood program-Jeevika on household wellbeing in Bihar. Using the propensity score matching impact evaluation technique, the study found that the program positively impacts the household wellbeing of the participants than the non-participants. Specifically, the program benefited the participated women for the empowerment measured by various dimensions.

Similarly, Shimizu et al. (2016) evaluated the impact of livelihood programs on the living conditions of people living with HIV in Cambodia. The study used quasi-experimental data of 357 people living with HIV who participated in the livelihood program and 328 non-participant people from six provinces in Cambodia. The study adopted a propensity score matching approach and observed that participated households were less likely to have depressive symptoms than counterfactuals.

A study by Patnaik and Das (2017) examined the impact of the livelihood program-WORLP in western Odisha, India, using 800 repeated household data. The study adopted a difference-in-difference (DID) approach and observed that LP improved the income of the beneficiaries and improved the coping capacity of the beneficiaries. More specifically, the improved income ranges between 8-11% and 4% improved on the coping capacity for the beneficiary households than the non-beneficiaries. The study further shows that the program significantly reduced the migration rate by providing work facilities in the region. The study suggested activities for promoting food security, livelihood diversification, and poverty reduction.

Another study in India by Patnaik et al. (2017) used 800 household data and investigated the impact of the livelihood program-WORLP on reducing VtP in western Odisha. The study employed VEU approach and quantile regression for the analysis. The study concludes that the benefited households are less vulnerable compared to their counterfactuals.

The study made in Ethiopia by Kebebe and Shibru (2017) assessed the impacts of participating in alternative livelihood activities on household welfare and environmental protection in rural Ethiopia. The study assessed the difference in household welfare between project participants and non-participants by utilising the PSM technique and a cross-sectional survey of 450 sample households. Participation in alternative livelihood activities has resulted in an increase in overall grain production, higher household income, and adoption of natural resource management technology. More specifically, beneficiary households consumed a wider variety of foods and earned an additional $35 per month. In this context, Hidrobo et al. (2018) used the meta-analysis technique to study the impact of various social protection programs on household wellbeing. The study found that an employment generation program improves household wellbeing, productive assets and reduces poverty.

Recently, Patnaik et al. (2019) examined the impact of livelihood program-WORLP, adoption decision, and farmer’s wellbeing in rural Odisha, India. The study used 549 household data and adopted an endogenous switching regression approach to estimate the impact on farmers’ wellbeing. The study found that the livelihood program enhances the likelihood of undertaking farm-level adoption measures. Further, the study demonstrates that adoption leads to significant gains in income from cropping.

Furthermore, Christian et al. (2019) examined the impact of livelihood program-TRIPTI on reducing the effect of an adverse event in coastal Odisha, India. The study used two-year survey data. The baseline data of 2875 households was collected in 2011 and the end line data of 2874 households was collected in 2014. The study adopted a DID impact evaluation approach and observed that the LP is able to reduce the effect of adverse events for the beneficiary households than their counterfactuals.

Another recent work by Do et al. (2019) undertook a study to evaluate the impact of livelihood production program on rural poverty and perceived shocks in Vietnam. The study adopted PSM and DID approach and 8090 household data for 2007 and 2013 to estimate the poverty reduction effect. Further, dynamic econometric models are applied to study the determinants of livestock assets. The findings show that large livestock significantly reduces the depth of poverty and consumption inequality among the poor.

b) A Literature Survey on Impact of Social Protection on Vulnerability to Poverty

Several impact evaluation studies have been undertaken to evaluate the impact of social protection on poverty reduction and have produced many interesting findings. These findings in social protection and poverty literature are mixed, ranging from the positive effect of social protection to the inverse and neutral effect. As described earlier, in recent years, the issue of vulnerability estimation in the economy has become popular in research and discussion. However, empirical studies devoted to the link between VtP and social protection are limited. A study by Swain and Floro (2012), using a cross-sectional 840 household survey data, assessed the impact of microfinance on vulnerability and poverty among India's low-income groups. The study employed two econometric approaches, namely FGLS and PSM. The findings of the study demonstrate that microfinance reduces poverty and vulnerability. Bronfman and Floro (2012) used both VEP and DID approaches to explore the impact of social protection programs on household vulnerability in Chile, involving 10,287 individuals during 1996-2006. The impact of programs is also studied on two household groups: the chronic poor and the transitory poor. The findings imply that monetary transfers have a mixed effect on vulnerability. It seems to help lower the transitory poor's vulnerability but has little impact on the chronic poor. Using a two-year survey data, Vo and Van (2019) studied the impact of health insurance on household VtP in Vietnam. The study employed two econometric approaches, VEP and VEU, to estimate VtP. Further, adopting the PSM approach, the study evaluated the impact of health insurance policy on VtP. The findings show that health insurance policy has a negatively significant impact on the VtP households. Another paper looking at the impact of social protection on household vulnerability to poverty is by Azeem et al. (2019). It estimated the impact of social protection on VtP in Pakistan. The results have been estimated in two steps. First, the study used a multilevel modeling approach to estimate vulnerability to poverty. Secondly, it used PSM and ESR techniques to estimate the impact of social protection household vulnerability. The study found that social protection policies have a positive and significant impact on household VtP. The study suggests that policy should be designed to include vulnerable households in order to reduce poverty.

In conclusion, despite the vast use of these approaches, a few limitations are associated with the quasi-experimental design models used to evaluate poverty and VtP. The most significant among them for PSM is 'hidden bias'. The approach has been criticized for the hidden bias arising from unobserved variables (Caliendo and Kopeinig, 2008). One strategy for addressing this problem is the Rosenbaum bound test, known as a sensitivity analysis (Rosenbaum, 2002). For the DID approach, if any other factors affect the difference in trends between the two groups, the estimation will be invalid or biased. In the case of the RD technique, the estimate cannot necessarily be generalized to units whose scores are further away from the cut-off score; this is where eligible and ineligible individuals may not be as similar. Relatively large evaluation samples are required to obtain sufficient statistical power when applying RD. Even with these limitations, quasi-experimental designs are widely used in the evaluation of social protection.

2.4.3 Impact Evaluation Using Non-Parametric Approach

Apart from the experimental and quasi-experimental approaches, the relevance of various policies and their impacts are evaluated using a non-parametric approach such as the Quantile Regression (QR) approach. Maciejowska (2020) using the QR approach, found that both renewable sources negatively impact the price level in Germany. Uematsu and Mishra (2012) used panel data of 121 countries from 2006, 2007, and 2008 from Agricultural Resource Management Surveys, and concluded that Natural amenity is positively correlated with farmland values and that its impact is often more pronounced at a higher price range of farmland. Altunbaş and Thornton (2020) studied the impact of financial development on income inequality using a panel of 121 countries. Barnwal and Kotani (2013) employed 34 years of data and found heterogeneity in climatic variables' impacts across agricultural crop yield distributions. Martinsa and Pereira (2004) studied the impact of education on wage inequality and suggested that schooling positively impacts within-level wage inequality. Keho (2017) used annual time series data for 19 selected countries and found a positive effect of remittances on household consumption in African and Asian countries. Lacalle-Calderon et al. (2018) concluded that there is a positive impact of microfinance on poverty among the poorest, using a panel-data for 57 countries for the years 2005, 2008, and 2011. Wang et al. (2019) examined the multiple impacts of technological progress on CO_2 emissions in China. Viola and Klotzle (2018) studied foreign exchange interventions in Brazil and their impact on volatility. Mahadevan and Suardi (2012) used the National Sample Survey (NSS) household database of 2004/2005 and concluded that the influence of socio-economic factors as well as social affiliation on living standards is shown to be contingent on the living standard status of the household in India.

In summary, the purpose of this review was to view the trends in impact evaluation studies and to see how evaluation strategies and models have changed, and are still changing. Despite the considerable progress in evaluation approaches, impact evaluation of policies is still being debated though and continues to be evaluated on ex-post poverty reduction. The ex-ante poverty impact has received less attention. This field of inquiry is significant as policymakers and researchers are more interested in the forward-looking impact of programs. Evidence-based impact evaluation becomes better policy guidance for designing forward-looking policies as the focus has shifted from current poverty to future poverty reduction.

2.5 Research Gap

Several research gaps have been found from the literature review in earlier sections; however, the present research has addressed some of these gaps. There is a broad consensus among the researchers that households in developing nations are chronic and transient poor, which suggests that households frequently move into and out of poverty due to a lack of adaptive management (Carter et al., 2007; Gunther and Harrtgen, 2009). Being able to identify the key influencing factors for chronic and transient poor is necessary for the government to design strategies for poverty reduction that are appropriate. In that context, the imperativeness of this study can be realized in a country like India, where households by and large live in rural areas and draw their mainstay from agriculture, which is mostly affected by climate disasters. Further, finding a way out by enhancing the households' coping strategies provides more insights into designing effective public policies. To obtain real insights into escaping poverty, it is necessary to study the factors that influence households in overcoming poverty. The importance of livelihood diversification and social capital on household wellbeing improvement is well established in the literature. However, there has been scant literature in India that studied the poverty reduction effect of livelihood diversification and social capital. Since the dynamics of poverty is better understood using panel data, research on poverty dynamics is limited in developing nations due to the absence of panel data (Dang et al., 2014; Naschold, 2012; Thorat et al., 2017).

Secondly, because adverse events are such a serious challenge, given the lack of coping mechanisms of rural households, a significant proportion of households are vulnerable to poverty. Household characteristics and proxy for adverse events are commonly used to estimate vulnerability to poverty in past studies. While adverse events negatively impact household well-being, both covariate and idiosyncratic shocks become important components while studying the impact of negative events or household vulnerability to poverty. In that context, the current study has used both covariate and idiosyncratic shocks to measure household vulnerability to poverty. The study further estimates vulnerability to multidimensional poverty using multiple deprivations of household wellbeing such as education, health, and standard of living, which received little attention in the literature discussed. In general, there are limited studies related to estimating vulnerability to poverty that induces risks and shocks and in relation to both the monetary and multidimensional measures (Günther and Harttgen, 2009; Chiwaula et al., 2011; Grimm et al., 2016; Dutta and Kumar, 2016). In particular, existing studies on vulnerability to poverty at the household level in India are scant (Dutta and Kumar, 2016).

Finally, knowing that the share of vulnerable households is higher than the currently classified poverty rate, several social protection measures are actively working to improve the standard of living of poor and vulnerable households. While social protection's potential to reduce ex-post poverty is theoretically and empirically supported, empirical evidence on its function in reducing ex-ante vulnerability is largely missing (Bronfmon and Floro, 2014; Azeem et al., 2019; Vo and Van, 2019). More specifically, the social protection impact is a well-established phenomenon on household wellbeing from different perspectives such as poverty, expenditure, income, and food security (Hidrobo et al., 2018). One critical weakness of the past studies investigating SP's impact is the lack of evaluation on ex-ante poverty, which is the impact of SP on the likelihood of falling into poverty. Therefore, given the objective of social protection to uplift both the poor and vulnerable groups, the impact of welfare program on ex-ante poverty needs to be studied to meet the SDGs 2030. By taking cognizance of this research gap, the current study has undertaken an attempt in that direction by observing changes in poverty status, measuring vulnerability to both monetary and multidimensional poverty, and the impact of welfare program on VtP in the state of Odisha, India.

CHAPTER 3
RESEARCH CONTEXT AND DATA DESCRIPTION

3.1 Introduction

It has now been widely recognized that policies aimed at combating poverty should concentrate not just on those currently living below the poverty line but rather on those who have the possibility of moving into poverty and those already trapped in it. This is why development economics research is increasingly focusing on the study of VtP. There is widespread poverty in rural areas compared to urban areas (Lowder et al., 2017). Among the poor, 78% live in rural areas that are vulnerable to environmental shocks (World Bank, 2015). Rural households are often subjected to extreme shocks of different natures, which can be categorized as idiosyncratic or covariate. While the former is exclusive to individuals or households, such as sickness, accident, or unemployment of household members, the latter is correlated across households within a community such as droughts, floods, or cyclones (Gunther and Harttgen, 2009; Nguyen et al., 2020). All of these types of shocks have the potential to reduce the welfare of rural households. Particularly, the impacts of shocks are much more severe in low-income countries, where credit markets and social insurance mechanisms are relatively limited (CRED, 2020; DeloAch and Smith-Lin, 2018). For example, the effect of adverse events decreases income and damages productive assets, forcing households to sell remaining assets or decrease spending on essential consumption items such as nutritional food or education (Janzen and Carter, 2019). As a result, not only does this have a negative impact on household welfare in the short run, it also has the potential to undermine household welfare in the long run (Nguyen et al., 2020).

Further, given the above scenario, it is a fact that the majority of the rural households derive livelihoods from agriculture and forest resources. The statistics about the economic losses due to adverse events indicate that the economic damages are much higher during 2000-2020 than in 1980-2000. Among the adverse events, the most frequently occurring disasters are floods (44%), storms (28%), and earthquakes (8%), respectively (CRED, 2020). Due to these uncertain negative events, most often, the livelihoods of these people are disrupted. Further, due to poor living standards (multidimensional indicators), many households are subject to various shocks such as health issues and unemployment. As a result of these negative events, many households remain poor and the non-poor are at a high risk of falling into poverty. Therefore, vulnerability analysis can help determine when and how society can focus its efforts to reduce vulnerability. Policy interventions that minimize household risk exposure can have additional benefits in avoiding ineffective risk coping mechanisms. In this regard, given the poor living standard and economic backwardness, many social protection measures are also implemented to uplift such poor and vulnerable households and the economic development of such regions. Unraveling the impact of such action programs on both poverty and VtP is important for choosing the optimal policy intervention.

This chapter explains the data sources used for the analysis in this study. Given the objectives as mentioned in chapter 1, we first used the national-level representative panel data available from the India Human Development Survey (IHDS) data for 2004-05 and 2011-12 ([dataset] Desai and Vanneman, 2005, 2012) to observe the changes in household poverty status over the seven years. This analysis shows that among other factors, social capital and livelihood diversification are the main determining factors for households falling into and escaping poverty. However, since the IHDS data did not have information on risks, shocks, and coping measures, we could not relate the changes in household poverty status to the risks and shocks that the households experience. Since vulnerability to poverty is linked with risks and lack of coping measures, it is important to identify the households affected by the shocks and their corresponding coping strategies. The empirical literature reviewed in chapter 2 also revealed that limited studies on estimation of vulnerability include information on shocks and coping mechanisms. In this regard, studies have suggested that household reported risks, shocks, and coping measures are important in VtP estimation (Swain and Floro, 2012; Gunther and Harttgen, 2009; Mahanta and Das, 2017). Therefore, we collected primary household survey data explicitly on household reported shocks and corresponding coping mechanisms to estimate household vulnerability to poverty. Further, we have collected information on social protection measures in order to investigate if they reduce household VtP by enhancing household coping mechanisms. The details of household survey design and descriptive statistics are explained in subsequent sections.

The rest of this chapter is structured as follows: the introduction is followed by section 3.2, which presents the context of the study area, where we have explained the overview of the economy of Odisha. After that, in section 3.3, the paper discusses the data used for the analysis. Section 6.6 concludes by providing a descriptive discussion of the survey data.

3.2 Context: Odisha

3.2.1 The Economy of Odisha: An Overview

In rural Odisha, there are compelling reasons to analyse the relationship between poverty and risk using the concept of VtP. As of 2011, an overwhelming majority of rural households were still living in poverty, accounting for around 33% of the state's total poor population (GoO, 2012). A recent study by Suryanarayana et al. (2016) observed that Odisha has improved in Human Development Index (HDI) from 22 ranks in 2007-08 to 19 in 2011, but still, it is considered as a state with a low HDI. The economy is contributing to the national GDP through the service sector (41%) and industrial sector (39.5%) (GoO, 2018). However, agricultural dominance for livelihood remains high in the state, where about 60% of households still depend for their livelihood (GoO, 2018).

Given the status of lowly ranked HDI state, poverty alleviation has been the priority of the state. Over the period of the last four decades, the poverty rate (headcount) in India, as well as in Odisha, has been declining gradually. But we noted that the poverty rate in the state of Odisha is 10% higher than the national average during the last four decades (1970-2010). Poverty in Odisha has declined from 66.18% in 1973-74 to 47.15% in 1999-00 and 32.59% in 2011-12 (GoO, 2012, 2013, 2014). The poverty rate in India declined from 54.88% to 26.1% and 21.92% over the same period, respectively (see Figure 3.1). Despite the fact that the poverty rate in Odisha has decreased, it still stands at 32.59% in 2011-12 (GoI, 2015), which is a cause of concern. The majority (83%) of people live in rural areas (GoO, 2013) with poor infrastructure, low human development index (HDI), and inadequate access to education.

The literature reviewed in chapter 2 shows that the poverty rate varies among the regions and within the state or country. In terms of geographical location, Odisha consists of 30 districts and is located in the eastern geographical area of India (Figure 3.2). These districts are further classified into three geographical divisions: southern Odisha consists of 12 districts, northern Odisha includes nine districts, and coastal Odisha consists of nine districts (GoO, 2010). In terms of economic development (e.g., living standard, net district domestic product), coastal Odisha is ahead of northern and southern Odisha (GoO, 2012). The coastal belt of Odisha is well-connected to the rest of India via rail and air transportation. Northern Odisha is located at the border of Jharkhand and Bihar states with few established industries such as Aluminum and steel plants. Southern Odisha is economically backward, wherein the majority of tribal people dwell. World Bank (2016) observed that 87% of households are poor in the southern region, 50% in the northern region, and 35% in the coastal region. Further, the poverty rate varies across the districts, some of the extremely poor districts are Kandhamal, Koraput, Malkangiri, Boudh, and Balangir (GoO, 2017b).

To address the regional disparity and to reduce the headcount poverty rate, the government of Odisha has adopted several region-specific action plans (GoO, 2013, 2014). For instance, TRIPTI is designed for coastal Odisha, OCTMP working in the northern region, and OTELP program functions in the southern region (GoO, 2013, 2014, 2017a) to combat rural poverty. The brief economic overview and characteristics of the regions are explained below.

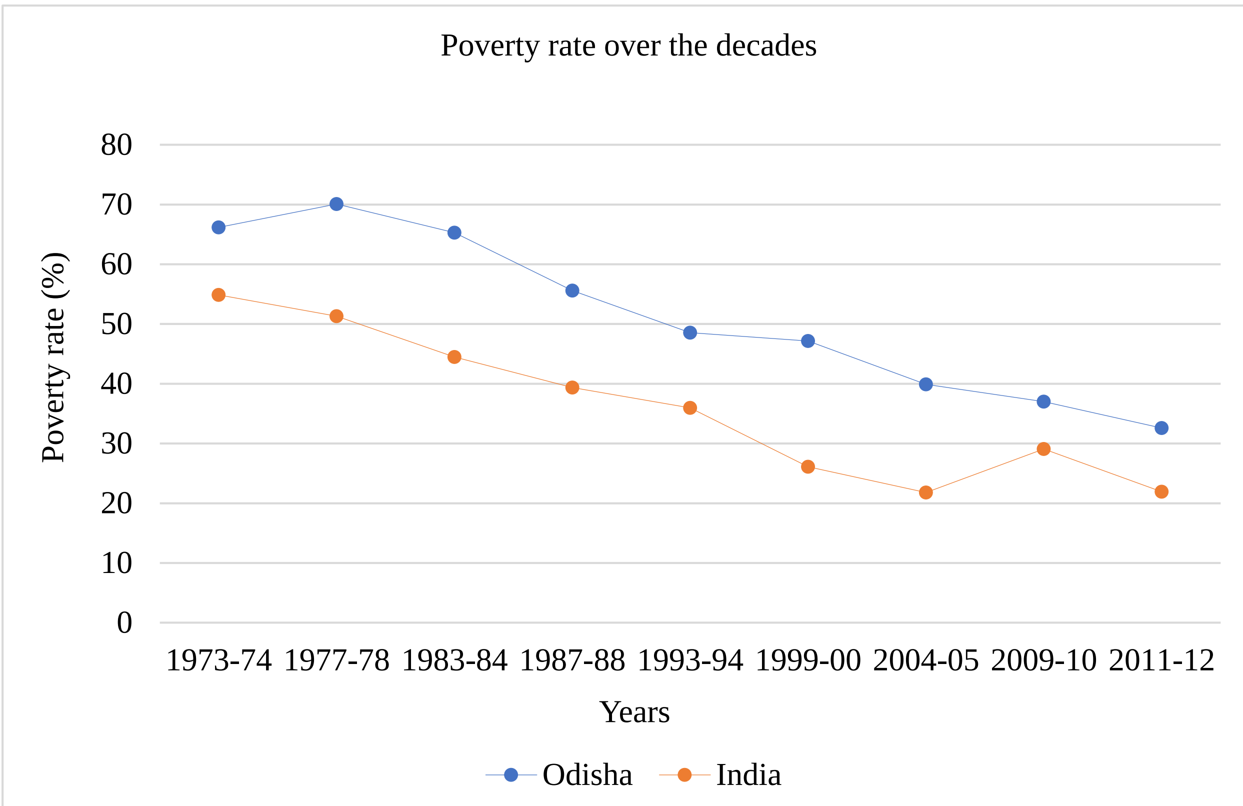

Figure 3.1: Poverty Level in Odisha

Source: GoO (2012, 2014).

3.2.1.1 Southern Region

The southern region covers an area of 71296 km2 and shares the border with Andhra Pradesh and Chhattisgarh. It has a total population of 13909247 (33.14% of the total population) inhabitants and 209000 villages (GoO, 2012). In this region, rural areas account for 89.27% of the population, while urban areas account for 10.63% of the population. The population density of the region is 192.42, with an average rainfall of 1428.83mm per annum. Compared to other regions, this region has a lower percentage of gross irrigated land (30.59%) and a lower literacy rate (59.15%) (GoO, 2012). However, rural literacy (56.3%) is even far lower than the other regions. The districts from this region are known for the tribal belt and poor living standards and provided a safety net program called the KBK scheme that covers the eight districts out of the total 12 districts in the region. Further, nine districts are identified as the most backward districts in India by the Integrated Action Plan (IAP) scheme; this scheme suggests providing special attention to the backward districts of the nation. The ration card holder is 2824067 (20.30% of the total population), and the average infant mortality rate is 61, and the under-five mortality rate is 87.42 (GoO, 2012). The districts under the southern region are presented in Table 3.1.

3.2.1.2 Coastal Region

The region is located at the head of the Bay of Bengal. This region covers an area of 27636 km2 which comprises 17.74% of the total areas in the state. It has a population of 15769052 (37.57%) inhabitants with a density of 585.11km2 (GoO, 2012). There are 15751 villages in the region, with rural areas accounting for 89.70% of the population. The average annual rainfall in this region is 1471.8 mm, and the gross irrigated area is 40.37 hectares. The literacy rate is highest among the regions, where 83.56% of the total population is literate, and it is 82.68 % in rural areas (GoO, 2012). The coastal region is comparatively more subject to risks and shocks, especially cyclones and floods (Yadav and Barve, 2017). Over the last 33 years, from 1975 to 2013, 14 damaging cyclonic storms hit the state. The ration card holders are 3108337 (19.71%) and the average under-five mortality rate is 78.44, whereas 60 is the infant mortality rate. The districts under this region are presented in Table 3.1.

3.2.1.3 Northern Region

The northern region covers an area of 14662 km2. It has a population of 12295919 (29.29% of Odisha) inhabitants with a density of 214.44. The region has 14662 villages, where 81.13% population live in rural areas (GoO, 2012). The normal average annual rainfall is

1461.08mm, and comparatively, the region has less irrigated land, that is, 31.77% area is gross irrigated land (GoO, 2012). In this region, 73.7% population is literate, whereas the rural literacy rate is 71.2% (GoO, 2012). The total ration card holders are 2489442 (20.25%), where the average under-five mortality rate is 69.11, and the average infant mortality rate is 55.11. This region is known for the drought that frequently occurs in some of the districts in the region (Patnaik et al., 2017; Panda, 2017). The districts under this region are presented in Table 3.1.

Table 3.1: Regions and Districts under Regions, Odisha

Serial number	Region	Number of districts	Districts under each region
1	Coastal region	9	Baleshwar, Bhadrak, Cuttack, Jagatsinghpur, Jajpur, Kendrapara, Khordha, Nayagarh, and Puri.
2	Northern region	9	Anugul, Bargarh, Deogarh, Dhenkanal, Jarsuguda, Keonjhar, Mayurbhanj, Sambalpur, and Sundergarh.
3	Southern region	12	Balangir, Boudh, Gajapati, Ganjam, Kalahandi, Kandhamal, Koraput, Malkangiri, Nabarangpur, Nuapada, Rayagada, and Sonepur/Subarnapur.

Source: GoO (2010, 2012).

The present study relies on comprehensive household survey data involving 479 households from the three southern districts of Odisha (Figure 3.2). Southern Odisha was purposively selected for the analysis because the region is characterized by a high poverty level, food insecurity, and high unemployment rate (Rahman, 2016; Panda, 2017; GoO, 2016; World Bank, 2016). Also, this part of Odisha is known for the Naxal ite insurgency and tribal population. Most households depend on the agricultural sector as their livelihood, and due to lack of education, many people also depend on the daily wage sector. Three districts, namely Kandhamal, Koraput, and Nabarangpur (Figure 3.2) are selected for this study, which aims to understand the risks and shocks and household coping strategies.

3.3 District Profiles

3.3.1 Kandhamal District of Odisha

The district was selected for three reasons. According to the official report, Kandhamal district is among the top poverty districts where more than 60% of households are living below the poverty line (GoO, 2017b). According to our district-wise analysis, the district is one of the top five extremely vulnerable districts. As per the Integrated Action Plan report (2012), the Kandhamal district falls under the most backward districts in India. The district has the lowest HDI rank, 29 out of 30 districts in the state (GoO, 2012). In addition, there is a lack of information in this area on strategies for risk coping and adaptation. To fill this gap, this analysis has been performed.

Kandhamal district was previously known as Phulbani until January 1994, which was separated from Phulbani into Kandhamal and Boudh districts. The district covers an area of 7654 square km, accounting for 1.8% of the total land area of Odisha. The district border with the district of Boudh in the North, the district of Rayagada in the South, the districts of Ganjam and Nayagarh in the East, and the district of Kalahandi in the West. It has a population of 7,33,110 people and the population density is 91 persons/km2. The literacy rate of the district is 64.1% (76.9% for males and 51.9% for females) (GoO, 2019). The people in the Kandhamal district derive their source of income mainly from farming.

The majority of the land area of the district covers forests (71%), and 12% of the land is cultivable. The households have land, but the landless is high, and the average landholding per household is one hectare. According to the 2011 census, 62.58% of households are marginal farmers, 26.70% are small farmers, and 0.10% are big farmers (GoO, 2019, p. 20). Besides, 9.7% of households are agricultural laborers who are indirectly dependent on the farming sector. The agriculture sector is predominantly rain-fed and only 37% of the net shown area is irrigated (GoO, 2019). The average rainfall recorded from June to September is 1522.95 mm. Paddy, maize, turmeric, a variety of millets, pulses, and oil are the primary agricultural products. The connectivity with other districts is poor. The district is surrounded by the rivers such as Salunki and Rushikulya. The district suffers from all types of covariate shocks, such as floods, droughts, cyclones, unseasonal cyclonic rain, hailstorm, etc. Further, health issues, unemployment, and poverty are being the primary challenge (GoO, 2019).

3.3.2 Koraput District of Odisha

The Koraput district, in the southern region of Odisha, was selected as the second study area. The official report of GoO shows that Koraput district is among the top five poverty districts in the state (GoO, 2017b). The HDI rank (27) of the district is quite low and stands at the bottom five districts (GoO, 2012). According to our district-wise analysis, the district is one of the top five extremely vulnerable districts. The poverty rate is higher among the districts in Odisha. According to the GoI Integrated Action Plan report (2012), Koraput falls under the most backward districts in India (GoI, 2012).

The district was part of the undivided Koraput districts, including the other three districts, namely Rayagada, Nabarangpur, and Malkangiri, until October 1992, when it was declared a separate district. The district shares its border with the extreme North bounded by Nabarangpur district, on the South by the district of Malkangiri, on the West by Bastar district of Chhattisgarh State, and on the East by the districts of Vizianagaram and Srikakulam of Andhra Pradesh State (GoO, 2017). The district consists of 13,79,647 populations and 239 Gram Panchayats functioning in the district (GoO, 2017). The average literacy rate in Koraput district as per census 2011 is 49.2%, of which 60.3 % of males and 38.6 % of females are literates, respectively. The economy of the Koraput district includes crop and livestock production, formal employment, fishing, and the sale of wood and wild fruits. Agriculture is the mainstay of the economy of the Koraput district, in which around 83 percent of the household depends on it (GoO, 2017). Figure 3.2 shows the location of the study area.

The Koraput district receives an average rainfall of 1567 mm during the rainy season. The district has three major rivers, namely, Kolab, Indravati, Machkund, over which Kolab reservoir, Muran dam, and Jalaput reservoir existed. According to the 2011 census, 51.02% of households are marginal farmers, 32.23% are small farmers, and 0.30% are big farmers (GoO, 2017, p. 14). Paddy, Finger millet, Niger, Maize, and Arhar are the major field crop in the Koraput district. The district is vulnerable to floods, fire accidents, drought, heatstroke, and earthquake (GoO, 2017, p. 19).

3.3.3 Nabarangpur District of Odisha

The district Nabarangpur was selected as the third district for the analysis. The poverty rate and literacy rate are quite low in the district (GoO, 2012). The HDI rank (26) of the district falls under the bottom five districts (GoO, 2012). The district is one of the top backward districts in the nation (GoI, 2012).

The district came into being in the year of 2nd October 1992 as a separate district from Koraput. The district is located in the southwestern part of the state, Odisha. The district is bordered by the eastern district of Kalahandi, the southern district of Koraput, and the northern and western districts of Raipur and Bastar of Chhattisgarh. The area covered by the district is 5290 sq. kilometers. The literacy level of the district is 46.4%, where 57.3% are male, and 35.8% are female.

The core livelihood activities in the area are agriculture and livestock rearing. The major crops grown are paddy, maize, ragi, millets, and pulses. The district has many rivers and perennial streams. Between Nabarangpur and Kundei can find a river in every four to five km distance like Indravati, the Tel, the Narangi, the Banjari, the Amarti, the Bhaskel, the Singari, the Belaji, and the Turi. According to the official report, 62.40% of households are marginal farmers, 30.21% of households are small farmers, and 0.32% of households are big farmers (GoO, 2018, p. 25). The district is vulnerable to frequent floods, droughts, lightning, and fire accidents (GoO, 2018, p. 30).

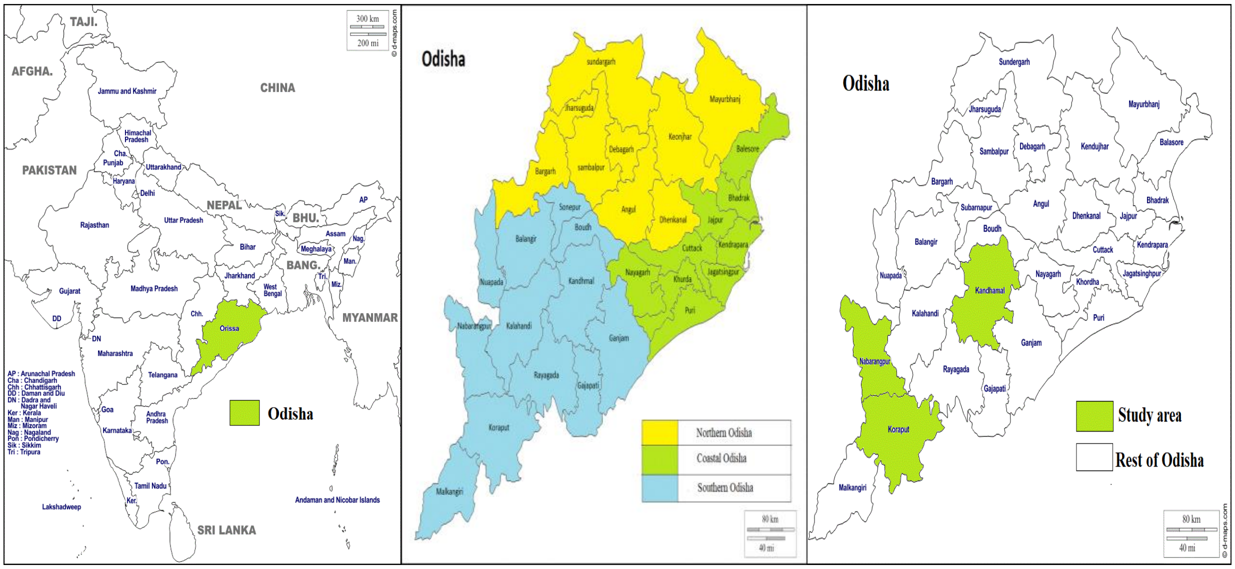

Figure 3.2: Map Showing Sample Distribution and Study Areas

3.4 Data Sources Used for the Analysis

As mentioned in Chapter 1 and above in the introduction of this chapter, the thesis is based on two data sets. We have first used IHDS data to observe the changes in household wellbeing over time, and then we conducted a household survey to analyze the risks, shocks and their impact on household vulnerability.

3.4.1 India Human Development Survey (IHDS) Data

The current research study for objective 1 uses the household panel data from the India Human Development Survey (IHDS) for the period between 2004-05 (2005) and 2011-12 (2012). The household panel data has been collected by the National Council of Applied Economic Research (NCAER), New Delhi, India. The surveys have covered 41,554 households in 2004-05 and 42,152 households in 2011-12 across the nation ([dataset] Desai and Vanneman, 2005, 2012). The household samples have been drawn using the stratified sampling method. The IHDS data provides detailed information on household demography, health, economic status, education, asset, government benefits, ethnicity, marriage, fertility, employment, and social capital. In particular, the IHDS data contains valuable information on household income and consumption; therefore, either of these two – household income and consumption - can be used to estimate the poverty dynamics. The present study has extracted the desired household panel data for the state of Odisha. IHDS-II reports that 83% of the households were re-interviewed in 2011-12. After attrition, the panel data for the study comprises 1353 rural households for both the survey years 2004-05 and 2011-12.

Panel data used by the dynamic approach has an advantage over the static approach. Panel data helps in identifying the households that have escaped poverty and the households that have descended into poverty by tracking the same households over the period. Further, it also helps to analyze whether households have followed the same livelihood strategies over the years or have switched to other activities. Tracking the activities followed by the households provides a better understanding of why some households escape or fall into poverty. To achieve the objective of understanding the changes in poverty status and various determining factors for the dynamics of poverty, we have used the panel data from IHDS for the period between 2004-05 and 2011-12.

3.4.2 Household Survey Data

As discussed in the introduction, we aim to investigate the impact of welfare program on household VtP. We begin with a presentation of the structure for sampling and the procedure for conducting the survey. A brief discussion of the context of the questionnaire is provided. In the final section, the household characteristics are explained.

3.4.2.1 Sample Selection

A multistage sampling approach has been used to conduct a household survey. In the first stage, three (Kandhamal, Koraput, and Nabarangpur) out of 12 districts in the southern region are purposely selected. Kandhamal, Koraput, and Nabarangpur districts have a higher poverty rate (GoO, 2017, p. 18), and Gender Development Index (GDI), Human Development Index (HDI), and Infrastructure Development Index (IDI) in these districts are considerably lower (GoO, 2012, p. 824). Further, these districts were selected based on their poverty dynamics and household vulnerability to poverty status. The second stage was the convenience selection of the block in the districts from each selected district. In particular, nine blocks from three districts were selected where the program OTELP has been implemented, and the details are presented in Figure 3.3. The final stage was the random selection of the 479 households from three districts. To make the sample representative, the number of households interviewed from each village was determined using a proportional factor based on the village household. Of the total 479 sampled responses, 201 were collected from Koraput, 103 from Kandhamal, and 175 from the Nabarangpur district (Table 3.1). The data were collected from July 2018 to February 2019 using a comprehensive questionnaire. Questionnaire pre-testing, involving 20 households and group discussion with the village ward members and elderly people, was also done to identify and remedy ambiguities in the instruments. Mostly the household head (male or female) was interviewed. In the rare case where the household head was absent, any adult person who is knowledgeable to answer questions from the household was interviewed.

The survey data contains information about household demographic variables, including gender, age, and household size. The household's economic well-being indicators include annual household income from various income sources and monthly household expenditure on different food and non-food items. The information collected on livelihood capital includes the various capital they have access to, such as social, physical, financial, human, and natural. In the vulnerability context, the information includes the covariate and idiosyncratic risks and shocks and coping strategies. Households were asked if, during the reference periods, they experienced any shock. They were further questioned about the type of risks and shocks, the severity of the shock, and income and asset loss from the shock. In addition, they were asked what they did to cope with the shock: coping strategies used by the households to recover from the shock. The questionnaire was written in English but translated into the local language- Odia.

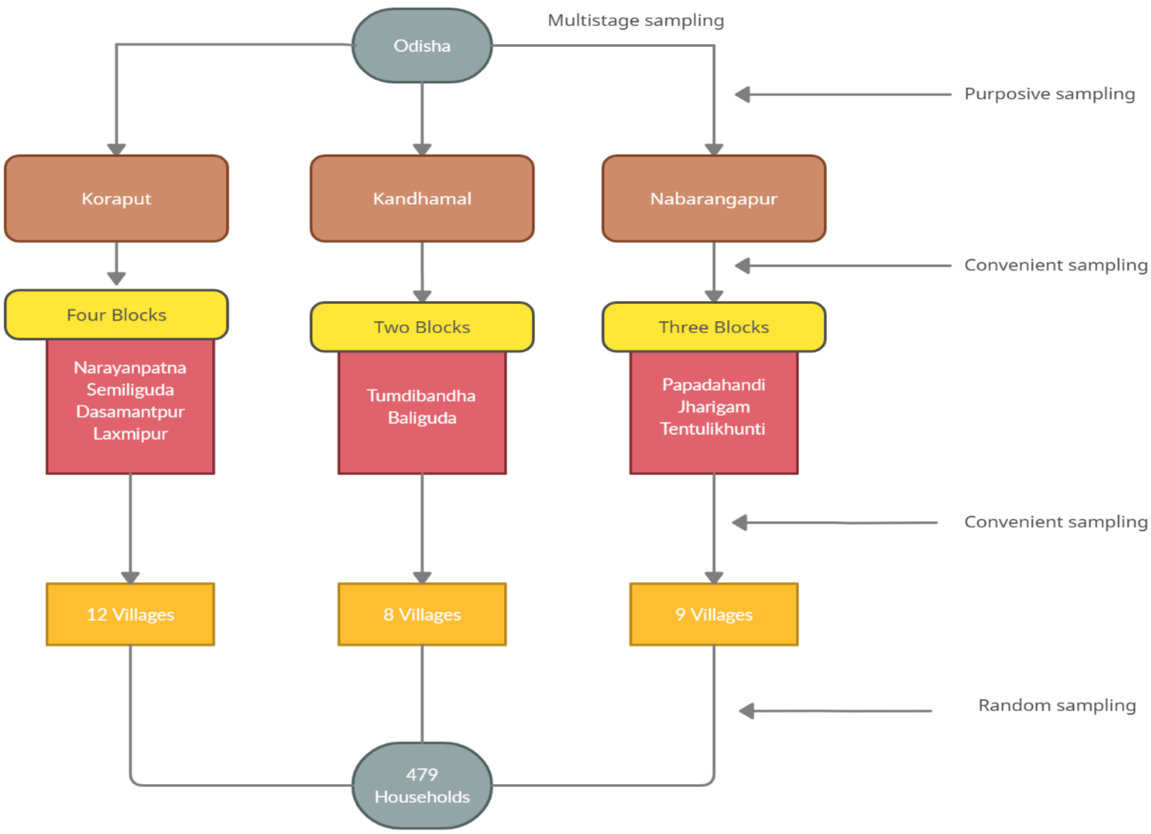

Figure 3.3: Sampling Distribution

3.4.2.2 Sample Size Calculation

The sample size for the analysis was determined using the Kar and Ramalingam (2013) statistical formula.

$$SS = \frac{Z^2 * (p) * (1-p)}{C^2} = 385$$

Where SS= Sample size, Z= z-value (e.g., 1.96 for a 95% confidence level), C= confidence interval, expressed as a decimal, and p= percentage of population picking a choice expressed as a decimal. The SS was calculated for the purpose of this analysis by using confidence level (Z)= 95%, expected variable understudy frequency (p)= 0.5, and confidence interval (C)= 0.05.

Table 3.2: Selected Districts for the Study

District Name	Population (Rural)	Population (%)	Sample Size Needed	Actual Sample Size Collected
Kandhamal	660831	22.42	86	103
Koraput	1153478	39.13	151	201
Nabarangapur	1133321	38.45	148	175
Total	2947630	100	385	479

Source: GoO (2012).

3.5 Key Characteristics of Households

Table 3.3 illustrates the socioeconomic characteristics of the respondents. In relation to occupation, households are grouped into three major income categories: farm employed, wage earners in non-farm, and self-employed in non-farm. Households that depended on agriculture were included in farming groups. Daily wage earners such as labor, black-smith, and carpenter are included in the wage earner in the non-farm group. Business owners, traders, and government employees are considered self-employed in the non-farm sector. A pension grant is provided to every citizen by the Indian government to the person who has attained 60year of age and older. These social grants are also given to poor households who have disabled persons and widows. Households with only dependent on pension were included in the occupational group based on their second income sources, such as farming or wage earners. In relation to occupation, 46.35% of households derive livelihood from agriculture, 42.38% from wages in non-farm, and 11.27% from self-employed in the non-farm sector. It is expected that households are deriving livelihoods from self-employed in non-farm to be better off than other categories of livelihoods (Albert and Vizmanos, 2018).

Previous studies have shown that households headed by the male person are less likely to be poor or vulnerable compared to female-headed households (Azeem et al., 2018). However, studies have also found the converse finding showing female-headed households are less vulnerable (Amin et al., 2003). The households in the sample are predominantly male-headed, that is, 89.6%. The variable age of household head is used as a proxy for work experience or older, suggesting a positive association between age and household wellbeing (Jha and Dang, 2010; Tsehay and Bauer, 2012; Azeem et al., 2018). The average age of household heads is 43.45 years. Again, household size and dependency ratio are expected to have negatively associated with household wellbeing (Jha and Dang, 2010). On average, each household has about five family members. Human capital plays a crucial role in economic development. It is expected that higher education levels would lead to a better standard of living (Jha and Dang, 2010). It was observed from the survey result that about 53% of households are literate, with an average year of schooling of 3.2 years of the household head. There is a positive association between ownership of assets and household wellbeing (Tsehay and Bauer, 2012). Households interviewed in the survey reported that about 64% of households owned farmland. Studies have observed that owning land help households to use for agricultural activities that produce income or to use for collateral to get other benefits (Tsehay and Bauer, 2012). In the case of durable and productive assets, the average households in the study areas possess durable and productive goods in number are about six and about one, respectively. The findings from the past studies show that a lower vulnerability level for the household with higher assets (Ersado, 2006).

In this study, the shocks were reported for the last five years. As stated in the introduction, to consider whole livelihoods and shocks, all aspects of shocks were reported: natural, economic, social, and demographic. The survey sample results indicated that most respondents (88%) experienced severe illness, and about 17% of households lost income earners during the specified period. As expected, the natural shocks were experienced by a majority of the respondents that participated in the research. Among the household reported shocks, the survey sample results indicated that drought (68%) and cyclone (69.7%) were experienced by more than 50% of the respondents. However, the households affected by the flood is 36% which shows that the western part of Odisha is less affected by the flood, which is on the expected line. During the rainy and winter seasons, the price of agricultural products goes down, resulting in losses for the farmers. On the contrary, they experience increasing prices for the input and other products that cause them to reduce another important expenditure on education and health. To mitigate such negative events, if households do not have enough coping strategies, they fall into extreme poverty or poverty trap.

The survey data shows that the households adopt many coping mechanisms when they experience a shock based on the severity, as indicated in Table 3.3. Generally, households retained the traditional system of coping with a shock by borrowing from the informal sector. In the case of coping strategies, it was common for households to borrow money from relatives (51%). Further, 38% of respondents admitted that they had borrowed from moneylenders to overcome the situation. It emerges from the results that households are more reliant on external support to deal with the negative events. Seeking loan and credit from a moneylender, relatives, and friends suggest that households frequently rely on the informal sector. This also implies that social capital plays a major role in reducing the severity of shocks, especially during a critical economic situation. Khosla and Jena (2020) observed that social capital helps households from escaping poverty. The majority of households are reported to have participated in various forms of social capital, such as self-help groups (SHG) (59%), attending public meetings (51%), and saving groups (14.4%). SHG is playing a crucial role in rural areas by supporting microcredit to the low-income groups (Swain and Flora, 2012). Attending gram sabha at the village levels provides important information regarding the government programs and also helps to enroll as a beneficiary for different government schemes (Jha and Dang, 2008). Membership in a saving group helps accumulate more money, leading to investing money in a profit-oriented business. Hence, it is expected that households being part of a saving group has a positive association with household wellbeing (Tsehay and Bauer, 2012). On the other hand, households attempted to overcome adverse events by selling various assets such as livestock, gold, and land. In particular, 4.2% of households sold gold, 9% of households sold land, and 24.4% of households mitigated negative events by selling livestock. It was observed from the past research that these asset losses can push many households into a poverty trap (Cater et al., 2007).

Finally, the conceptual framework of the study is depicted in Figure 3.4. Firstly, poverty is characterized as ex-post and ex-ante poverty. Secondly, the study estimated ex-post and ex-ante vulnerability for both the monetary and multidimensional measures. Finally, we assessed the impact of welfare program on both monetary and multidimensional vulnerability to poverty.

Table 3.3: Key Characteristics of Households

Variable	Unit	Monetary/ Multidimensional approach		Expected Sign (for monetary measure)	Sources
		Mean	Std. Dev.	(+/-)	Literature
Log consumption per capita (Outcome variable)	Rupees	7.0	0.54		Chaudhuri et al., 2002
Gender	1= male, 0= Female	89.56	30.61	+/-	Chaudhuri et al., 2002
Farm employed	1=yes, 0=otherwise	46.35	49.91	+/-	Albert et al., 2008
Wage in non-farm	1=yes, 0=otherwise	42.38	49.47	+/-	Albert et al., 2008
Self in non-farm	1=yes, 0=otherwise	11.27	31.66	+/-	Albert et al., 2008
Household size	Number	4.87	2.00	-	Chaudhuri et al., 2002
Dependency ratio	ratio	0.41	0.25	-	Chaudhuri et al., 2002
Age of head	Years	43.45	14.49	+/-	Chaudhuri et al., 2002
Years of schooling of head	Years	3.32	3.87	+	Chaudhuri et al., 2002
Own land	1=yes, 0=otherwise	63.46	48.20	+	Iqbal, 2003
Durable assets	Number	5.60	4.56	+	Ersado, 2006
Illness	1=yes, 0=otherwise	87.68	32.90	-	Makoka, 2008
Death of income earner	1=yes, 0=otherwise	16.91	37.52	-	Makoka, 2008
Cyclone	1=yes, 0=otherwise	69.73	45.99	-	Makoka, 2008
Flood	1=yes, 0=otherwise	36.33	48.14	-	Makoka, 2008
Drought	1=yes, 0=otherwise	68.48	46.51	-	Makoka, 2008

Sold livestock	1=yes, 0=otherwise	24.42	43.01	+/-	Makoka, 2008
Sold land	1=yes, 0=otherwise	9.00	28.61	+/-	Fenny and McDonald, 2016
Sold gold	1=yes, 0=otherwise	4.17	2.00	+/-	Fenny and McDonald, 2016
Borrowed from informal money lender	1=yes, 0=otherwise	37.79	48.54	+/-	Fenny and McDonald, 2016
Borrowed from relatives	1=yes, 0=otherwise	51.15	50.00	+/-	Fenny and McDonald, 2016
Productive assets	Numbers	0.79	1.02	+	McCarthy et al., 2016
Member in SHG	1=yes, 0=otherwise	59.29	49.18	+	Tsehay and Bauer, 2012
Member in saving group (credit/chit fund)	1=yes, 0=otherwise	14.40	35.15	+	Tsehay and Bauer, 2012
Attending public meeting (gram sabha)	1=yes, 0=otherwise	51.36	50.00	+	Jha et al., 2012

Source: Authors estimation using survey data.

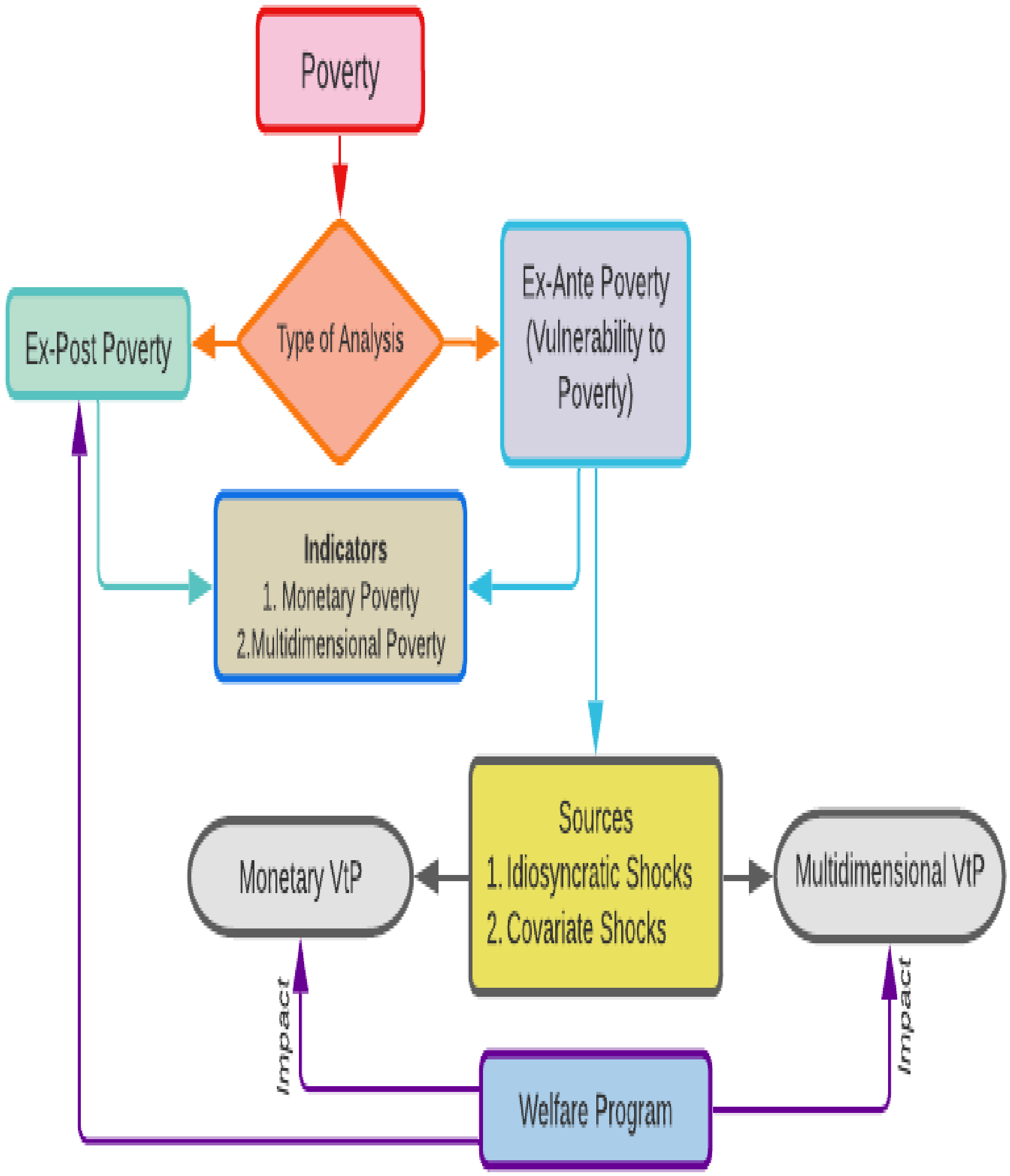

Figure 3.4: Conceptual Framework

Source: Adapted from Azeem (2016) and modified by Author.

CHAPTER 4

TO ESTIMATE THE CHANGES IN POVERTY STATUS AND THE FACTORS DETERMINE IT

4.1 Introduction

This chapter exhibits the changes in poverty status in rural Odisha. The empirical literature reviewed in chapter 2 reveals that some households come out of poverty over the period of time, but many other non-poor households fall into poverty due to several factors. For instance, millions of people in India fall into poverty every year due to health shocks and out-of-pocket expenditures (Goyanka et al., 2019; Berman et al., 2010; Shahrawat and Rao, 2012). Empirical evidence from previous studies suggests that the most effective way to combat poverty is to prevent them from falling into poverty (Chaudhuri et al., 2002). Therefore, knowing the factors that push the households to move in or escape poverty provides insights to design appropriate policies to alleviate poverty (Radeny et al., 2012; Thorat et al., 2017).

Recent researchers on poverty have suggested two different sets of the programs to eradicate poverty effectively: one, to uplift the households that are already poor and are likely to stay poor, and the other is to help households that are at the risk of becoming poor (Baulch and McCulloch, 2002; Krishna, 2003; Kristjanson et al., 2007; Krishna, 2011; Radeny et al., 2012). To formulate such varying but effective sets of policies, it is necessary to identify exclusively the households that needs these programs to overcome poverty and the households that need programs for building their resilience in order to minimize the likelihood of falling into poverty (Carter and Barrett, 2006; Radeny et al., 2012). The categories of poverty are mainly identified as ‘chronic poor’, ‘transient poor’ and ‘non-poor’ (Jalan and Ravallion, 2000; Baulch and Hoddinott, 2000; Lawson and Mckay, 2002). Estimating different categories of poverty, which observes whether a household’s status changes or does not change over time, is called ‘the dynamics of poverty’ (Chronic poverty research centre (CPRC), 2004; Radeny et al., 2012). In past studies, it has been observed that households stay in poverty for several years; however, it has also been recognized that while many poor households have moved out of poverty, many non-poor households have slipped into poverty (Baulch and Hoddinott, 2000; Duncan et al., 1993; Lawson et al., 2006). Those households which continue to live in poverty for a long time are said to be in 'chronic poverty' (CPRC, 2004; Ward, 2016). Due to various positive (livelihood diversification, asset building, and government support) and adverse events (job loss/income loss, death of breadwinner, accident, and natural calamities), households move out and move into poverty. The households which alternately move in and out of poverty are said to be in 'transient poverty' (CPRC, 2004-05; Ward, 2016).

Among these poor, 85% live in rural areas (Oxford Poverty and Human Development Initiative (OPHDI), 2014; Alkire et al., 2014), and various targeted policies, social protection, and safety nets have been implemented to uplift these poor households. However, apart from government support through various policies, these households themselves practice many strategies to overcome poverty and to remain non-poor. Therefore, understanding the activities/practices adopted by the households to escape poverty facilitates designing appropriate policies to alleviate poverty. The following gaps in the existing literature motivate the present research: previous studies have reported that empirical research on poverty dynamics is limited in developing countries due to the absence of panel data (Ward, 2016; Dang et al., 2014; Naschold, 2012). In the Indian scenario, only a few studies have focused on the poverty dynamics (Krishna et al., 2003; Krishna et al., 2004; Bhide and Mehta, 2004; Dhamija and Bhide, 2010; Dang and Lanjouw, 2015; Thorat et al., 2017). The findings from these studies are mainly related to changes in poverty status, and determinants are largely assessed in relation to household characteristics. Previous studies have found out that livelihood diversification and social capital are the main drivers for escaping poverty in rural areas (Ellis, 2000; Tesfaye et al., 2011, Gentle and Maraseni, 2012; Adi et al., 2021). There has been substantial theoretical work on livelihood strategies and poverty reduction (Ellis, 2000; Sen, 2003). However, there has been a limited number of empirical studies that explain the relationship between livelihood strategies and poverty dynamics. Further, the review of the literature shows that little focus has been given to the role of social capital strategy on poverty reduction and poverty dynamics (Islam and Alarm, 2018; Adi et al., 2021). In addition, social capital plays a significant role in rural poverty reduction because it builds a network, eliminates barriers to have an access to loans, reduces income inequality, and helps in local development (Islam and Alarm, 2018; Adi et al., 2021). In view of achieving the international goal of poverty reduction, understanding the livelihood strategies and social capital adopted/participated by different poverty groups helps design effective policies for reducing the chronic poor and the households likely to fall into poverty and also aiding households to escape poverty.

Keeping all this in view, the primary goal of this chapter is to address the following two research objectives – (i) to estimate the changes in the poverty status of rural households in Odisha, India (ii) to examine the role of livelihood diversification and social capital on poverty dynamics, both in terms of the households' movement into and out of poverty. In this study, we have used household panel data for the period between 2004-05 and 2011-12 from the India Human Development Survey (IHDS) to distinguish households into the categories of chronic and transient poor.

The rest of this chapter is structured as follows: the introduction is followed by section 4.2 which outlines the analytical framework used for the analysis; Section 4.3 provides the estimated results and discussions; Section 4.4 concludes with the key messages of this study.

4.2 Analytical Framework and Econometric Specification

The following section discusses in detail the methodology adopted for the study. It describes the method used for measuring poverty dynamics and the multinomial logistic regression model specification for determinants analysis.

4.2.1 Method of Poverty Measurement

Previous studies have used income/consumption per capita to identify the individual/household poverty level and poverty dynamics (Kurosaki, 2003). The present study assessed poverty dynamics using household consumption per capita. Studies have suggested consumption per capita over income per capita to estimate poverty and vulnerability due to the less volatile nature of household consumption (Dercon and Krishnan, 2000). A predetermined poverty line has to be fixed to measure the poverty level. The Indian planning commission defines the state-specific poverty line for the nation (GoI, 2014). The present study adopts the pre-specified poverty line defined by the Suresh Tendulkar Committee for 2005 and 2012, as reported in Table 4.1.

Table 4.1: Predetermined Poverty Line for Rural Odisha

Place	Poverty Lines (Per Capita in Rupees)	
	2004-05	2011-12
Rural Odisha	407.78	695

Source: Government of India (2014).

4.2.2 Model Specification

a) Changes in Poverty Status/ Poverty Dynamics

The theoretical discussion of the study is based on the chronic poverty report 2004. The household has been segregated into different economic groups based on their economic activities: chronic poor, transient poor, and non-poor, reported in Figure 4.1 and Table 4.2. As explained in the chronic poverty report 2004, five different categories of poverty are observed from past studies. Households who remain poor for a long duration are called always poor. Usually poor are the households whose income/consumption mostly remains below the poverty line. The income of the household that fluctuates more within the poverty line is considered as churning poor. Occasionally poor are those that their income remains above the poverty line but sometimes fall below the poverty line. Never poor are those whose income always remains above the poverty line. The report further classified these five different groups into three groups: chronic poor (always and usually poor), transient poor (churning and occasionally poor), and non-poor. In relation to livelihood strategies, social capital, and poverty dynamics, the present study has used panel data and has then tracked their economic wellbeing with respect to different poverty groups.

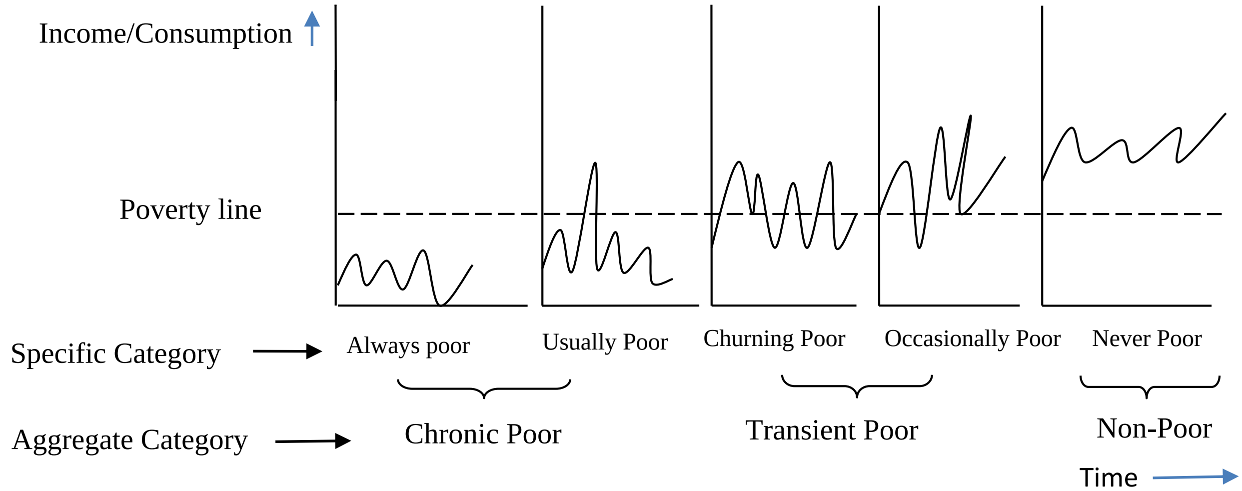

Figure 4.1: Poverty Categorization

Source: Chronic poverty report 2004.

Chronic poverty report 2004 devides poverty dynamics into three main poverty categories, as reported in Table 4.2. Since the IHDS has two waves of data, four categories of changes in poverty status are possible, as presented in Table 4.2. The present study has adopted the following classification.

Table 4.2: Classified Poverty Groups

Types of Poor based on IHDS Panel Data (2004-05 and 2011-12)	Description	Classification of Poverty for the Analysis of the Present Study
Always poor	Remained poor in 2004-05 and 2011-12	Chronic poor
Escaped (ascended out of poverty)	Poor in 2004-05 but became non-poor in 2011-12	Transient poor
Fallen (descended into poverty)	Non-poor in 2004-05 but became poor in 2011-12	
Non-poor	Remained non-poor in 2004-05 and 2011-12	Non-poor

Source: Author's classification based on the chronic poverty report 2004.

The strategy adopted in this study is also in line with previous research studies by Kurosaki (2003), Bhide and Mehta (2004), Arif and Bilquees (2007), and Thorat et al. (2017). However, in the present study, the households which demonstrate movement into and out of poverty — are identified as "transient poor" and not "vulnerable to poverty" (Arif and Bilquees, 2007). The concept of vulnerability is defined if it is estimated using risks and shocks and applying an advanced, forward-looking econometric model. This is clearly explained in chapter 5. Therefore, the transient poor referred here is not vulnerable due to shocks.

Further, this study adopted the rural livelihood approach devised by Ellis (2000) to track the changes in household's activities among the dynamic poverty groups. According to Ellis (2000), livelihood is defined as "the activities, the assets, and the access that jointly determine the living gained by an individual or household". Rural livelihood diversification is defined as "the process by which households construct a diverse portfolio of activities and social support capabilities for survival and in order to improve their standard of living"

(Ellis, 2000; Sen, 2003). The activities refer to the different assets/capitals that households practice for income generation (Ellis, 2000; Tesfaye et al., 2011, Gentle and Maraseni, 2012).

b) Multinomial Logistic Regression

The present study utilizes the Multinomial Logistic Regression model for understanding the determinants of poverty dynamics. The outcome variables in the study are the four distinct variables: the chronic poor, ascended out of poverty, descended into poverty, and the non-poor.

The Multinomial Logistic Regression model determines the probability that a household i experiences one of the J mutually exclusive outcomes. This probability is given in:

$$p_{ij} = P(Y_i = j) = \frac{e^{\beta_j x_i}}{\sum_{k=1}^{J} e^{\beta_k \chi_i}}, \ j = 0, 1, 2 \ldots, J \qquad (4.1)$$

Where Y_i is the outcome experienced by the household i, β_κ are the set of coefficients to be estimated, and χ_i includes the various covariates. As suggested by Greene (2003), to identify the model, one of the β_j must be ‘set zero’ (the base category), and all other sets are estimated in relation to this benchmark. For this study, one of the β_j is set to be zero, so that the above probability function can be written as:

$$p_{ij} = P(Y_i = j) = \frac{e^{\beta_j \chi_i}}{1 + \sum_{k=1}^{J} e^{\beta_k \chi_i}}, \text{ for j= 1, 2…, J and } p_{i0} = P(Y_i = 0) = \frac{1}{1 + \sum_{k=1}^{J} e^{\beta_k \chi_i}} \qquad (4.2)$$

In the present study, J=4. $P(Y = 0)$ is the probability of a household being non-poor, $P(Y = 1)$ is the probability of a household being chronic poor, $P(Y = 2)$ is the probability of a household escaping poverty, and $P(Y = 3)$ is the probability of a household falling into poverty.

Thus, the specific model applied in the present study when standardizing β_0 equals zero gives out as below:

$$p_{ij} = P(Y_i = j) = \frac{e^{\beta_j x_i}}{1+\sum_{k=1}^{3} e^{\beta_k \chi_i}}\text{, for } j=1, 2, 3 \text{ and } p_{i0} = P(Y_i = 0) = \frac{1}{1+\sum_{k=1}^{3} e^{\beta_k \chi_i}} \qquad (4.3)$$

One further step of estimating marginal effects has been performed for the ease of interpretation. The marginal effects are estimated as

$$\frac{\partial P_{ij}}{\partial x_i} = p_{ij}(\beta_j - \sum_{k=1}^{3} p_{ik}\beta_k) \qquad (4.4)$$

4.3. Results and Discussions

4.3.1 Analysis of Poverty Dynamics

This section discusses the estimated results of poverty dynamics, that is, changes in poverty status between 2004-05 and 2011-12. Further, it explains the magnitude of changes in poverty status for the state as well as the regional levels and also the various livelihood strategies adopted by the households in the specified period. The section begins with a discussion of the poverty level in both the survey years.

The poverty incidence for rural Odisha is presented in Table 4.3. Between 2004-05 and 2011-12, the percentage of the population living below the poverty line decreased from 62.30% to 33.41%. Although the poverty rate has declined by 28.89% during the seven-year period (2005-2012), the rural poverty rate (33.41%) is still widespread and acute in Odisha. Table 4.3 shows that the highest rate of decline in rural poverty has been observed in the coastal region (32.99%), followed by the northern region (31.83%) and the southern region (22.15%). It has also been found that in both the survey years, the incidence of poverty was highest in the northern region, followed by the southern region.

Table 4.3: Poverty Incidences in Odisha and its Regional Divisions

Poverty Level 2004-05 and 2011-12 (%)						
Region	Headcount (P_0) α=0		Poverty Gap (P_1) α=1		Poverty Severity (P_2) α=2	
	2004-05	2011-12	2004-05	2011-12	2004-05	2011-12
Northern	68.23	36.40	22.60	8.61	9.52	2.91
Coastal	63.92	30.93	19.57	5.80	7.77	1.82
Southern	54.41	32.26	16.65	7.05	6.94	2.33
Odisha	62.30	33.41	19.71	7.27	8.14	2.40

Source: The statistics are based on the data for 1353 households in each year.

Note: The poverty incidences are based on Foster et al. (1984).

The results of the poverty dynamics in rural Odisha are presented in Table 4.4. The findings show that one-fourth of rural households were chronically poor, that is, they were poor in both 2004-05 and 2011-12. It is also observed that, during the seven years studied, 37% of households escaped from poverty, but at the same time, 8% of households have fallen into poverty. The remaining 29.50% of households were non-poor. The finding shows that about 30% of households in rural Odisha were able to remain above the poverty line during the period. These results are consistent with previous studies that have analyzed poverty dynamics and suggested different policies for chronic and transient poor (Baulch and McCulloch, 2002; Krishna, 2003; Lawson et al., 2006; Kristjanson et al., 2007; Krishna, 2011; Radeny et al., 2012). The following section explains the probable reasons for escaping and falling into poverty through livelihood diversification and social capital. The findings are further analyzed by household-specific marginal effects for each outcome variable by modelling them into a multinomial logistic regression.

Table 4.4: State-level Poverty Dynamics

Change in Poverty Status between Two Rounds 2004-05 and 2011-12	Households (%)
Chronic poor	25.26
Ascended out of poverty	37.04
Descended into poverty	8.20
Transient poor (Ascended + Descended)	45.24
Non-poor	29.50
Total households	100

Source: The statistics are based on the data for 1353 households in each year.

Table 4.5 shows the changes in poverty status across the regional divisions. The chronic poor households were found in highest percentage in the northern region, followed by the southern region, and the coastal region. On the other hand, the percentage of the households that ascended out of poverty was the highest in the coastal region, indicating that the chronic poverty rate was low in the region as many households escaped poverty. Further, among all the divisions, the percentage of households escaping poverty was the lowest, and the percentage of those falling into poverty was higher in the southern region, following the coastal region. Interestingly, the non-poor households were found to be greater in percentage in the southern region, which has been infamously known for hunger and malnourishment (Panda, 2017).

Table 4.5: Regional Level Poverty Dynamics

Region	Change in Poverty Status at Regional Level between the Two Rounds 2004-05 and 2011-12 (%)									
	Chronic poor	Rank	Transient poor (Escaped + Descended)	Rank	Escaped poverty	Rank	Descended into poverty	Rank	Non-poor	Rank
Northern	29.04	1	46.39	2	39.18	2	7.21	3	24.56	3
Coastal	21.71	3	51.68	1	42.38	1	9.30	1	26.87	2
Southern	24.09	2	38.71	3	30.32	3	8.39	2	37.20	1

Source: The statistics are based on the data for the 1353 households in each year. Note: rank is assigned based on the highest value.

4.3.2 Characteristics of the Dynamic Poverty Groups

The primary income sources of poverty groups in rural Odisha are presented in Table 4.6. It was observed in the study that the agriculture sector continues to be the dominant income source in rural Odisha, where 40.13% and 42.79% of households depended on agriculture for 2005 and 2012, respectively. The second most income source was from the wage sector (21.93%), followed by agriculture labor (13.48%), salaried job holders (8.06%), and petty shops (5.01%). It was also observed that the households have switched their activities from one sector to another during the seven years. Specifically, there was a significant decline in the wage sector (10.71%), followed by those receiving a pension (1.56%), petty shops (1.47%), salaried (0.89%), and other sectors (0.88%). On the other hand, there was also a positive shift observed from the sectors such as business (1.33%), professional (0.51%), farming (2.66%), and agricultural labor (9.83%). This indicates that most households derived livelihoods from farming, agriculture labor, and daily wages.

Looking at the regional divisions, it was also observed that farming activities were the main livelihood sector of the three regional divisions. However, households engaged in the farming sector in the coastal region is 20% higher than other regions. Further, the highest percentage of salary job holders was found in the northern region, and less in the coastal region. In the southern region, it was observed that there was a decline in agriculture dependency, and at the same time, there was an increase in non-farm activities (Table 4.6).

4.3.2.1 Chronic Poor

Table 4.7 presents the average income from various livelihood sources generated by each poverty group. For the sake of comparison, income has been measured in percentage (%), that is, the contribution of the particular livelihood sources to the total household income. The findings show that there was less contribution of income from the non-farm sector such as salary and business for chronically poor households. The main income sources were from the wage sector (33.5%), farming (22.5%), and agriculture-labor (21%), respectively (Table 4.7). Further, the results also show that there was a significant reduction of income contribution from the non-farm income sector in 2012. In particular, there was a 4% decline in the business sector, followed by a 2% decline in the other income sources, salary sector, and in the agriculture labor. The results also show that there was a 9% increase in income contribution in the daily wage sector over the period. The daily wage sector has been considered as a highly vulnerable sector, where low pay and uncertainty of work lead the households to remain in poverty. The result suggests that households remain poor due to loss of income from non-farm income sources such as salaried jobs and businesses.

The various household activities adopted and assets/capitals possessed by the poverty groups are presented in Table 4.8. It has also been observed that the household size was large in the chronic poor, among whom the majority were engaged in farming and the daily wage sectors. Households with higher education levels are observed to have been engaged in non-farm diversified activities (Rahut et al., 2015; Jiao et al., 2017). In the case of human capital (mainly the education level), as expected, the year schooling completed by the household head, the household adult, the adult male, and the adult female of the chronic poor was the lowest among the poverty groups. This suggests that lower education level is positively associated with chronic poor and shows the significance of education for household's wellbeing. When one looks at land holdings, which is considered the main asset for rural households to generate income, the study shows that land ownership was comparatively less in the chronic poor households.

4.3.2.2 Households Ascended out of Poverty

It has been observed that income diversification plays a major role in helping households escape poverty (Ellis, 2000; Sen, 2003). The same result has been obtained in the case of rural Odisha: income sources were observed to have been diversified among the households who escaped poverty (Table 4.7). Moreover, there was a higher percentage of income contribution from business and remittance income among the poverty groups. On the other hand, it has also been observed that those households who escaped poverty switched their livelihood from the farming and agriculture labor sector to the business sector. Households engaged in a new job and those starting a new enterprise have been found to be more likely to escape poverty (Paudel Khatiwada et al., 2017). The result indicates that households could escape poverty as they switched their strategies to non-farm activity sources such as business and salaried jobs. It has been further observed that the remittances received by the ascended households were the highest (5% increased) among the poverty groups. Previous studies found out that migration was one of the rural livelihood strategies that was positively related to the living standard (Ward, 2016; Adams and Cuecuecha, 2010; Anyanwu and Erhijakpor, 2010; Wagle and Devkota, 2018; Vacaflores, 2018).

Further, Table 4.8 represents the activities followed by the households those that ascended out of poverty over the years. It is expected that households with small family sizes, higher education levels, engaged in non-farm diversified activities are more likely to escape poverty. The analysis shows that the size of the household of the ascended household was smaller, and there was also a declined in the household size during the period of research comparatively. Further, as expected, the number of members of the household working in the service sector has increased over the period of time for the groups that escaped poverty. It is expected that households with higher total holding are more likely to remain non-poor as they practice more diversified products (Iqbal, 2013). It is observed that the ownership of land remained the same, whereas land cultivation size increased over the years for the ascending households. Apparently, an increase in the cultivated land size resulted in the higher income level of the households that escaped poverty. Further, higher education level is seen to have been positively associated with poverty reduction (Rahut et al., 2015; Jiao et al., 2017). In the case of the groups that escaped poverty, comparatively, the education level has been higher than the chronic poor and the households that descended into poverty.

It is observed that social capital in group membership helps the households engage in more profitable farm and non-farm activities (Paudel Khatiwada et al., 2017). It is shown that social capital would help the households in getting credit facilities from the government and in starting up small enterprises (Islam and Alarm, 2018; Paudel Khatiwada et al., 2017; Adi et al., 2021). The analysis shows that there has been higher participation in social capital from the households who ascended out of poverty (Table 4.9).

4.3.2.3 Households Descended into Poverty

Households fall into poverty due to various reasons: one possible reason could be the lack of income diversification (Paudel Khatiwada et al., 2017). The results obtained in the present study show that the primary income sources for the descended households were mostly from the farming and the daily wage sector (Table 4.7). It has been further observed that there was a significant decline of income contribution from the salaried sector (7%), followed by business (3%), and farming sectors (2%) between 2004-05 and 2011-2012. On the other hand, a 12% increase in income contribution from the wage sector was observed in 2011-2012. Given the uncertainty in the daily wage sector, households with high dependency on the daily wage sector often fall into poverty. An explanation for this result is that the lack of work availability in Odisha, on an average, 36 days in a year was observed for MGNREGA (Raghu et al., 2013; Breitkreuz et al., 2017).

The literature on poverty dynamics has observed that larger family sizes, unemployment, and extreme events cause households to fall into poverty (Krishna et al., 2007; Radeny et al., 2012). The current study results also show that there has been an increase in household size for the households that descended into poverty (Table 4.8). Further, it has also been observed that comparatively, there has been a larger decline in the number of members working in various activities in such households than that of the members in the households of other poverty groups. This is suggestive of the fact that the proportion of dependency is more in the households that descended into poverty. It indicates that increasing household size and losing jobs, or high unemployment, and the proportion of dependency ratio in a household result in poverty. Households holding more land sizes are more likely to engage in diversified commercial products (Paudel Khatiwada et al., 2017). Since land is a major factor in poverty reduction, there has been a land reduction followed by less cultivation size in the households that descended into poverty. Households having more education levels are expected to engage in diversified livelihood strategies and remain non-poor (Rahut et al., 2015; Jiao et al., 2017; Paudel Khatiwada et al., 2017). In the case of human capital, there has been a relatively low education level among the household heads, adult higher education level, male higher education level, and female higher education level in the households descended into poverty (Table 4.8).

The households that engaged in the greater social network have been observed to get more information and financial support (Islam and Alarm, 2018; Adi et al., 2021). The analysis has also found that participation in social capital has comparatively been less for the households that descended into poverty (Table 4.9).

Table 4.6: Household's Main Activities for Income Generation, 2004-05 and 2011-12 (%)

Main Income Sources of Rural Household, 2004-05 and 2011-12 (%)									
Variables	unit	Odisha		Northern		Coastal		Southern	
		2005	2012	2005	2012	2005	2012	2005	2012
Farming activities	%	40.13	42.79	39.00	33.60	58.51	52.58	32.26	36.77
Agriculture wage labourer	%	8.57	18.40	17.80	10.40	15.46	7.47	23.01	7.53
Daily wage labour	%	27.27	16.56	18.60	30.40	6.44	17.27	22.80	32.26
Artisan/Independent	%	2.07	3.25	3.20	2.20	3.87	2.06	2.80	1.94
Petty shops	%	5.76	4.29	5.20	6.60	3.09	6.19	4.09	4.52
Organized business	%	0.44	1.77	1.40	0.80	1.55	0.26	2.37	0.22
Salaried job holder	%	8.50	7.61	9.60	11.60	4.64	4.90	7.96	8.17
Profession	%	0.96	1.47	1.40	1.20	2.84	1.03	0.65	0.65
Pension/Rent	%	4.14	2.58	2.60	2.20	2.84	5.93	2.37	4.73
Other	%	2.14	1.26	1.20	1.00	0.77	2.32	1.72	3.23
Total	%	100	100	100	100	100	100	100	100

Source: The statistics are based on data for the 1353 households in each year.

Table 4.7: Income Diversification by the Poverty Groups in Rural Odisha, 2004-05 and 2011-12

Household livelihood sources	Chronic poor		Ascended out of Poverty		Descended into Poverty		Non-poor	
	2005 * (%)	2012 (%)	2005 (%)	2012 (%)	2005 (%)	2012 (%)	2005 (%)	2012 (%)
Income from daily wage	29	38	22	26	18	30	7	11
Income from salary	9	7	18	12	23	15	34	38
Income from agriculture labour	22	20	15	12	13	13	4	2
Income from business	10	6	10	15	10	7	21	18
Income from farming	23	22	25	24	30	28	23	18
Income from remittances	1	3	2	7	2	3	3	4
Income from government benefits	3	3	2	2	2	3	1	1
Income from other sources	3	1	6	4	2	1	7	8
Total	100	100	100	100	100	100	100	100

*Source: The statistics are based on data for the 1353 households in each year. * represents Income contribution to the total income in %.*

Table 4.8: Asset Base and Activities by Poverty Groups, 2004-05 and 2011-12 (%)

Variables	Unit	Odisha		Chronic poor		Ascended out of Poverty		Descended into Poverty		Non-poor	
		2005	2012	2005	2012	2005	2012	2005	2012	2005	2012
Labour force Household size	Number	5.32	4.98	5.83	5.89	5.45	4.63	4.74	5.08	4.89	4.62
Member in farming sector	Number	1.84	1.80	2.23	2.06	1.82	1.90	2.13	1.77	1.44	1.45
Member in daily wage sector	Number	1.89	1.41	2.13	1.77	1.90	1.48	2.03	1.51	1.61	0.98
Member in service sector (salary and business)	Number	0.43	0.35	0.29	0.21	0.29	0.31	0.43	0.29	0.72	0.54
Natural Asset Own land	%	0.74	0.71	0.74	0.68	0.74	0.74	0.76	0.67	0.75	0.72
Cultivated land	Acre	1.14	1.77	0.90	1.48	0.99	1.67	1.36	1.89	1.46	2.11
Irrigated land in acre	Acre	0.35	0.60	0.19	0.43	0.23	0.49	0.38	0.82	0.61	0.84
Human Asset Average year of schooling of head	Years	3.62	4.02	2.19	3.00	3.39	3.89	3.07	3.49	5.28	5.22
Highest adult education	Years	5.77	6.62	4.02	5.33	5.24	6.11	5.61	6.04	7.98	8.54

Highest male education	Years	5.17	6.24	3.64	4.86	4.64	5.76	5.04	5.69	7.18	8.19
Highest female education	Years	3.01	4.07	1.69	2.69	2.66	3.61	2.62	3.54	4.70	6.02
Financial Asset Bank saving	%	0.17	0.49	0.09	0.35	0.15	0.54	0.13	0.31	0.27	0.59
Self-help group	%	0.26	0.53	0.24	0.59	0.26	0.55	0.28	0.53	0.27	0.44
Any loan	%	0.66	0.51	0.61	0.46	0.64	0.55	0.62	0.42	0.73	0.53
How many loan have availed	Number	4.08	0.94	3.65	1.06	3.39	0.92	3.70	0.77	5.42	0.90
Physical Asset Agriculture productive assets	Number	0.90	0.41	0.89	0.32	0.87	0.34	0.87	0.38	0.96	0.57
Non-agricultural assets	Number	6.48	9.73	4.60	6.51	5.52	9.37	5.98	7.42	9.45	13.62

Source: The statistics are based on data for the 1353 households in each year.

Table 4.9: Involving in Various Social Capital by Poverty Groups, 2004-05 and 2011-12 (%)

Involving in Various Social Capital by Dynamic Groups, 2004-05 and 2011-12 (%)																	
Variables	Unit	Odisha			Chronic poor			Ascended out of Poverty			Descended into Poverty			Non-poor			
		2005	2012	a	2005	2012	a	2005	2012	a	2005	2012	a	2005	2012	a
Member in mahila mandal	%	0.10	0.05	-	0.07	0.03	-	0.11	0.04	-	0.06	0.09	+	0.11	0.05	-
Member in business union	%	0.01	0.01	=	0.01	0.00	-	0.01	0.02	+	0.00	0.00	=	0.02	0.02	=
Member in credit/saving	%	0.12	0.07	-	0.07	0.04	-	0.12	0.08	-	0.10	0.05	-	0.18	0.08	-
Member in caste association	%	0.03	0.30	+	0.03	0.24	+	0.03	0.28	+	0.02	0.29	+	0.06	0.36	+
Member in development	%	0.01	0.15	+	0.00	0.11	+	0.00	0.16	+	0.00	0.16	+	0.02	0.18	+
Member in cooperative	%	0.01	0.01	=	0.15	0.00	-	0.01	0.01	=	0.00	0.01	+	0.03	0.02	-
Member attending public meeting	%	0.32	0.33	+	0.35	0.34	-	0.29	0.36	+	0.32	0.31	-	0.34	0.28	-

Source: The statistics are based on data for the 1353 households in each year. Note: a denotes changes in social capital (- (negative)sign shows reduced and + (positive) sign shows increased the participation).

4.3.3 Factors Influencing Poverty Dynamics

4.3.3.1 Factors Influencing Chronic Poverty

The factors influencing chronic poverty are presented in Table 4.10. The statistical test such as multicollinearity and correlation matrix for covariate variables is presented in Table A4.1 and Table A4.2. The results from the multinomial logistic regression show that household size is significant and positively associated with chronic poverty in rural Odisha. Increasing household size is likely to put an extra burden on the household expenditure pattern (Lawson and Mckay, 2002). The discussion in above section 4.3.2.1 also shows that households with larger families are chronically poor. In the present study, it is observed that households with larger family sizes have been observed to be more likely to stay poor for an extended period. This shows that the addition of a new member in the household increases the probability of remaining chronic poor by 4.4% (Table 4.10). Similar logic applies to the proportion of dependency ratio of children and elders in the household: an increase in one dependent person in the household increases the probability of remaining chronic poor by 30.5%. The variable 'household age' is observed to be negatively significant for chronic poverty, showing that increasing the age of the head reduces the likelihood of households remaining as chronic poor. The variable 'age of the household head' is used as a proxy for the work experiences (Jha and Dang, 2010; Tsehay and Bauer, 2012; Azeem et al., 2018). Working experience always helps to engage in a job; it shows that regular income source helps households remain non-poor. In the case of the gender of the household head, it is observed that there has been no association between the gender of the head and chronic poverty.

Education has been the main determinant of poverty reduction. A household head having higher education helps him/her to engage in the non-farm sector, which increases the household income and improves the living standard (Rahut et al., 2015; Jiao et al., 2017). The comprehensive literature reviewed in chapter 2 shows that households with highly educated heads or members of the household are able to cope with adverse events effectively (Azeem et al., 2018; 2019; Jha et al., 2010; Gunther and Harttgen, 2009). The result shows that an additional year of schooling of the household head would decrease the probability of remaining chronically poor by 1.6%. Consistent with other studies (Anyanwu and Erhijakpor, 2010; Adams et al., 2010; Wagle and Devkota, 2018; Vacaflores, 2018), remittance is further seen negatively associated with chronic poverty. Due to the lack of employment opportunities in the local areas, remittance play a crucial role in rural living standards.

As expected, 'land ownership' one of the variables is statistically significant and has a negative association with chronic poverty. The result shows that acquiring an additional unit of the land reduces the probability of remaining chronic poor by 2.1%. This finding is consistent with the previous study that observed a positive association between land ownership and household wellbeing (Iqbal, 2013; Jha and Dang, 2010). Economic activity, particularly engaged in different job activities, is significantly correlated with chronic poverty. As per the findings of other studies (Albert and Vizmanos, 2018), household members engaged in a secure job always protects households and helps them remain non-poor. A household member working in the salaried job and running a business is found to be negative and statistically significant. It suggests that other things remaining constant, the addition of one member in these activities reduces the risk of remaining chronic poor by 6.6%. However, various possibilities such as poor education make rural households depend for their livelihood on a highly vulnerable sector like farming and daily wage activities. It is found in the study that members engaged in farming and wage-earning jobs are positively associated with chronic poverty. The result shows that members engaged in farming and wage-earning jobs increase the likelihood of households remaining in chronic poverty by 3.7% in both cases. This finding corroborates the above discussion (section 4.3.2.1) which shows chronic poor households are likely to share more income from agriculture and wage in the non-farm sector. Further, it was also observed that the number of individual engaged in these sectors are relatively large for the chronic poor group.

Livestock has usually been seen as an income booster and coping instrument in rural areas (Do et al., 2017). The result of the current work shows that additional livestock reduces the likelihood of remaining chronically poor by 5.3%. This finding is consistent with the previous studies that observed a positive association between livestock ownership and household wellbeing (Mburu et al., 2017; Do et al., 2019). The location of the household plays a crucial role in the household's living standard. A location with more opportunities for economic activities will help the household to manage a reasonable living. However, a location in remote areas as well as the danger of various adverse events leads to more income volatility (Ellis, 1999). The dummy variable 'northern region' has a significant and negative association with chronic poverty. In other words, being in the northern region reduces the probability of staying as chronic poor. However, the probability of remaining in chronic poverty reduces to a larger extent if households belong to the southern region. It is observed from the poverty dynamics (Table 4.5) that northern region households have been more chronically poor than the other regions. Hence, it is discernible that a particular policy should be targeted that aimed to uplift the rural poor from the region. It has also been observed that market distance is positively associated with chronic poor.

Social capital plays a crucial role in reducing poverty in rural areas, as discussed and seen in section 4.3.3. Households that are the participant of social capital are more likely to diversify their livelihood (Adi et al., 2021). The result shows that households being part of the credit or saving group and development or NGO group is negatively significant, suggesting that social capital reduces the probability of remaining chronically poor.

4.3.3.2 Factors Influencing Movement into and out of Poverty

Table 4.10 also presents the factors that help households ascend out of poverty and descend into poverty. As seen earlier, social capital not only reduces the likelihood of households remaining chronically poor but also plays a major role in households escaping poverty. It helps in accessing credit facilities and provides platforms to engage in diversified activities (Paudel Khatiwada et al., 2017). The results from the present study show that being a member of a saving group increases the probability of escaping poverty by 10.5%. It is established in the literature that households being part of a saving group saves the part of their income and to invest their savings in profitable avenues. Since they remain as a group, they share the information on various profitable activities and help each other to flourish in their respective businesses (Adi et al., 2021). In the present study, the results show that remittance is positively associated with escaping from poverty. As it has been seen in Income diversification (Table 4.7), the households that ascended out of poverty have been supported by higher contributions from the remittance. The finding suggests that the increase in household remittance increases the probability of escaping poverty. Specifically, it suggests that if a household receives remittance, then the probability of escaping poverty increases by 1%.

The results show that household size has a negative association with escaping poverty. It is expected that particularly in rural areas, large family households are more likely to engage in the farming activities due to the lack of human capital. Accordingly, the results of our study suggest that the addition of a new member in the household reduces the probability of escaping poverty by 3.5%. Similarly, it is observed that increasing additional dependence reduces the likelihood of escaping poverty by 25.8%. This is because rural households are largely dependent on farming and wage in the non-farm sector for their livelihood, which is more exposed to negative occurings. Due to lack of decent income sources, they lack spending on education and providing nutritious food. As they have to send their children for work, the living standards remain lower compared to the urban households.

The result further indicates, households that reside in the coastal region were more likely to escape poverty. It is also seen that the percentage of households that escape poverty is highest in the coastal region (Table 4.5). It could be due to various factors, however, the coastal region is better in terms of literacy rate and transportability in Odisha (GoO, 2012).

Two of the major factors that mainly influence households to descent into poverty are the dependency ratio and the number of members in a household engaged in the daily wage activities. The finding shows that the number of dependent members increases the probability of households falling into poverty by 11.3%. Similarly, additional members engaged in the daily wage activities increases the probability of the respective household falling into poverty by 2.2%.

Table 4.10: Results from Multinomial Logistic Regression Model

Outcome variable: Change in poverty status: 0= Non-poor,1= Chronic poor, 2= Ascended out of poor, 3= Descended into poverty	Chronic poor/Non-poor	Ascended out of poverty/ Non-poor	Descended into poverty/ Non-poor
	Coefficient (Robust standard error)	Coefficient (Robust standard error)	Coefficient (Robust standard error)
Head gender	0.021 (.040)	0.076 (.047)	-0.035 (.024)
Age of the household head	-0.003*** (.000)	-0.002 (.001)	0.000 (.000)
Household head's years of schooling	-0.016*** (.003)	-0.005 (.004)	-0.001 (.002)
Log income remittances	-0.009** (.004)	0.009** (.004)	-0.004 (.003)
Cultivated land in acre	-0.021*** (.006)	-0.005 (.006)	0.003 (.003)
Household size	0.044*** (.006)	-0.035*** (.009)	0.003 (.004)
Proportion of dependent	0.305*** (.052)	-0.258*** (.060)	0.113*** (.032)
Number of member engaged in farming sector	0.037*** (.008)	0.023** (.011)	-0.000 (.006)
Number of member engaged in daily wage sector	0.037*** (.014)	0.014 (.018)	0.022** (.009)
Number of member engaged in service sector	-0.066*** (.023)	0.000 (.026)	0.003 (.016)
Member in credit or savings	-0.158*** (.056)	0.105* (.061)	-0.008 (.037)
Member in caste association	-0.027 (.031)	-0.023 (.036)	0.008 (.022)
Member in development/NGO	-0.116*** (.041)	0.071 (.045)	-0.002 (.026)
Member in cooperative	-0.329 (.286)	0.155 (.198)	0.023 (.094)
Owns livestock	-0.053* (.032)	0.015 (.040)	0.003 (.022)
Market distance	0.005* (.003)	0.004 (.003)	-0.001 (.002)
Northern region	0.070** (.029)	0.098*** (.037)	0.002 (.021)

Coastal region	-0.006 (.035)	0.150*** (.043)	0.022 (.022)
Constant	-1.049* (.544)	0.613 (.445)	-0.926*** (.638)
Observation	1353		
Pseudo R^2	.1391		

*Source: The statistics are based on data for the 1353 households. Note: *<0.1, **<0.05, ***<0.01 shows significant at 10%, 5%, and 1% respectively.*

4.4 Conclusion

This study has attempted to examine the role of livelihood diversification and social capital on poverty dynamics in rural Odisha. Using panel data of 1353 households for the period between 2004-05 and 2011-12, the study has found out that at the state level, 25.26% of the households have been chronic poor, 45.24% of the households have been transient poor, and remaining 29.50% of households have been non-poor during the phases mentioned above. Further, it has also been discovered that, out of the transient poor, 8.20% of the households have descended into poverty, and 37.04% of households have ascended out of poverty during the same period.

The findings from the livelihood approach show that there is a positive relationship between non-farm activities and escaping poverty. This indicates that non-farm income diversification assures income and thereby enables the household to escape poverty. The anti-poverty policies, creating opportunities by investing in a sustainable financial system, helps thereby to expand rural non-farm activities. It is further observed that households that escaped poverty are characterized by smaller family size, higher educated household heads, more household members participated in the non-farm sector, and possess more assets than the chronic and transient poor households.

The results from Multinomial Logistic Regression indicate that social capital in the form of group membership in different saving schemes and social groups could help escape poverty traps. World Bank report shows that social capital in the form of group memberships receives more benefits from the government and non-governmental organizations (NGOs) than the independent households (World Bank, 2000). Social group membership supports poor households in obtaining vital information circulated within the group. It works as a pledged asset by eliminating the barriers to have access credit from the banks for the households who do not have enough social security. The illiterate and unskilled people and households lacking financial support also has benefited greatly through social capital. Awareness and women empowerment is also shown to be achieved through social capital. However, NGOs working on poverty reduction in various parts of the remote areas require more social capital to be successful. Therefore, it can be surmised that creating more social capital through NGOs, expanding microfinance in remote areas, providing regular training, and educating people through social capital reduces poverty in rural areas.

It has also been found out that households are less likely to remain as ‘chronic poor’ if they have access to higher education, asset, ownership of land. Besides, household members engaged in the salaried and business sector, and being part of social groups, are also unlikely to stay chronic poor. On the other side, households with large family sizes, a higher proportion of dependency ratio, members engaged in the farming sector, and the daily wage jobs are more likely to remain as ‘chronic poor’.

Recently, literature from different nations observed that poverty is persistent due to various shocks such as illness, disability, job loss, accident, flood, drought, and cyclone. In this regard, researchers and policymakers are more interested in understanding the impact of both idiosyncratic and covariate risks on household poverty dynamics. Hence, incorporating those risk factors, analyzing their impact on households’ wellbeing, and designing various coping strategies for mitigating such events would probably shed more light on poverty dynamics in Odisha. In this line of argument, the next chapter estimates household VtP using both the risk factors and coping measures of the household.

CHAPTER 5

MEASURING HOUSEHOLD VULNERABILITY TO POVERTY USING BOTH THE MONETARY AND MULTIDIMENSIONAL APPROACHES

5.1 Introduction

This chapter presents the vulnerability to poverty estimation for monetary and multidimensional measures. The recent statistics on adverse events show that US$ 2.97 trillion economic losses are observed for the year 2000-2019 (0.15 trillion/annually) due to various adverse events (Center for Research on Epidemiology of Disaster (CRED), 2020). Globally, 1.23 million people died, and 4.03 billion were affected due to various adverse events for the same period (CRED, 2020). Over the last two decades, the economic damage and frequency of adverse events have increased many folds. For instance, the number of reported disasters is 7348 during 2000-2019 compared to 4212 for 1980-1999 (CRED, 2020). Each year, on an average, 367 disaster events occur, the majority of which are caused by floods (44%) and storms (28%) (CRED, 2020). Further, such events are expected to be more frequent and severe in the future (IPCC, 2014). The developing countries are expected to be more adversely affected by such events (CRED, 2020).

In developing economies, a significant proportion of the population lives in rural areas, and their livelihoods are reliant on agriculture and natural resources, exposing them to greater risks and shocks (World Bank, 2014b; McCarthy et al., 2016). These households are frequently hit by severe risks of different nature, such as covariate shocks (e.g., drought, flood, and cyclone) and idiosyncratic shocks (e.g., job loss, death, disability, and health shocks) (Nguyen et al., 2020; Gunther and Harttgen, 2009). Generally, households from low-income countries have relatively limited social insurance mechanisms and credit markets which force them to sell productive assets and reduce spending on important consumption items such as nutritious food or education (Deloach and Smith-lin, 2017; Nguyen et al., 2020). Because of the lack of coping measures and the severe impacts of various covariate and idiosyncratic shocks, many households are at high risk of falling into poverty (Gunther and Harttgen, 2009; Dercon, 2005; Berman et al., 2010; Bonu et al., 2007; Garg and Karan, 2009; Shahrawat and Rao, 2012). In the last two decades, the investigation of such vulnerability and the livelihood effects of shocks has become an important issue of research and discussion in development economics. In the literature of vulnerability, a number of methodological studies (Jalan and Ravallion, 1999; Glewwe and Hall, 1998; Morduch, 2005; Christiaensen and Boisvert, 2000; Skoufias and Quisumbing, 2004; Dercon, 2003; Dercon and Krishnan, 2000) and empirical studies (Dercon, 2005; Azeem et al., 2019; Dercon and Krishnan, 2003; Chaudhuri et al., 2002; Imai et al., 2011; Gunther and Harttgen, 2009) have been conducted using different approaches and country cases. These empirical studies have observed that the share of households at risk of falling into poverty is higher than the currently classified poverty rate. However, the empirical literature on VtP that has been reviewed in chapter 2 reveals that due to lack of adequate panel data, most studies rely on cross-sectional data. Yet even when panel data is available, the VtP estimation is often based on the household characteristics and proxy for the adverse events and coping strategies (Liebenehm, 2017; Mahanta and Das, 2017 McCarthy et al., 2016; Gunther and Harttgen, 2009; Azeem et al., 2018). As a result, more research is needed to uncover the relationship between idiosyncratic shocks, covariate shocks, household reported coping measures, and the VtP estimation (Gunther and Harttgen, 2009; Dutta and Kumar, 2016; Feeny and McDonald, 2016; Azeem et al., 2019).

In addition, in recent years, the literature on measuring multidimensional poverty (MDP) has expanded rapidly (Dehury and Mohanty, 2015; Alkire and Seth, 2015). This is reflected in the post-2015 global development agenda known as Sustainable Development Goals (SDGs) 2030. The SDGs aim to end poverty in any form, such as malnutrition and access to basic healthcare, education and clean drinking water. In this context, the United Nations Development Program (UNDP) estimated that 1.5 billion people are multidimensional poor at the global level (UNDP, 2015; Alkire et al., 2015). Further, the UNDP report stressed that the global Multidimensional Poverty Index (MPI) complements the $1.25/day measure of poverty and observed that 29.6% are MDP poor and 23.3% are monetary poor. In fact, UNDP reports and studies using cross-sectional and panel data have observed that the headcount poverty reduction is higher in terms of monetary measures than multidimensional measures (UNDP, 2019; Baulch and Masset, 2003; Gunther and Klasen, 2009; Clark and Hulme, 2005; Tran, 2013; Salecker et al., 2020). While the current policy design is based on the monetary headcount poverty, results from vulnerability to multidimensional poverty further deepen our understanding and facilitate the design of forward-looking anti-poverty policy measures to prevent the households at risk from falling into multidimensional poverty. Although the past empirical studies focused on monetary and multidimensional ex-post poverty, limited studies estimated ex-ante poverty (vulnerability) using both approaches. Therefore, a thorough study of the effects of different types of shocks, coping strategies and the outcome in terms of both monetary and multidimensional vulnerability is an important contribution of this chapter to the literature on vulnerability.

Against this backdrop of the aforementioned limitations, the research question is answered in the context of rural Odisha in India. More specifically, the objective of the study is to measure household vulnerability to poverty using both monetary and multidimensional measures. The results have been estimated in two steps using three econometric approaches. The study first estimated monetary poverty using the Foster et al. (1984) method and then estimated multidimensional poverty adopting a counting approach developed by Alkire and Foster (2011a, 2011b) and UNDP (2014) method. For monetary poverty, household consumption has been used and in the multidimensional approach, several indicators under the dimensions of education, health, and standard of living have been used to estimate the MDP (deprived score). The second part estimates household vulnerability to poverty for monetary and multidimensional measures using the Feasible Generalized Least Squares (FGLS) approach.

The empirical dataset we used for the analysis comes from a cross-sectional survey of 479 rural households living in the southern region of Odisha, which is a poverty-stricken and hunger-prone region of India. This study contributes to the literature of estimating vulnerability to poverty and the different factors influencing in increasing the former in the following ways. First, unlike previous studies that provided an ex-post poverty estimation, this study estimates the ex-ante poverty (households VtP) for both monetary and multidimensional measures. Secondly, the study included explicit information on the household observed shocks and coping strategies to estimate VtP, which was largely missing in the VtP analysis. Further, empirical findings suggested that targeting at the disaggregated level helps to achieve poverty reduction higher than at the national level target (Elbers et al., 2007; Agostini and Brown, 2011). Additionally, because the nature of shock and coping mechanisms vary by location and region, the empirical findings are from India's most hunger-prone region. The findings of the study provide information on household wellbeing in terms of both monetary and multidimensional measures and insights for possible revision of policies.

The rest of this chapter is structured as follows: the introduction is followed by section 5.2, which provides an analytical framework and econometric specification for VtP estimation. After that, in section 5.3, the paper discusses the estimated results of both the VtP and VMDP. Section 6.6 concludes with the key messages of this study.

5.2 Analytical Framework and Econometric Specification

This section explains the econometric specification for the vulnerability estimation approach for monetary and multidimensional measures.

5.2.1 The Outcome Variable and Control Variables

Given our objective and based on the literature surveyed, we primarily use a set of explanatory variables to estimate the relationship between shocks, coping strategies, and vulnerability—the probability of falling into monetary and multidimensional poverty.

As mentioned in the introduction, this study used two outcome variables for vulnerability estimation. First is the household ‘consumption per capita’ derived from the household expenditure. Second is the ‘deprived score’ derived from the multidimensional poverty index using the counting approach devised by Alkire and Foster (2011a, 2011b). Following the literature, we used three household well-being dimensions: education, health, and standard of living. The details are presented in Table 5.1. The explanatory variables are categorized into household characteristics, household experienced shocks, and household adopted coping strategies, presented in Table 5.2. Further, the statistical test such as multicollinearity and correlation matrix is presented in Table A5.4 and Table A5.5.

5.2.2 Analytical Strategy

a) Identification of Monetary Poverty

The poverty incidences are calculated using the poverty estimation method devised by Foster et al. (1984).

$$P(\alpha) = \frac{1}{N}\sum_{i=1}^{n} \left(\left(\frac{z - y_i}{z}\right)^{\alpha}\right) I(y_i < z) \tag{5.1}$$

Where N is the population size, y_i is the level of consumption welfare of i[th] household, z is the predetermined poverty line, I (.) is a function with a value of one when the criteria are satisfied or zero otherwise, α is the measure of the sensitivity of the index of poverty and the poverty line.

b) Assessment of Multidimensional Poverty

Following Alkire and Foster (2011a, 2011b), three steps are used to estimate multidimensional poverty (MDP). In the first step, various dimensions and household well-being indicators are defined. In this scenario, three core dimensions, namely education, health, and living standards, are used in recent studies. However, different authors used various sets of indicators under the specified three core dimensions based on the nature of the data (Table A5.1). The details of the dimensions and indicators used in this study are presented in Table 5.1.

The second step in the calculation of MDP is to assign weights to each dimension and indicator and cutoff points to the selected indicators. Following the literature, we have assigned equal weights to each core dimension as well as to the indicators under each dimension. The weight of 1/3 (33.33%) is equally assigned to the three core dimensions, namely education (1/3), health (1/3), and standard of living (1/3). Further, an equal weight of 1/6 is given to each indicator under the education dimension, namely year of schooling (1/6) and school attendance (1/6). Similarly, an equal weight of 1/6 is given to each indicator under health dimensions, and an equal weight of 1/18 is given to each indicator under the standard of living dimension (Table 5.1).

Following the VMDP pioneering work by Feeny and McDonald (2016), we have also used two cutoffs; deprivation cutoff and poverty cutoff. The deprivation cutoff is used to identify whether a household is deprived or not for the specific indicator. The poverty cutoff relates to the number of indicators a household is deprived of for identifying a household is multidimensional poor or non-poor. The total deprivation score is calculated using the weights, which is the total weighted sum of its deprivation. Following Feeny and McDonald (2016), we have used the poverty cutoff of 33%. The household is considered multidimensional poor if the deprivation score is greater than 33%.

In the final step, using the following formula, the multidimensional poverty index (MPI) or adjusted headcount ratio (Mo) is calculated.

$$M_o = H \times A \qquad (5.2)$$

Where H is the proportion of multidimensional poor households, and A is the average share of deprivation among the poor. A detailed explanation can be found in Azeem et al. (2018) and Alkire and Foster (2011a, 2011b).

c) Dimensions, Indicators, Deprivation Cut-Offs, and Weights

The multidimensional poverty index used in this analysis is based on the international MPI, which was published in the 2014 Human Development Report (UNDP, 2014). Because people typically live in households and share common resources, deprivation and poverty level are calculated at the household level. If a household is deprived in one indicator, it is considered that all of its members are deprived in that indicator as well. Likewise, if a household is multidimensionally poor, all members are considered multidimensionally poor (Alkire and Foster, 2011a; 2011b).

In the case of the educational dimension, the education indicators and cutoffs are identical to those in the 2014 Human Development Report. If none of the members of a household have completed at least five years of schooling, the household is considered to be deprived of years of schooling. A household is deprived of child enrolment if a 6-14-year-old child in the household does not attend school for years 1-8 (Table 5.1). The educational indicators are the same for the different literature (Azeem et al., 2018; Freeny and McMaccum, 2016).

It should be noted that the two indicators of the health dimension are not constant because of the lack of such data availability. Several studies have used different indicators on health dimensions based on the available data. The most used two indicators are nutrition deficiency, child death, health insurance adoption, Body Mass Index (BMI) of children, and health functioning (Table A5.1). This study focuses on child death and health functioning. A household is deprived of child death if any child died in the house in the last five years. A household is deprived of its health status if any person is affected by chronic disease or disability in the household (Table 5.1). This lower cutoff (health functioning) is equivalent to other empirical studies such as Hameed et al. (2017) and Fransman and Yu (2018).

The six living standard indicators and their cutoffs are identical to those in the 2014 Human Development Report. The household is deprived of cooking fuel if it uses dung, wood, rice, or charcoal as its main cooking fuel. Household is deprived of sanitation if sanitation facilities are not available, not improved or shared with other households. A household is deprived in drinking water if it uses water from the river and/or pond. A household is deprived of electricity if the household has no electricity connection. This study also focuses on different types of housing conditions instead of flooring because the household survey has better information on the types of houses. A household is deprived of housing if the household lives in a kutcha or tiled house. Lastly, a household is deprived of assets if it owns no more than one of the following: radio, television, telephone, bike, motorbike, or refrigerator, and if the household does not own a car or tractor. The three dimensions are given equal weights of 33.33 percent each, and indicators belonging to the same dimension are given equal weights as well (Table 5.1).

Table 5.1: Dimensions, Indicators, Weights, Cutoff points, and Resulting Rates of Deprivation for Rural Odisha

Dimensions	Weights	Indicators	Cut-off points	Deprived (%)
(1)	(2)	(3)	(4)	(5)
Education (1/3)	1/6	Year of schooling	No household member has completed five years of schooling.	25.68
	1/6	School attendance	At least one school-aged child is not attending school I to VIII.	5.22
Health (1/3)	1/6	Health functioning	Any adult or child suffering from chronic disease.	56.16
	1/6	Child mortality	A child from the house has died in the last 5 year.	8.35
Standard of living (1/3)	1/18	Housing	The household lives in a kaccha/tiled house.	43.84
	1/18	Cooking fuel	The household cooks with dung, wood or charcoal.	66.81
	1/18	Drinking water	Drinking water sourced from pond or river.	19.62
	1/18	Electricity	The household has no electricity.	20.25
	1/18	Sanitation	The household does not have sanitation, or the household’s sanitation facility has not improved.	81.84

	1/18	Asset ownership	The household does not own more than one of radio, telephone, TV, bike, motorbike, or refrigerator; and does not own a car or truck.	47.18

Source: Based on UNDP (2010, 2014), Alkire and Foster (2011a, 2011b). Deprivation rate is the authors' estimation using survey data.

5.2.2.1 Vulnerability as Expected Poverty

The present study adopted the Vulnerability as Expected Poverty (VEP) approach devised by Chaudhuri et al. (2002) to estimate household vulnerability to poverty in the less favored region of Odisha, India. Given the absence of household panel data, the VEP approach has the advantage of estimating VtP by applying it to cross-sectional data. There has been extensive use of this approach by researchers (Christiaensen and Subbarao, 2004; Calvo, 2008; Günther and Harttgen, 2009; Vo, 2018), details of which are reported in the literature review of chapter 2, section 2.5. The following model has been adopted from the study by Chaudhuri et al. (2002).

The probability of household *h* will be below the poverty line at time t+j; this can be expressed as;

$$V_{ht} = P_r(\ln C_{h,t+j} < \ln z) \tag{5.3}$$

Where V_{ht} denotes the vulnerability of household at present time t, P_r represents the probability of household falling into poverty in the time of t+j, $\ln C_{h,t+j}$ represents the future consumption level of household *h* at time t+j, z shows the pre-specified poverty line. To estimate VtP, a model has to be defined (Haughton and Khandker, 2009). The model can be written as:

$$\ln C_h = \beta_0 + \beta_1 X_h + e_h \tag{5.4}$$

Where $\ln C_h$ is the monthly consumption per capita of household h, β_0 is the intercept, β_1 is the slope coefficient, X_h is observable household characteristics, and e_h is the zero-mean disturbance error term.

To estimate the variance of household consumption, the heteroscedastic term (e_h) is allowed to depend on the same household characteristics as given in equation (5.4). The equation is as follows;

$$\hat{\sigma}^2_{OLS,h} = X_h\theta + \eta_h \tag{5.5}$$

We proceed to obtain the asymptotically efficient estimates of $\hat{\beta}$ and $\hat{\theta}$ using FGLS in three steps suggested by Amemiya (1977) and used by Chaudhuri et al. (2002). In the first step, using the Ordinary Least Squares (OLS) method, equation (5.4) is estimated. In the next step, we square the estimated residuals obtained from the 5.4 equation and allow them to depend on the same household characteristics used in 5.4. The predicted values from equation 5.5 are used to transform equation (5.5) as follows:

$$\frac{\hat{\sigma}^2_{OLS,h}}{X_h\hat{\theta}_{OLS}} = \left(\frac{X_h}{X_h\hat{\theta}_{OLS}}\right)\theta + \frac{\eta_h}{X_h\hat{\theta}_{OLS}} \tag{5.6}$$

The transformed equation is estimated using the OLS method to obtain an asymptotically efficient FGLS estimate of household consumption variance. The following equation obtains the standard deviation of the variance.

$$\hat{\sigma}_{e,h} = \sqrt{X_h\hat{\theta}}_{FGLS} \tag{5.7}$$

At the last step of the FGLS procedure, we use estimates $\sqrt{X_h\hat{\theta}}_{FGLS}$ to transform equation (5.4) as;

$$\frac{\ln C_h}{\sqrt{X_h\hat{\theta}}_{FGLS}} = \left(\frac{X_h}{\sqrt{X_h\hat{\theta}}_{FGLS}}\right)\beta + \frac{e_h}{\sqrt{X_h\hat{\theta}}_{FGLS}} \tag{5.8}$$

The OLS estimates from the transformed equation provide consistent and asymptotically efficient estimates β. The FGLS estimates of $\hat{\beta}$ and $\hat{\theta}$ are used to estimate the expected mean and variance for each household as mentioned below:

$$\hat{E}[\ln C_h \mid X_h] = X_h \hat{\beta} \text{ (Estimated mean)} \tag{5.9}$$

$$\hat{V}[\ln C_h \mid X_h] = \hat{\sigma}^2_{eh} = X_h \hat{\theta} \text{ (Estimated variance)} \tag{5.10}$$

Using the expected mean (Eqn. 5.9) and variance (Eqn. 5.10); VtP is estimated using the following equation: $\hat{V}_h = \hat{P}_r(\ln C_h < \ln z \mid X_h = \Phi\left(\frac{\ln z - X_h \hat{\beta}}{\sqrt{X_h \hat{\theta}}}\right)$ (5.11)

Where $\hat{V}$ is the estimated ex-ante vulnerability of the household h indicates the probability $(\hat{p}_r)$ that the household's log consumption per capita $(\ln C_h)$ will fall below the predetermined poverty line $(\ln z)$. Φ represents the cumulative density function of the standard normal curve. $X_h \hat{\beta}$ and $\sqrt{X_h \hat{\theta}}$ are the estimated mean and variance of household consumption, respectively.

5.2.2.2 Poverty and Vulnerability Threshold

Since the poverty threshold level is necessary for the calculation of VtP, we have used a state-specific poverty line laid down by the Planning Commission of India (recently renamed as National Institution for Transforming India (NITI) Aayog). The country and states' poverty rates are estimated using the nationally representative consumer expenditure data collected by the National Sample Survey Office (NSSO), constituted by the Government of India (GoI). The government-appointed two committees, namely the Suresh Tendulkar Committee and Lakdawala Committee, established the poverty threshold level and recommended a state-specific poverty line for the country. The present study used the poverty line of INR 816 for rural Odisha, which is based on the minimum subsistence requirement for consumption, defined by the Suresh Tendulkar committee for the year 2011-12 (GoI, p, 2014, p. 28).

Further, a vulnerability threshold must be specified to classify households into vulnerable or non-vulnerable groups. In the past literature, this threshold is considered as 0.5 (50%) on the estimated vulnerability scale that varies from 0 to 1 (Haughton and Khandker, 2009; Gunther and Harttgen, 2009, p. 1229). The current study used the same vulnerability threshold to classify the households. This kind of prediction entails that a household classified as vulnerable may fall below the poverty threshold at least once in the next two years (Demissie and Kasie, 2017, p. 7).

5.2.2.3 Assessment of Vulnerability to Multidimensional Poverty

Following Feeny and McDonald (2016) and Azeem et al. (2018), this study estimates the VMDP in rural Odisha using cross-sectional data. There is no single optimal approach for estimating household VtP (Ligon and Schecter, 2004). The method of preference is determined mainly by the nature of the data (Chaudhuri et al., 2002). Ideally, panel data with a sufficient period and large sample size will be more effective in explaining household VtP (Calvo and Dercon, 2013). However, nationally representative panel data are rare in developing countries (Morduch, 1994; Chaudhuri et al., 2002; Gunther and Harttgen, 2009). In the absence of nationally representative panel data, VtP can be estimated using the vulnerability as expected poverty (VEP) approach devised by Chaudhuri et al. (2002). Building on the VEP approach, Feeny and McDonal (2016) have recently estimated VMDP in the case of Melanesia, Azeem et al. (2018) for Pakistan, and Tigre (2019) for Ethiopia.

The reduced form equation of household deprived is given as:

$$d_{it} = f(X_i, S_{it}, C_{it}, e_{it}) \tag{5.12}$$

Where d_{it} denotes household i's weighted deprivation score. X_i represents household characteristics. S_{it} is the shocks experienced by household i, and C_{it} represents various coping strategies adopted to overcome the shocks by household i. e_{it} is the error term. The detailed derivation of the estimation process can be found in studies by Feeny and McDonald (2016) and Tigre (2019).

The probability of household *i* that is, the deprivation score will be above the critical threshold (z) at time t+1 can be expressed as; $V_{i,t} = P_r(d_{i,t+1} > z)$ (5.13)

To estimate VtP a model has to be defined (Haughton and Khandker, 2009). The model can be written as:

$$d_i = \beta_0 + \beta_1 X_i + e_i \tag{5.14}$$

Where β_0 is the intercept, β_1 is slope coefficients, X_i is observable household characteristics, and e_i is the zero-mean disturbance random error term.

We do not provide the detailed derivation for estimating VMDP, as it follows the same method and steps as explained above for the case of the monetary approach (section 5.2.2.1).

After estimating variance and deprivation mean values using the following formula directly, VMDP can be estimated as:

$$\hat{V}MDP_{i,t} = \hat{P}_r(d_{i,t+1} > z \mid X_i) = \Phi\left(\frac{X_i\hat{\beta} - z}{\sqrt{X_i\hat{\theta}}}\right) \tag{5.15}$$

where, $\hat{V}MDP_{,i}$ is the estimated ex-ante vulnerability of the household i, indicating that the probability $(\hat{P}_r)$ that the household's deprivation (d_i) will fall above the predetermined deprivation cutoff (z). Φ represents the cumulative density function of the standard normal curve. $X_i \hat{\beta}$ and $\sqrt{X_i \hat{\theta}}$ are the estimated mean and variance of the household deprivation, respectively.

Finally, in order to minimize the sampling bias, the analysis used bootstrap standard error of 1000 replications in the VtP estimation. This technique takes the sample data obtained during a study and repeatedly resamples it to generate several simulated samples. At the end of the procedure, the simulated datasets contain many alternative combinations of the values that were present in the original dataset.

5.3 Results and Discussion

This section presents the empirical results in two parts. The first part explains the factors influencing both monetary as well as multidimensional vulnerability to poverty. The second part presents the results from both monetary and multidimensional measures of vulnerability to poverty. The section begins with an explanation of factors influencing both monetary and multidimensional vulnerability.

5.3.1 Factors Influencing the Monetary VtP

The results for the estimates of factors influencing vulnerability to poverty using the 3-FGLS approach are presented in Table 5.2. Consistent with other studies (Gunther and Harttgen, 2009; Azeem et al., 2016; Azam and Emai, 2009; Ersado, 2006), the coefficient of years of schooling of the household head is positive and significant. Our results confirm that higher education of the household head significantly increases household consumption expenditure. An explanation for this result is that the education of the household head plays a crucial role in household wellbeing, as higher educated households are better able to diversify their income sources. In terms of demographics, the household size and dependency ratio coefficient are negative and significant, indicating that a household with many family members and dependent members has lower well-being. This finding is consistent with the past empirical VtP studies, which observed a negative association between household size and household consumption expenditure (Azeem et al., 2019; Azam and Emai, 2009; Jha and Dang, 2010).

Based on occupation, the households are categorized into three categories: farm employed, wage earner in non-farm, and self-employed in non-farm sectors. In the present study, the dummy variable occupation – "self-employed in the non-farm sector" is the base category. The findings show that mean consumption per capita in the farm employed, and wage earner in non-farm employed groups is lower by 1274 rupees (antilog) and 1394 rupees (antilog) than the benchmark category. The regression results also indicate that the coefficient of land ownership is positive and significant, which suggests that keeping other factors constant, land ownership increases the household consumption level. This finding corroborates the previous studies that observed a positive association between land ownership and consumption per capita (Iqbal, 2013; Jha and Dang, 2010).

Among the adverse events, the coefficient of the flood is negative and significant, suggesting reduced consumption per capita. It is established in the literature that shocks have a negative impact on household wellbeing (Carter and Barrtte, 2006). Similarly, the coefficient of coping strategies such as 'sold livestock' is negatively significant, but the variable- 'borrowed from a moneylender' is positively significant, indicating the importance of livestock assets and borrowing for coping with adverse events.

In the case of social capital, the coefficients of saving and SHG groups show a significant and positive association with household consumption per capita, which implies participating in group membership leads to an increase in household consumption per capita. This finding is consistent with the past study that observed a positive association between social capital and escaping poverty in rural Odisha (Khosla and Jena, 2020). The regression results also indicate that households with durable assets and productive assets are positively associated with consumption per capita. Households owning more assets spend more on food; they can also convert it into cash or use it as collateral for various purposes. This finding is in line with the past studies that observed a positive association between asset ownership and household wellbeing (Ersado, 2006; Carter and Barrtte, 2006).

5.3.2 Factors Influencing the Vulnerability to Multidimensional Poverty

The results from Table 5.2 show the key factors influencing the vulnerability to multidimensional poverty. The result from the FGLS model for factors influencing multidimensional poverty indicates that there is a negative association between the years of schooling of the household head and deprivation. This result is established in the literature (Fenny and McDonald, 2016; Azeem et al., 2018), indicating that households with more educated household heads are more resilient to shocks. An additional year of schooling of the household head reduces the deprived score by 1%. The coefficient of the variable household size is negative and significant, which indicates that the household with a large number of family members and dependent members has lower wellbeing. Studies have argued that larger households with less dependency ratio supply more labor hours (Tsehay and Bauer, 2012). This finding is consistent with the study that observed a negative association between household size and lower deprivation (Tran, 2013).

In the case of asset ownership, the coefficient of durable asset ownership shows a significant and negative association with deprivation, which implies that possessing more durable assets leads to lower deprivation. This finding is consistent with the past study that observed a lower vulnerability for the household with higher assets (Ersado, 2006). Recently, the estimation of poverty is extended to asset ownership, suggesting that households with better access to assets have more chances to escape poverty (Carter et al., 2007; Carter and Barrett, 2006). This study adds to the growing body of evidence demonstrating the vital importance of preserving a strong asset base in order to combat poverty and vulnerability. Turning to the household's observed experiences of shocks, it is observed that having experienced illness and death of income earners is positively associated with deprivation. This result is the core issue of VtP and is consistent with the past VtP literature (Gunther and Harttgen, 2009; Azeem et al., 2018). The probability of becoming deprived increases by 7% and 3% when household members suffer severe illness and are affected by the flood, respectively, keeping all other variables in the model constant. Generally, rural households, due to less coping capacity unable to mitigate adverse events. Considering the low income per capita, any shock can cause severe damage to the livelihoods of the households. And to overcome these negative events, households apply several strategies, and such choices can lead to persistent poverty (McCarthy et al., 2016). It is observed that if the household had borrowed from informal moneylenders to cope with the negative events, the likelihood of deprivation increases by 5.3%. The finding shows the importance of insurance for coping with negative events.

Social capital within the community is expected to play a key role in disseminating information. This is confirmed by the negative association between participation in group membership and the deprived score of the household. Specifically, if the household is associated with a social network such as a member in a saving group and attending a public meeting like gram sabha, the probability of becoming deprived reduces by 5.7% and 3.2%, respectively. There is a positive association between saving and household wellbeing, and it helps households accumulate more money for further investment (Tsehay and Bauer, 2012). It is expected that households with good savings can use the amount to overcome the negative adverse events. Similarly, household attending gram sabha gets more information on the available government policies and can enroll to avail various benefits from the programs. It was observed from the literature that due to lack of information, a significant proportion of households could not enroll in various programs (Devadasan et al., 2013).

Table 5.2: Factors Influencing Household VtP

Variable	Log consumption per capita		Expected mean consumption		Deprived score		Expected mean deprived	
	Coeff	Std. Err.	Coeff	Std. Err.	Coeff	Std. Err.	Coeff	Std. Err.
Gender (1=male, 0=female)	0.16**	0.07	0.15	0.09	0.02	0.02	0.03	0.02
Farm employed	-0.24***	0.07	-0.42***	0.10	0.01	0.02	-0.04	0.03
Wage in non-farm	-0.15**	0.06	-0.46***	0.09	0.003	0.02	-0.04*	0.02
Household size	-0.11***	0.01	-0.18***	0.02	-0.01**	0.003	0.004	0.003
Dependency ratio	-0.36***	0.08	0.60***	0.10	0.04	0.02	0.05	0.02
Age of head	0.001	0.001	0.02***	0.002	0.0003	0.001	0.003***	0.0003
Years of schooling of head	0.01*	0.01	0.05***	0.01	-0.01**	0.002	0.002	0.002
Own land (1=yes, 0=otherwise)	0.19***	0.05	-0.06	0.07	-0.02	0.01	-0.03**	0.02
Durable assets	0.03***	0.01	-0.04***	0.01	-0.01***	0.002	-0.02***	0.002
Illness (1=affected, 0=otherwise)	-0.05	0.06	-0.23***	0.08	0.07***	0.02	0.09***	0.02
Death of breadwinner (1=affected, 0=otherwise)	0.02	0.05	0.002	0.07	0.02	0.02	0.01	0.02
Cyclone (1=affected, 0=otherwise)	-0.06	0.04	-0.13**	0.06	0.02	0.01	-0.01	0.02
Flood (1=affected, 0=otherwise)	-0.20***	0.04	-0.20***	0.06	0.03**	0.01	0.01	0.02

Drought (1=affected, 0=otherwise)	-0.05	0.05	-0.12*	0.07	-0.004	0.01	-0.02	0.02
Sold livestock (1=yes, 0=otherwise)	-0.09*	0.05	-0.25***	0.07	-0.01	0.02	0.01	0.02
Sold land (1=yes, 0=otherwise)	-0.02	0.07	-0.15	0.1	0.01	0.02	0.00	0.03
Sold gold (1=yes, 0=otherwise)	0.06	0.10	-0.50***	0.14	-0.05*	0.03	-0.04	0.03
Borrowed from informal money lender (1=yes, 0=otherwise)	0.16***	0.04	0.32***	0.06	0.05***	0.01	0.05***	0.02
Borrowed from relatives (1=yes, 0=otherwise)	-0.01	0.04	0.26***	0.05	-0.02	0.01	-0.02	0.01
Productive assets	0.10***	0.02	-0.02	0.03	0.01	0.01	0.01	0.01
Member in SHG (1=yes, 0=otherwise)	0.07*	0.04	0.29***	0.06	-0.01	0.01	-0.01	0.01
Member in saving group (1=yes, 0=otherwise)	0.25***	0.06	0.36***	0.09	-0.06***	0.02	-0.02	0.02
Attending public meeting (1=yes, 0=otherwise)	0.02	0.04	0.28***	0.06	-0.03*	0.01	-0.02	0.01
Constant	7.39***	0.13	7.22***	0.19	0.30***	0.04	0.21***	0.04
Observation	479		479		479		479	
Adjusted R-square	0.45		0.53		0.31		0.57	

Note: asterisks denote the following: *** = significant at 1% level, ** =significant at 5% level, *= significant at 10% level. *Standard error is created by Bootstrap replication of 1000.*

5.3.3 Household Vulnerability to Poverty: Monetary Measure

The results from the FGLS estimate show that 34.65% of the households have a greater than 50% chance of falling into poverty (Table 5.3). In other words, we found that about 35% of total sample households are vulnerable to poverty in the future compared to a current poverty headcount rate of about 29%. This finding is consistent with the previous VtP studies, which have observed that the expected poverty rate is more than the current poverty rate (Chaudhuri et al., 2002, p. 12; Demissie and Kasie, 2017, p. 12; Azam and Imai, 2009, p. 19). Following previous studies on VtP measurement (Demissie and Kasie, 2017; Azam and Imai, 2009), we group the sample households into different poverty and vulnerability categories (Table 5.3). The VtP classification helped us classify the households into four groups based on their predicted change in poverty from the current year to the following year. These groups are – chronic poor, transient poor, escaped poverty, and non-poor (Table 5.4 and Table 5.5). If the household is currently poor and is predicted to be poor in the future, it is classified as 'chronic poor', however, if it is predicted to be non-poor, then it is termed as 'escaped poverty'. On the other hand, a currently non-poor household if predicted to fall below the poverty line, it is classified as 'transient poor', but if it remains non-poor in the future, then the household is considered 'non-poor'. In light of this consideration, it is further observed that 13.36% of poor households of the total sample households are likely to remain poor, and 21.29% of non-poor households are at risk of falling into poverty. This suggests that poverty remains high due to the risk household experience and falls into poverty, in line with past empirical findings (Mahanta and Das, 2017; Ersado, 2006). Therefore, long-term poverty alleviation strategies will be necessary to assist the former group (chronic poor) to come above the poverty line. The latter group (transient poor) has a high risk of becoming poor in the future due to the lack of coping mechanisms. This group is particularly prone to fall into poverty if they are subjected to an adverse shock. This group needs to be assisted with consumption and income stabilization interventions, which are excluded in the current anti-poverty policy implementations. Further, we find that 15.24% of households are escaped poverty, and 50.1% of households are non-poor.

In this scenario, to understand the impact of shocks on VtP, we presented the decomposition of shocks, coping strategies, and different VtP categories (Table A5.2 and Table A5.3). It is observed that the chronic poor are the households who experienced high risks and fewer coping measures. On the other hand, the transient poor households also experienced higher risks. The non-poor, on the other hand, have encountered fewer shocks than the chronic poor and transient poor. This evidence tells us that chronic poor and transient poor households lack coping measures and need assistance from the government to overcome the poverty trap.

Table 5.3 also represents vulnerability and its components by districts. Our analysis shows that future expected poverty is not uniform. Among the districts analyzed, Koraput district has been observed to be the most vulnerable district, followed by Kandhamal and Nabarangpur districts, where 39%, 36%, and 29% of households respectively have a chance of falling into poverty. In the case of VtP categories, Kandhamal district is found to be highest in chronic poor and Koraput district is found to be highest in transient poverty. With 19% and 29% poverty and vulnerability, the Nabarangpur district is the least poor and vulnerable among the districts.

Table 5.3: Household Vulnerability to Poverty (%)

Variable	Overall VtP	Chronic poor [Poor and vulnerable]	Vulnerable to transient poverty [Non-poor and vulnerable]	Escaped poverty [Poor and non-vulnerable]	Non-poor [Non-poor and non-vulnerable]
Overall (Study area) (%)	34.65	13.36	21.29	15.24	50.1
Koraput (%)	39.30	21.36	14.56	30.1	33.98
Kandhamal (%)	35.92	13.43	25.87	11.44	49.25
Nabarangpur (%)	28.57	8.57	20	10.86	60.57

Source: Authors' estimation using survey data. Standard deviation is in the parenthesis.

The incidence of poverty and vulnerability varies widely across livelihood sectors. Figure 5.1 demonstrates the distribution of population across vulnerability categories by sector of occupation of the household head. Among the occupations analysed, farm-employed households were the highest VtP groups, followed by wage earners in non-farm and self-employed in non-farm sectors (Figure 5.1). It is a well-known fact that the majority of the poor in Odisha are in the agricultural sector. In both the poverty and vulnerability context, the proportion of the total sample households in this sector is much higher than the other sectors, namely, wage earner in non-farm and self-employed in non-farm. Tables 5.4 and Figure 5.1 indicate that households engaged in agriculture exceed the poverty rate of other sectors and have a much higher proportion of VtP. In the case of chronic poor, 19.82% of farm-employed households are chronic poor, whereas it was about 7.78% for the wage earner in non-farm and 7.41% for self-employed in non-farm households. About 24% of farm-employed households are more likely to fall into poverty (vulnerable to transient poverty), whereas 21.18% and 12.96% of households have a chance of falling into poverty for a wage earner in non-farm and self-employed in non-farm households. The finding is in line with past results, showing that there is a negative association between engagement in the non-farm sector and household wellbeing. Particularly, employment in non-farm sectors leads to less poverty and vulnerability as households engaged in farming is more exposed to shocks (Ersado, 2006). Since the weather shocks are becoming more frequent in the study areas, farmers are most likely to be affected by the climate shocks. It should be noted that, these findings are based on the unidimensional method-consumption per capita, but the VtP may vary in the case of multidimensional analysis.

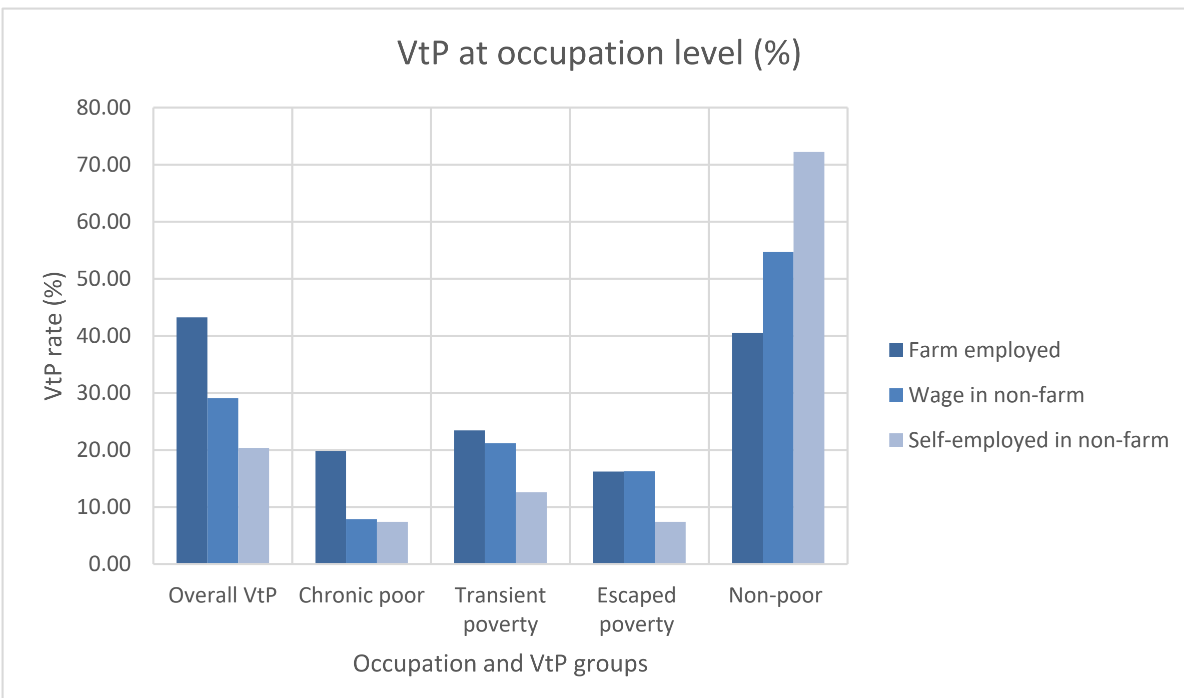

Figure 5.1: Vulnerability to Poverty at Occupation Level (%)
Source: Authors estimation using survey data.

5.3.4 Household Vulnerability to Poverty: Multidimensional Approach

This section provides and discusses the results of vulnerability to multidimensional poverty. The section begins with the discussion of multidimensional poverty.

5.3.4.1 Multidimensional Poverty Index

The counting approach estimates show that despite the fact of various developmental interventions, a significant proportion of households, that is, 47.18% of households, are multidimensional poor (Table 5.4). The findings indicate that households have poor education, poor health, and low state of living standards in the study area. As stated in the introduction, the region is a backward tribal zone of the nation with a high poverty rate, and households derive livelihoods from agriculture (World Bank, 2016). All these results suggest that the government ought to implement policies that will improve people's living standards in this region.

Since the MDP measure is based on the three dimensions such as education, health, and standard of living, analysing the deprivation of each indicator helps us understand the processes underpinning this likelihood. In the case of education, it is established in the literature that education is a significant factor in reducing poverty (Fekadu, 2013). The dynamic role of education on household wellbeing in terms of enhancing risk reduction capacity is detailed in Olopade et al. (2019), Jha and Dang (2010), and Schultz’s (1975). Our results showed that about 26% of households reported to have been deprived of primary education, and children not attending primary education have been observed for 5.22% of households (Table 1, Column 5). This result is in line with the state's educational status. The official report notes that the districts in the southern region have a much lower literacy rate than coastal and northern regions (GoO, 2010). In fact, these districts' education ranks fall under the bottom-educated district within the state as per the 2011 census data. For example, 43.9% of people are literate in Nabarangpur, whereas 42.4% for Koraput, and 61.5% for Kandhamal as compared to Jagatsinghpur (86.5%), Cuttack (83.5%), Puri (84.2%), and Khurdha (83%) (GoO, 2012).

In the health dimension, a significant proportion of households are observed to have severe health issues such as a disability or chronic disease. Since health is directly related to labor supply, this causes a long-term impact on household wellbeing. For example, if one person has a chronic disease that necessitates the assistance of another person, the household must reduce its labor supply, which impoverishes the household. Further, it was also observed that about 8% of households observed to have child death in the household. The official reports show that infant mortality, birth, and death rates are higher in the southern region than in other regions (GoO, 2012). In comparison, the World Bank (2016) documented that the southern region is mostly the poorest region among the regional divisions, with 87% living below the poverty line compared to 50% in the northern region and 30% in the coastal region. The government has, however, implemented universal health policies to help low-income households with health shocks' expenses. The existing literature on the impact of health policy- Rashtriya swasthya bima yojana (RSBY), documented mixed results in reducing the out-of-pocket expenditure for the poor (Boyanagari and Boyanagari, 2019; Singh and Kumar, 2017; Taneja and Taneja, 2016; Azam, 2018). More research is needed, however, to understand its impact on reducing poverty and vulnerability.

Moreover, a number of policies have been introduced, including Deen Dayal Upadhyaya Gram Jyoti Yojana for electricity, Ujjwala for a gas connection, Pradhan Mantri Gramin Awaas (Indira Awas Yojana) for the house provision, and Swatch Bharat Abhiyan campaign for sanitation support for poor households in rural areas. However, it was also observed from the standard of living indicators that the majority of households depend on firewood for cooking, and a significant proportion of households still live in a kutcha/tiled house (Table 5.1, Column 5). While specifically comparing, the Net District Domestic Product (NDDP) for these districts is much lower than the Coastal and Northern Districts. For example, the NDDP for Cuttack, Sundergarh, and Khordha is 4-5 times higher than that of Koraput, Nabarangur, and Kandhamal districts (GoO, 2014). These findings suggest that evaluation of the implemented schemes is necessary to enhance rural development.

The estimates also present the results in relation to the livelihoods (Table 5.4). As expected, the MDP was observed to be highest in the farmer group (54.50%). Due to the fact of climate variability and lack of credit facilities, the majority of households remain in MDP for an extended period. In almost every indicator of the three dimensions, the deprivation rate is observed to be highest for the households engaged in farming than the wage earner in non-farm and self-employed in non-farm sectors (Figure A5.1).

The MDP rate (43.35%) is comparatively low for households engaged in the wage earner in the non-farm sector than the farm employed households. However, the deprivation rate is also observed to be high for the wage earner in the non-farm households. In particular, among the livelihoods, the deprivation rate in health function and sanitation is observed to be highest for the wage earner in non-farm households (Figure A5.2). These are the group of households that also have high chances of falling into poverty due to a lack of work facilities (Khosla and Jena, 2020). In addition, a study by Breitkreuz et al. (2017) showed that a household gets 36 days in a year to work, which shows the lack of working apportunities in the state. Given their vulnerable situation due to the lack of work facilities, low standard of living, poor health care and lack of education, they lead households to remain poor for a long time. Finally, as expected, the lowest MDP rate (31.48%) among the livelihoods is observed for the self-employed in non-farm households.

Table 5.4: MDP Rate in the Study Area (%)

Indicators	MDP rate	Average Intensity	MPI (M0)	Monetary Poverty (headcount)
Total sample (Aggregate)	47.18	0.50	23.59	28.60
Farm employed	54.50	0.51	27.80	36.04
Wage earner in non-farm	43.35	0.51	22.11	24.14
Self-employed in non-farm	31.48	0.43	13.54	14.81
Koraput	57.71	0.53	30.59	24.88
Kandhamal	35.92	0.43	15.45	51.46
Nabarangpur	41.71	0.49	20.44	19.43

Source: Authors estimation using survey data and UNDP (2010, 2014) method.

5.3.4.2 Household Vulnerability to Multidimensional Poverty

The findings from the FGLS estimate for multidimensional measures indicate that 55.11% of households are vulnerable to multidimensional poverty (Table 5.5). This implies that ex-ante multidimensional poverty is higher than the ex-post multidimensional poverty rate of 47.18%. This finding is consistent with the previous VMDP studies, which have observed that the vulnerability to multidimensional poverty rate is more than the current multidimensional headcount poverty rate (Azeem et al., 2018; Feeny and McDonald, 2016; Tigre, 2019). Based on the VtP categories, we find that 35.49% of poor households are likely to be chronically poor and 19.62% of non-poor households are at a high risk of becoming multidimensional poor.

Further, we report the results on vulnerability decomposition by various shocks and coping strategies for different VtP categories for the case of vulnerability to multidimensional poverty (Table A5.2 and Table A5.3). We find that chronic poor households are more affected by both covariate and idiosyncratic shocks. This evidence tells us that shocks impact severely chronic poor households because they lack coping measures and tend to remain poor for a long time. Similarly, transient poor households are associated with exposure to shocks and as a result, they are at the risk of falling into poverty. However, as seen for the monetary measure, we find that non-poor are comparatively less affected by the various shocks. This underlines the significance of coping measures to support vulnerable households. Therefore, the implication is that if policies that target poverty also target VtP households and this can result in reducing the risk of falling into poverty.

In addition, the VtP rate varies substantially across measures of vulnerability to multidimensional poverty for the districts analysed. A nearly 70% of households in the district of Koraput were at a high risk of falling into poverty, followed by districts of Kandhamal and Nabarangpur, where 68.16%, 44.66%, and 46.29% of households respectively have a chance of falling into poverty (Table 5.5). In the case of VtP categories, the shares of chronically and transient poor households in the Koraput district are higher than the Kandhamal and Nabarangpur districts. The results are further compared with the multidimensional indicators to understand how the households from one district differ from the households of other districts. Figure A5.1 reflects deprivation of the three districts in three dimensions. It is observed that the deprivation rate for most indicators under all three dimensions is observed to be more for the households living in the Koraput districts.

Table 5.5: Household Vulnerability to Multidimensional Poverty (%)

Variable	Overall VtP	Chronic poor	Vulnerable to transient poverty	Non-poor	Escaped poverty
Overall (Study area) (%)	55.11	35.49	19.62	33.19	11.69
Kandhamal (%)	44.66	21.36	23.30	40.78	14.56
Koraput (%)	68.16	51.24	16.92	25.37	6.47
Nabarangpur (%)	46.29	25.71	20.57	37.31	16

Source: Authors' estimation using survey data.

The analysis was also carried out for various livelihoods, including farm employed, wage earner in non-farm, and self-employed in non-farm sectors. Among the occupation analysed, farm employed (61.26%) households have been observed to be the highest VtP group, followed by wage earner in non-farm (51.72%) and self-employed in non-farm (42.59%) (Figure 5.2). In the case of chronic poor, 41.89% of farm-employed households are chronic poor, while they are around 31% for a wage earner in non-farm, and 25.93% for self-employed in non-farm. About 19% of farm-employed households are at a high risk of falling into poverty (vulnerable to transient poverty), while 20.69% and 16.67% of households have a chance of falling into poverty for a wage earner non-farm and self-employed in non-farm sector households. It should be noted that these estimations are based on the multidimensional method, but the VtP may vary in the case of monetary analysis.

Overall, the vulnerability rate in both the measures indicates that a large share of households is at a higher risk of falling into poverty than the currently classified poverty rate. In the case of VtP categories, nearly 38% and 48% of households are chronically poor, while about 15% and 38% are transient poverty for both monetary and multidimensional measures, respectively. Among the livelihood categories, the share of VtP households is higher for the multidimensional measure than the monetary measure. Similarly, the VtP rate is observed to be higher for the multidimensional measure than the monetary measure for the districts. The conclusion can be derived from the findings that policy should target the multidimensional indicators to achieve the goal set by SDGs, that is, to end poverty in every form by 2030.

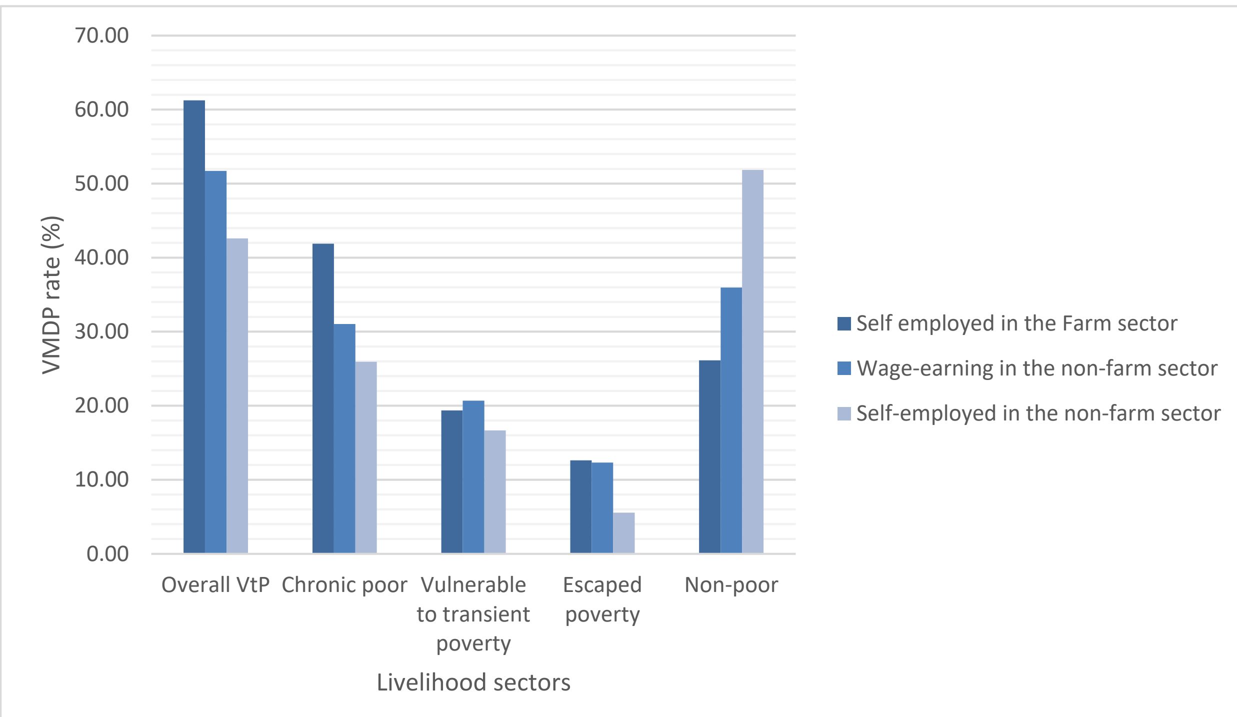

Figure 5.2: Vulnerability to Multidimensional Poverty at Occupation Level (%)

Source: Authors' estimation using survey data.

5.4 Conclusion

Households in developing nations are often hit by risks and shocks, which have a significant negative effect on poor and vulnerable households' livelihoods due to their lack of resistance to these incidents. A large percentage of already poor households will remain poor due to lack of coping strategies and the non-poor will fall into poverty as a consequence of shocks. Furthermore, the nature of household shock and coping strategies differs by place and region, meaning that a common (universal) policy may not be successful across the state or country. Understanding the household's dominant risks and shocks and their coping mechanisms will facilitate the development of forward-looking policies, including implementing preventive measures to reduce damages from risk events that reduce the household's chance of falling into poverty. The literature reviewed in chapter 2 reveals that most VtP estimation studies lack information relating to shocks and coping measures. Further, past literature on VtP estimation is largely available on monetary measures. Given the importance of multidimensional measures, as prioritized in SDGs, vulnerability to poverty estimation should also be based on a multidimensional approach. This study adds considerable value to the vulnerability literature by using the 479 rural households survey dataset from Odisha and estimating VtP for both monetary and multidimensional measures.

The main findings from the FGLS estimation for the monetary VtP show that around 35% of the total sample was at the risk of becoming poor in the near future. The empirical analysis also reveals that factors like gender, landholding, years of schooling of the head, access to productive and durable assets, SHG, and saving groups have a significant positive association with the likelihood of increasing household consumption. On the other hand, households engaged in the farm, wage, household size, dependency ratio, flood and sold livestock have a significant inverse association with the likelihood of reducing household consumption. From the VtP categories, approximately 13% of the total sample is identified as chronic poor, with the possibility of remaining poor, whereas 21.29% of non-poor households have a high risk of falling into poverty. Among the districts analyzed, the proportion of households that are at high risk of falling into poverty is highest in the Koraput district, followed by Kandhamal and Nabarangpur districts. Further, households engaged in farming are observed to be most vulnerable, followed by those engaged in wage in non-farm and self-employed in non-farm. It was observed that chronic and transient poor are mostly experienced shocks, which is in line with the theoretical explanation of VtP.

With regard to the MDP estimation, the empirical findings show that 47% of the total sample are identified to be MDP, which is higher than the 29% monetary poverty rate. A heterogeneity MDP rate is observed for the households among the occupation and districts. In the context of livelihood categories, the proportion of households living in MDP is found to be highest for the households depending on the agriculture sector, followed by the wage earner in non-farm and self-employed in non-farm sectors. Approximately 58% of the total sample households are identified as MDP in the Koraput districts. In contrast, an MDP rate of 36% was observed for Kandhamal and 42% for Nabarangpur districts.

The FGLS estimate for multidimensional poverty shows that about 55% of households are more likely to fall into MDP in the near future. The factors influencing VMDP demonstrate that years of schooling of the household head, household size, household possessing durable assets, households belonging to a saving group, sold gold, and household members attending public meetings reduce the deprivation. On the other hand, illness of the household member, flood, and borrowed from informal money lender increases the deprivation of households. From the VtP categories, it was further observed that about 36% of currently identified MDP households are likely to remain MDP and about 20% of non-poor households are identified to be at the risk of falling into MDP. Further, the proportion of households at risk of falling into poverty for farm-employed is 43.24%, whereas it was observed to be 29.06% for a wage earner in non-farm, and 20.37% for the self-employed in non-farm households. The findings also demonstrate that the VMDP rate is found to be highest in the Koraput district, followed by Kandhamal and Nabarangpur districts. The overall conclusion from these approaches is that the rate of households having a risk of falling into poverty is higher than the currently classified poverty rate. Further, VtP rate observed in the multidimensional measure is higher than the monetary measure.

Unlike many other studies, we do have a fair amount of information on shocks actually experienced by the households. The aggregate impact of observed shocks substantially impacts poor and vulnerable households, as observed both from quantitative and subjective assessments. In line with these results, since VtP is linked with shocks and lack of coping measures, it would be interesting and useful to investigate the relationship between shocks and social protections in reducing vulnerability in future research. Given the lack of household coping strategies, the government has implemented social protections to enhance household coping strategies through insurance, food security, employment programs, and credit access to reduce poverty and vulnerability. Therefore, analyzing the impact of social protection on reducing vulnerability will provide more effective ways of ending poverty. In this framework, the next chapter examines the impact of social protection on household VtP.

CHAPTER 6
TO ASSESS THE IMPACT OF WELFARE PROGRAM ON HOUSEHOLD VULNERABILITY TO MONETARY AND MULTIDIMENSIONAL POVERTY

6.1 Introduction

The extreme poverty (<$1.25/day) rate has declined in low and middle-income counties, but poverty is still persistent in many countries (United Nations (UN), 2015; International Monetary Fund (IMF) and World Bank (WB), 2015, p, 22). The recent estimate shows that about 2 billion people still live below the poverty line of $2.00 per day (Croppenstedt et al., 2017, p. 2; Lowder et al., 2017, p. 1; IMF and WB, 2015). Further, due to the rise in risks and shocks at the global level, the poverty rates are expected to increase and remain persistent in many countries (WB, 2020; The Intergovernmental Panel on Climate Change (IPCC), 2012). To make the matter worse, the recent economic shocks arising from the COVID-19 pandemic have pushed millions of people in developing countries into the poverty trap (World Bank, 2020). As a result of increased adverse events (both idiosyncratic and covariate shocks) and resulting vulnerability but limited resilience capacity, the poverty dynamics and vulnerability to poverty (VtP) have recently drawn tremendous interest in identifying vulnerable households and designing the social safety net. Shocks and the limited resilience capacity of the poor household constraints the global effort to achieve the sustainable development goal of zero poverty and other allied goals such as zero hunger, quality education, good health, gender equality, clean drinking water, and sanitation. Several studies in developing countries suggest that enhancing their risk coping capacity through inclusion in social protection policies helps them from falling into poverty traps (Choudhuri et al., 2002; Azeem et al., 2019; Vo and Van, 2019; Vo, 2018; Tran, 2015; Azam and Imai, 2009).

Moreover, studies have also estimated that the population living above the extreme poverty line is 4-5 times likely to fall into poverty due to a high degree of vulnerability and lack of or limited capacity to cope with the shock (Lopez-Calva and Ortiz-Juarez, 2014; Desai and

Rudra, 2019, p. 1). In addition to this, recent gains in poverty reduction will become fragile without social protection (Croppenstedt et al., 2017, p. 2; Desai and Rudra, 2019). The empirical literature from the developing countries reviewed in chapter 2 reveals that the ex-post poverty studies have found a positive impact of social protection on poverty reduction (Galasso and Ravallion, 2004; McCord, 2009; Hidrobo et al., 2018). However, limited attention has been given to ex-ante poverty analysis on social protection (SP) and vulnerability to poverty, i.e., the likelihood of falling into poverty (Heltberg and Lund, 2009; Gentilini, 2009; Elkins, 2014; Azeem et al., 2019).

Given the prevalence of the extreme poverty rate in rural areas (Lowder et al., 2017; Ravallion et al., 2007; International Food for Agricultural Development (IFAD), 2010), many developing countries, including India, employ rural development strategies that focus on job creation, access to credit for small farmers, infrastructure development, educational improvement, and delivery of health care services (Tiwari, 2017) to combat poverty and vulnerability. In the international context, existing literature has been reviewed in chapter 2 found that rural livelihood programs are key drivers for improving the well-being of rural households (Olson, 2007; Gotor and Irungu, 2010; Sparling and Gordon, 2011; Hagen-Zanker, 2011; Shimizu et al., 2016; Hidrobo et al., 2018). In the Indian context, rural livelihood programs- the alternative programs for livelihoods- are targeted in backward states like Odisha and Bihar to enhance the standard of living of poor and vulnerable groups (Christian et al., 2018; Datta, 2015). Odisha is one of the Indian states with a high poverty rate and the state also experiences substantial risks from multiple sources (GoO, 2012). Moreover, given the current low level of living standards and the presence of high poverty rates in rural areas, livelihood programs have been introduced in the Indian state of Odisha by targeting specific areas and communities since 2005 (GoO, 2014; World Bank, 2016). Past studies on the impact of livelihood programs mostly focused on poverty reduction along with other issues such as well-being, food security, and reduction of migration (e.g., Christian et al., 2018; Hidrobo et al., 2018; Barrett et al., 2014; Deka and Panda, 2015; Bawelle, 2016; Datta, 2015). Therefore, it is necessary to understand whether the livelihood programs enhance the resilience capacity of the targeted households and help vulnerable families from falling into poverty.

Thus, this study finds the answers to the research question in the context of rural Odisha, a less favored region of the country. More specifically, the purpose of this study is to empirically investigate whether participating in a livelihoods program (LP) reduces household VtP in rural Odisha. The study estimated the impact of LP on household VtP in the context of two approaches: monetary and multidimensional measures. Household VtP score has been used from the Feasible Generalized Least Squares (FGLS) econometric approach (detailed in chapter 5) and the impact of LP on household VtP has been investigated employing the Propensity Score Matching (PSM) with sensitivity analysis suggested by Rosenbaum (2002). Further, we have employed the Endogenous Switching Regression (ESR) method to control the hidden bias arising from unobserved variables.

The study used the primary data collected in 2018-19 from 479 households. This study contributes to the literature of estimating vulnerability to poverty and the role of social protection in reducing the former in the following ways. First, this study investigates the potential impact of livelihoods program on ex-ante poverty (households VtP). This is in contrast to previous research that examined the ex-post poverty impact of livelihood programs. The sampled districts represent the tribal region of Odisha that is heavily gripped by the Maoist insurgents of eastern India. This region is geographically disadvantageous due to its mountainous terrains and infrastructural poor. Secondly, we analyzed the impact of LP not only on monetary vulnerable households but also on multidimensional vulnerable households. The findings of the study provide causal impacts of LP and insights for possible revision of policies.

The rest of this chapter is structured as follows: the introduction is followed by section 6.2, which provides a brief description of the poverty level and development interventions in Odisha. After that, in section 6.3, the analytical frameworks for impact evaluation are explained. In section 6.4, the paper discusses the estimated results of both the PSM and ESR, the average impact of rural LP on household VtP. Lastly, section 6.5 concludes with the key messages of this study.

6.2 Poverty and Development Interventions in Odisha

As mentioned in chapters 1 and 3, the poverty rate has been declining, but the poverty rate is still challenging in Odisha. In particular, 35.69% are still living below the poverty line (GoI, 2015). In this progression of argument, several social protection policies have been implemented in India and, in particular, Odisha to uplift the poor and vulnerable groups, which is summarized in Table 6.1. Many central government schemes such as Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA), National Rural Livelihood Mission (NRLM), and Swarna Jayanti Gram Sahari Yojana (SGSY) are targeted for employment generation. Targeted Public Distribution System (TPDS), Antyodaya Anna Yojana (AAY), Midday Meal Scheme (MDS), and Special Nutrition Program (SNP) to ensure food security in the country. Indira Awas Yojana (IAY) and Pradhan Mantri Awas Yojana (PMAY) focusing at housing provision. Other social security schemes like the old-age pension have been actively functioning in the state.

Table 6.1: Key Interventions for Poverty Reduction in Odisha

Serial number	Programs	Objectives	Targeted group
1	Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA), National Rural Livelihood Mission (NRLM), Swarna Jayanti Gram Sahari Yojana (SGSY).	Employment generation	Unemployed persons in the unorganized labor force
2	Rupee one kg of rice, Targeted Public Distribution System (TPDS), Antyodaya Anna Yojana (AAY), Midday Meal Scheme (MDS), Special Nutrition Program (SNP)	Food security	Persons identified as poor
3	Madhubabu Pension Yojana (MPY)	Social security	Poor persons
4	Indira Awas Yojana (IAY), moKudia, Biju Pucca Ghar	Housing provision	Economically weaker, houseless, and lower-income group
5	Critical irrigation projects	Improvement of economic condition	Rural poor

6	Rashtriya Gram Swarojgar Yojana, Aam Aadmi Bima Yojana (AABY)	Economic upliftment	Poor persons
7	Odisha Tribal Empowerment and Livelihoods Program (OTELP), Western Odisha Rural Livelihood Project (WORLP), Odisha Rural Livelihoods Program (ORLP)/JEEBIKA, Targeted Rural Initiatives for Poverty Termination and Infrastructure (TRIPTI), Orissa Community Tank Management Project (OCTMP)	Livelihood improvement	Tribal and other vulnerable communities

Source: GoO (2015, 2017b).

Apart from these schemes, the Odisha government has implemented - separately for different regions - several key interventions focusing on enhancing household capacity to escape the poverty trap and coping with the external shock, and preventing households from falling into the poverty trap. For improving the livelihood of tribal and other vulnerable communities, livelihoods program (LP) have been implemented with active support from several external donor agencies and international organizations such as the World Bank, IFAD, Department for International Development (DFID), and World Food Program (WFP) (GoO, 2016, 2018).

As reported in Table 6.1, under the livelihood improvements, livelihoods programs have been implemented for different zones of Odisha. The Odisha Tribal Empowerment and Livelihoods Program (OTELP) targets the tribal community to enhance the quality of life through livelihood support in the southern region, while the Western Odisha Rural Livelihoods Program (WORLP) addresses poverty reduction in rain-fed areas of western Odisha. The 'Jeebika' scheme addresses issues related to improving quality of life, such as preventive health measures, sanitation, drinking water, and food security of tribal households. Targeted Rural Initiative for Poverty Termination and Infrastructure (TRIPTI) addresses extreme poverty in the backward regions through small credit and self-help groups (SHG) and the improvement of traditional water bodies in the coastal belt of Odisha. The Odisha Community Tank Management Project (OCTMP) is the initiative in the state to develop minor irrigation in 12 northern districts of Odisha. In addition, efforts have been undertaken to construct check dams and to perform mega lift irrigation projects on a vast scale in order to increase irrigation capacity in the state. The details of objectives, the budget allocation of these programs, and outcomes can be found in Odisha Economic Survey (GoO, 2015, 2017) and World Bank reports on Odisha rural livelihood project (Independent Evaluation Group (IEG) Review Team, 2016; World Bank, 2016; GoO, 2016).

However, OTELP mainly functions in the study areas among the livelihood programs. Accordingly, a binary variable is generated with 1 and 0, where 1 is assigned to households that participated in the livelihoods program and 0 to the non-participants. The primary objectives of this program are to help the tribal and vulnerable community to improve their livelihood and standard of living through agricultural development and farm and non-farm enterprise development.

This scheme-OTELP has been implemented in the most backward blocks in seven districts, namely Gajapati, Kalahandi, Kandhamal, Koraput, Malkangiri, Nabarangpur, and Rayagada in South-West Odisha (GoO, 2016). These blocks have been selected based on the degree of backwardness in terms of socio-economic indicators such as food insecurity, the concentration of Below Poverty Line (BPL) population among Scheduled Tribes (ST) and Scheduled Castes (SC), infant and child mortality, malnutrition, risks of natural disasters like drought and cyclone so on and so forth. The program has been implemented in villages where the scheduled tribes and scheduled castes constitute not less than 60% of the population and where the majority of households live below the poverty line have been identified eligible for coverage. From the external donors, the OTELP received an overall budget allocation of USD 91.19 million in 2016 (GoO, 2016, 2018).

This program is designed to eradicate poverty and improve the standard of living of the tribal zone by providing opportunities for work engagement and farm and non-farm enterprises. In particular, the program in the tribal zone of Odisha consisted four sets of activities: (1) "to build the capacity of marginal groups"; (2) "to enhance the access of poor tribal people to natural resources and increase its productivity"; (3) "to encourage and facilitate off-farm enterprises"; and (4) "to ensure basic entitlements of tribal households" (GoO, 2016).

A number of studies in the different country cases have assessed whether the LP has achieved the objective of reducing poverty (e.g., Christian et al., 2018; Hidrobo et al., 2018; Barrett et al., 2014; Deka and Panda, 2015; Bawelle, 2016; Datta, 2015). These studies have attested that the LP has reduced poverty and improved the well-being of the household. Exploring beyond poverty, this study investigates if LP reduces household vulnerability to poverty. In other words, does LP reduce the household exposure to negative shocks and improve their ability to cope with them? Answering this question is crucial since the goal of poverty alleviation is not just about improving household welfare via increased income or consumption. It is also about devising means for preventing households from falling into poverty and enabling them to meet their survival needs, including food security, to make productive investments, and to avoid selling their limited resources in times of risks or shocks. The participation rate of the LP program is provided in Figure 6.1.

As mentioned above, the program has different components to build the rural area and uplift the tribal population. In particular, about 52% of the sampled households reported having benefited from the livelihoods program for the last five years from the date of the survey (Figure 6.1). It is observed that about 48% of the total sample have participated in the different daily wage work offered by the LP program. The program builds rural infrastructure in the tribal zone by constructing a micro shed, check dams, pipe water supply, and community buildings at the village (GoO, 2016). It was also observed that about 24% of households have received loans to start a small business, farm, and non-farm activity. Similarly, about 11% of the total sample households reported having received training to help them improve their livelihoods. The program assists the unemployed youth to be engaged in the labor force by providing vocational training in the area such as sewing, stitching, tailoring, and mechanic courses (GoO, 2016). It was also observed that about 8%

of households received agricultural instruments such as machinery and subsidies to improve their agricultural productivity.

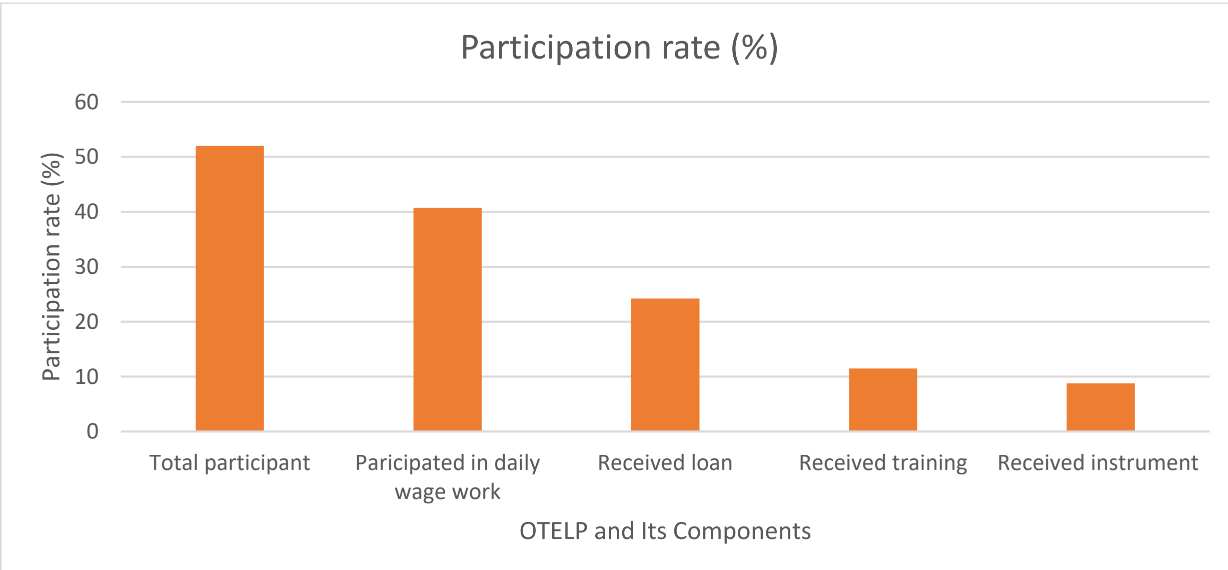

Figure 6.1: Livelihoods Program-OTELP

6.3 Analytical Framework and Econometric Specification

This section explains the econometric specification for impact evaluation approaches that are used for the analysis. We begin with a presentation of the PSM framework used in the study.

6.3.1 Propensity Score Matching (PSM) Approach

Establishing the causal effects of program participation on household well-being, in terms of poverty reduction, asset building, increase in income and consumption, and household livelihoods are some of the crucial tasks of applied research in developing economics. Several measures exist in the impact evaluation literature to restrain the endogenous bias to the minimum to allow for causal claims. Randomized Control Trials (RCTs) are the gold standard to identify causal effects for most empirical researchers. However, researchers are often not in control of the dissemination of programs, forcing them to search for non-experiment designs to evaluate the program.

Estimating the welfare gain from the participation in LP based on non-experimental observations is not trivial because of the need to identify the counterfactual situation had they not participated in the LP. In experimental studies, this problem is addressed by randomly assigning households to treatment and control groups, where welfare outcomes observed on the control households (non-participants) are statistically representative of what would have occurred without participation for treated households. However, households are not randomly distributed to the two groups of participants and non-participants, but rather it is the households that make their participation choices or are systematically selected by government agencies and/or by the project administrator based on their selection criteria to participate in the livelihoods program. Therefore, participants and non-participants may be systematically different. Thus, possible self-selection due to observed and unobserved variables and household characteristics makes it difficult to perform an ex-ante assessment of gains from participation in the program using observational data.

We propose using PSM and ESR to address the above econometric challenges. One popular and widely adopted approach is the PSM approach that estimates the impact by creating counterfactual based on observable variables, assuming impacts are based on observable factors. A shortcoming of PSM is that it does not explicitly account for unobservable variables that may affect both the outcome variables and the choice of participation. It assumes selection is based on observable variables. The existence of unobserved characteristics in the PSM might result in mismatching and biased estimators, which are undesirable outcomes. To address this problem, we also employed ESR that assumes selection on unobservable. The seminal explanation of the PSM method is available from Rosenbaum and Rubin (1983), and its strength and weaknesses are elaborated, for example, by Heckman et al. (1998), Dehejia and Wahba (2002), Caliendo and Kopeining (2008), and Smith and Todd (2005).

In order to investigate the impact of LP on household VtP, we first employed PSM, a method that has been widely used in the impact evaluation literature (Mensah et al., 2010; Aggarwal, 2010; Trujillo et al., 2005). In summary, PSM seeks to create a control group by selecting non-participants who share as many observable features as feasible with participants. The main challenge of a reliable impact assessment is to create a counterfactual outcome; that is, identifying what would have happened to the VtP households that participated in livelihoods program (LP) in the absence of LP. Further, the same analysis was also carried out for the multidimensional vulnerability to poverty. The cross-sectional data usually has non-experimental biases, such as selection bias (Wooldridge, 2002). PSM has been developed to help design and analyse non-randomized observational studies in order to mimic some of the features of a randomized control trial (Rosenbaum and Rubin, 1983).

The PSM corrects the selection bias caused due to observables by matching a sub-sample who participated in LP with those who did not participate in LP but have similar observable characteristics and by making comparisons in the region of common support (Becker and Icnino, 2002). The present study evaluates the impact of LP on only VtP households (estimated using the FGLS approach), showing similar characteristics. The average treatment effect on the treated (ATT), which is the impact of LP on those VtP households that have participated, has been estimated as follows:

$$ATT = E[\Delta_i \mid T_i = 1] = E[Y_{1i} \mid T_i = 1] - E[Y_{oi} \mid T_i = 1] \tag{6.1}$$

where, T_i refers to the treatment status of VtP household i, and takes two values $T_i = 1$ if a household has participated in LP, and $T_i = 0$ if a household has not participated in LP. $Y_{1i} = 1$ is the outcome variable for a household which has participated in LP, $Y_{0i} = 0$ is the outcome variable for a household which has not participated in LP. E is the expectation operator and Δ_i is the treatment effect. The ATT captures the change in the outcome for a household that participated in LP and a counterfactual outcome where the same household had not participated.

Matching requires building a new control group with similar characteristics so that for every treated observation (households who participated in LP), there is an untreated one (households who did not participate in LP). PSM constructs a probability that household's access to LP becomes conditional on its characteristics. This is done by running a logit model of 'participated in LP' and 'did not participate in LP' on the set of observable baseline characteristics. It can be written as:

$$p(x) = p_r[T = 1 | X] = x_i, x_2, ..., x_n] = E(T | x) \tag{6.2}$$

where, $T = 1$ for the VtP households that participated in LP, and 0 for those who did not participate in LP, and X is the vector of observable household characteristics. Two assumptions have to be fulfilled to validate the matching: common support for overlap and conditional independence. We have used three matching methods, namely nearest neighbour, Kernel, and Radius methods, in which VtP household with access to LP has been matched with its neighbour, based on the propensity score.

As mentioned above, although the PSM method reduces the bias due to observable variables, it has been criticized for the hidden bias arising from unobserved variables. One strategy for addressing this problem is the Rosenbaum Bound test, known as a sensitivity analysis (Rosenbaum, 2002). This allows the analyst to determine how strongly the unobserved variables affect the selection of treatment. The details on derivation, estimation, and interpretation can be found in Rosenbaum (2002) and DiPrete and Gangl (2004). This approach of sensitivity analysis to reduce the bias arising from the unobserved variables has been widely used by impact evaluation researchers (DiPrete and Gangl, 2004; Jena and Grote, 2017; Jena et al., 2017).

6.3.2 Endogenous Switching Regression (ESR) Approach

Although we have conducted a sensitivity analysis to check the bias arising from the unobserved variables, it is important to assess the impact of participation using an alternative model that includes unobservable influence. We also employed the ESR analysis that assumes selection on unobservable to control the hidden bias.

ESR defines two regimes – the first is a household that has participated in the LP and the second is a household that has not participated in the LP. The ESR estimation follows two-stage, and for the latent variable model, the equation (6.3) is estimated as follows:

$$A_i^* = Z_i\alpha + v_i \text{ where } A_i = \begin{cases} 1 & \text{if } Z_i\alpha + v_i > 0 \\ 0 & \text{otherwise} \end{cases} \tag{6.3}$$

A vulnerable household i takes part in LP when the predicted benefit from participation is greater than that of non-participation. Let A_i^* be a latent variable that captures the benefit of participation by the ith household. Z_i is a vector of explanatory variables that describes how the regimes are selected. The parameter vector is α and the error terms is v_i. The outcome equation is then estimated in the second step. The observations from the first-stage selection equation are used to determine which of the two regimes to join. The following are the outcome equations for two regimes: participation and non-participation corrected for endogenous adoption:

Regime 1: $Y_{1i} = X_{1i}\beta_1 + \sigma_{1u1i}\hat{\lambda}_{1i} + u_{1i}$ if $A_i = 1(Participation)$ (6.4a)

Regime 2: $Y_{2i} = X_{2i}\beta_2 + \sigma_{2u2i}\hat{\lambda}_{2i} + u_{2i}$ if $A_i = 0(Non-participation)$ (6.4b)

where Y_{1i} and Y_{2i}, $i = 1, \ldots, N$, denote the dependent variables in each of two regimes. X_{1i} and X_{2i} are the explanatory variables relevant to each regime, β_1 and β_2 are the parameters that needs to be estimated, and the corresponding error terms are u_{1i}, u_{2i}. λ_{1i} and λ_{2i} are the inverse Mill's ratios (IMR) estimated from the equation of first stage selection, and are included for correction for selection bias in the equations (6.4a) and (6.4b).

Four estimates are computed by the second-stage outcome regressions, such as (a) real scenario outcome from participation, (b) real scenario outcome from non-participation, (c) counterfactual outcome scenario from participation (i.e., what would have happened if the participating households had opted not to participate) and (d) counterfactual outcome scenario for non-participation (i.e., what would have happened if the participating households had agreed not to participate). The situations (a) and (b) are observed from the survey data and hence are real scenarios, whereas (c) and (d) are the hypothetically expected situations (counterfactual scenarios) where the treated were found to be untreated, and the untreated were found to be treated. The average treatment effect on the treated (ATT) is computed as (a)–(c), and the average treatment effect on the untreated (ATU) is computed as (b)–(d).

Both the PSM and ESR approaches are employed to estimate the impact of LP on household VtP for both monetary and multidimensional measures. As explained above, ESR is carried out in two steps. The first step, the probit model, uses the binary livelihood participation program variable as the outcome variable. The second stage is the outcome regression, where the vulnerability score is used as the outcome variable.

6.4 Results and Discussion

This section presents the empirical results of both PSM and ESR approaches that explain the outcome of the study as to whether LP decreases vulnerability to poverty for monetary and multidimensional measures. There are three sub-sections in this section. Firstly, it explains the participation of households in the LP with respect to various VtP groups. Next, it presents the results from the PSM model with respect to monetary and multidimensional VtP. Finally, it discusses the impact of LP on vulnerable households of both monetary and multidimensional measures using the ESR approach.

6.4.1 A Comparative Analysis of VtP Groups and Participation in LP

Since the interest of the study outcome is vulnerability reduction, we presented the household participation from different VtP groups for both monetary as well as multidimensional measures. The details of the different VtP categories estimation are explained in chapter 5, which are derived from the vulnerability estimation. As shown in above Figure 6.1, about 52% of the total sample has participated in the LP, which shows the importance of LP in rural areas. Further, this entails that most households get benefits from the programs. It is also expected that the program will improve the household's wellbeing as a higher participation rate can result in availing loan facilities, employability, and other benefits of the program. There seems to be a difference in the participation rate for the LP across both the measures for the different VtP categories (Figure 6.2). Although the participation rate varies among the monetary VtP groups, it was observed that the participation rate is lower in the chronic poor and the highest participation rate is observed for the non-poor households. This shows that participating in LP enables households to remain non-poor and escape monetary poverty. On the other hand, it is possible that there is a mismatch (exclusion and inclusion error) in the program distribution, as was the case for other government programs (Balani, 2013; Boyanagari and Boyanagari, 2019). Further, it should be noted that criteria for selecting beneficiaries may vary and our analysis used household consumption per capita.

In the case of multidimensional VtP categories, the participation rate in chronic poor is observed to be more than vulnerability to transient poor and escaped poverty groups. Comparatively, the participation rate is higher in the case of monetary VtP than multidimensional VtP. However, these inferences are drawn based on the participation rate by the different groups observed from the vulnerability analysis, but the causal inferences from the participation are analyzed in section 6.4.5.

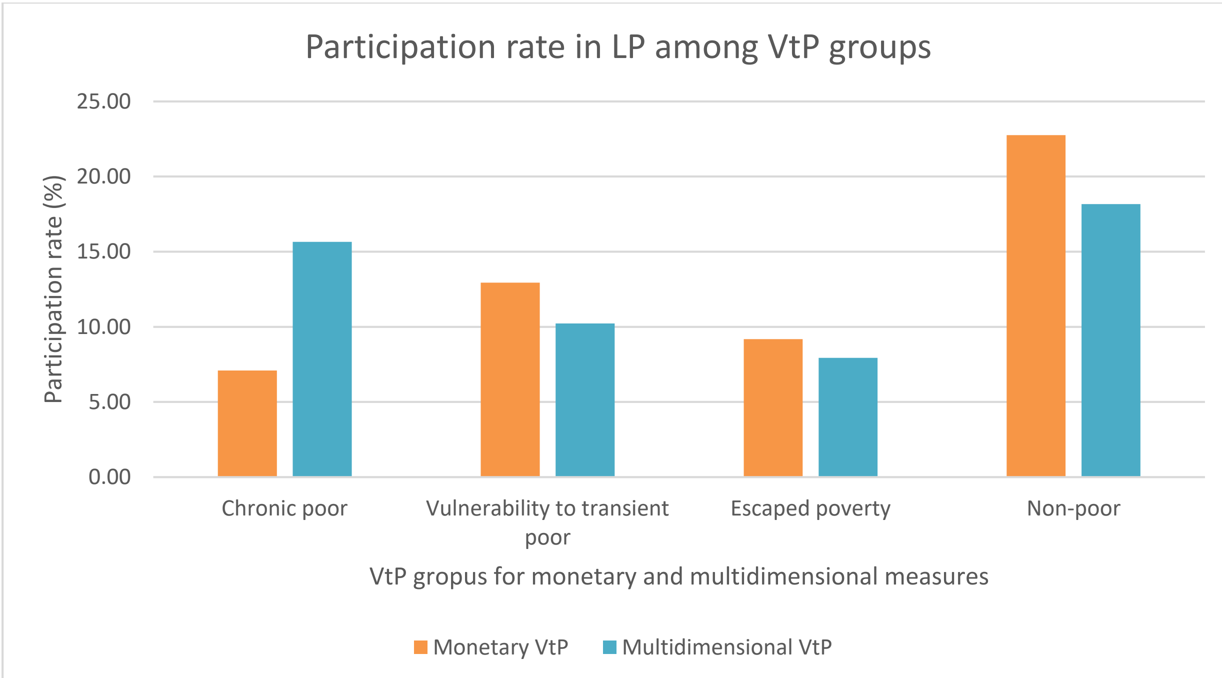

Figure 6.2: Participation in LP Among VtP Groups for Monetary and Multidimensional Measures

Source: Authors estimation using survey data.

6.4.2 Impact of Livelihoods Program on VtP

This section provides the average treatment effect on the treated (ATT) for the livelihoods program in rural Odisha, India, estimated using the PSM and ESR methods. The outcome variable used is the "vulnerability to poverty score" of the only vulnerable households (both monetary as well as multidimensional), estimated using the 3-FGLS approach (explained in detail in chapter 5). The empirical results of propensity score matching are discussed in three parts: comparison among the participants and non-participants in LP, determinants of participation in LP, and impact of LP on household VtP. The discussion begins with the explanation of comparison among the participants and non-participants in LP.

6.4.2.1 Comparison Among the Participants and Non-participants in LP

In this study, participants are classified as vulnerable households (monetary and multidimensional) who participated in the LP program. For the present study, the dataset contains 166 monetary VtP households (34.65% of the total sample) which are separated from non-vulnerable households and 264 multidimensional VtP households (55.11% of the total sample). On the whole, about 58% of vulnerable households of monetary VtP and about 47% of VMDP have participated in LP.

Table 6.2 reports the pre-intervention statistical difference between participants and non-participants and observed that there is a significant difference between households who participated in LP and those who did not participate with respect to household characteristics. There seems to be a significant difference between the income earners of households that participated in LP and those who did not participate in it. The number of income earners of households with access to LP is comparatively lower than that of households without access to LP. An explanation for this result is that the household having fewer income earners is more likely to participate in the LP, which is expected. Concerning other characteristics, it has been found that participation in social capital shows a significant difference between the two groups. The rate of household membership in the saving group is significantly lower than the non-participants. Households who belong to social groups are comparatively larger than the non-participants. It is also observed that participant households had a significantly higher percentage of access to media. In terms of households owning livestock, it is comparatively larger than the non-participants.

The multidimensional vulnerable households with participating in LP are characterized by the less income earner, less participation in the saving group, young age household heads, less household size, less land ownership, and fewer SC households but the more participation in the social group, attending the public meeting, head with higher years of schooling, majority of ST, higher livestock owners, and higher media exposure as compared to households without LP. There seems to be a significant difference between the income earners of households that participated in LP and those who did not participate in it. The share of income earners is higher for the non-participants than the participants. This is expected because the household with more income earners is less likely to engage in the LP. There is a significant difference between households who participated in LP and those who did not participate with respect to households attending the public meeting, such as gram sabha and poli sabha. The share of household participation in the public meeting is higher in the participants, suggesting that the information on various programs and the benefits help in engaging the LP. The t test shows a significant difference between participants and non-participants for the years of schooling of the household head. It is observed that higher educated households for the participant as compared to their counterfactual. In the case of ST, there is a significant difference between participants and non-participants.

Households who participated in LP are comparatively larger than the non-participants, suggesting that households that belong to ST category are more likely to participate in LP. An explanation for this result is that ST households are economically backward compared to other castes, as observed from other empirical studies (Thorat et al., 2017). There is a significant difference between households who participated in LP and those who did not participate with respect to media exposure. Participation in LP shows that household exposure to media is comparatively greater than in non-LP households, suggesting that access to information positively affects participation in LP. The rate of household ownership of livestock is significantly higher than the non-participants, suggesting that participation in LP is expected to be higher for the livestock owner households. This is because LP provides support for the non-farm enterprise and the households having livestock get more benefit as they can increase their livestock.

Table 6.2: Comparison Among the Participant and Non-participant in LP for Vulnerable Households

Variable	Monetary poverty approach					Multidimensional poverty approach				
	Participated in LP		Did not participate in LP		Statistic test (t-test)	Participated in LP		Did not participate in LP		Statistic test (t-test)
	Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.	
Gender	.92	-	.94	-	0.04	.89	-	.86	-	-0.56
Income earner	1.68	.76	2.04	.97	2.72***	1.60	.83	1.82	.85	2.24**
Member in social group	.44	-	.31	-	-1.61	.52	-	.28	-	-4.05***
Member in saving group	.03	-	.14	-	2.68***	.06	-	.12	-	1.58
Attending public meeting	.46	-	.38	-	-1.01	.40	-	.32	-	-1.38
Age of head	40.40	11.77	41.21	12.59	0.43	45.65	15.26	48.85	15.21	0.53
Household size	6.10	1.73	6.39	2.05	0.99	4.65	1.87	4.76	2.24	0.40
Own land	.77	-	.80	-	0.45	.57	-	.66	-	1.53
Education of head	2.15	3.30	2.23	3.24	0.12	2.70	3.49	1.93	3.18	-1.88*
Schedule caste	.35	-	.37	-	0.23	.35	-	.40	-	0.75
Schedule tribe	.44	-	.37	-	-0.85	.43	-	.29	-	-2.29**
Media exposure	.39	-	.27	-	-1.67*	.32	-	.15	-	-3.38***
Owns livestock	.83	-	.68	-	-2.25**	.59	-	.55	-	-0.63

*Source: Author's calculation using household survey data. Note: asterisks denote the following: ***= significant at 1% level, **=significant at 5% level, *= significant at 10% level.*

6.4.2.2 Determinants of Participation in LP (Estimation of Propensity Score)

The results from the logistic model used for estimating the propensity score are presented in Table 6.3. The estimation was run using STATA-13 software. The dependent variable of the logit model takes a value of 1 (one) if a vulnerable (monetary and multidimensional) household has participated in the LP and 0 (zero) if the household has not participated in the LP. The covariates, which were included in the logit model, refer to pre-intervention characteristics of the LP participants and non-participants. Several researchers have noted that choosing relevant covariates is a difficult task in the empirical evaluation of the social programs (Admassie et al., 2009). However, researchers have no general guideline regarding which covariates should be included (or excluded) in the PSM specification (Caliendo and Kopeing, 2005; Smith and Todd, 2005). In this regard, researchers can get useful guides from previous empirical studies, economic theory, and institutional settings (Smith and Todd, 2005). In this paper, covariates are chosen to reflect household's participation in the LP based on the criteria and objective of the program (GoO, 2016). Thus, we decided to include a different set of covariates into the participation in the LP model to control for heterogeneity resulting from various sources. In other words, we tried to include all variables that influence the household's eligibility for initial participation in the LP program.

It has been observed from the analysis that the control variables are quite consistent with our expectations and most of the variables show the expected sign to participate/not to participate in LP. In the case of monetary VtP, the variable household with income earners is significant and negatively associated with participation in LP. An explanation for this result is that households with more income earners diversify their income sources and are less likely to participate in the LP. This is due to the fact that household prefers permanent work over temporary work. Household access to the media is associated with a 23% higher likelihood of participating in LP. This finding is consistent with past results that indicate households reading/watching the news are positively associated with participating in various programs (Dutta and Kumar, 2016). This is also reported by other studies that suggested that lack of information in various policies is a hindrance to policy impact (Devadasan et al., 2013). In this scenario of information dissemination, social capital plays a key role in disseminating information on various aspects through groups. Household membership in social groups is associated with increased chances of participation in LP because they ease access to and facilitate the exchange of important information about the benefits of programs. This is reflected in our result that household member in a social group is 25% likely to participate in LP. However, household members in saving groups are less likely to participate in LP, suggesting that households that are already engaged in diversified works are less likely to participate in LP. It is further observed that households with access to livestock are 28% more likely to participate in LP than their counterfactuals. This is because the program supports micro-credit and other forms of non-farm enterprise that attract livelihood-dependent households to improve their livelihoods by raising more livestock. More importantly, the policy is designed to support such households that depend on unorganized sectors for their livelihood in rural areas.

In the case of multidimensional vulnerability to poverty, as expected, households belonging to the marginalized group such as the ST category are positively associated with LP participation. The explanation for this is because the program-OTELP is particularly targeted to such households to improve their livelihoods in the tribal zone (GoO, 2016). The results show that if the household belongs to the ST category, the likelihood of participating in LP increases by 15%. The significant and positive estimated coefficients of variables such as household members in social groups and media exposure highlight the importance of information access in participating government-sponsored programs. The finding indicates that the probability of households participating in LP increases by 25% if that household is part of the social group. Similarly, the probability of participating in LP increases by 23% if the household has access to media. As expected, the households with a TV or people reading newspapers get more information on various government schemes, which help them engage in the various programs. Concerning livestock ownership, there is a positive influence on the participation decision for the households with livestock than the non-participants. The probability of household participation in the program increases by 13% for the household owning livestock. This is because the program is designed to support poor households through micro-credit for livestock raising.

Table 6.3: Determinants of Participation in LP

Variable	Monetary poverty approach		Multidimensional poverty approach	
	Marginal effect		Marginal effect	
	Coefficient	Standard error	Coefficient	Standard error
Gender	-0.07	0.17	-0.03	0.11
Income earner	-0.14**	0.05	-0.06	0.04
Member in social group	0.25***	0.09	0.25***	0.07
Member in saving group	-0.50***	0.10	-0.22**	0.10
Member in attends public meeting	-0.06	0.10	-0.04	0.08
Age of head	0.001	0.004	-0.002	0.002
Household size	0.01	0.03	-0.02	0.02
Own land	-0.11	0.11	-0.06	0.08
Education of head	-0.01	0.01	0.02	0.01
Schedule caste	0.01	0.11	0.02	0.09
Schedule tribe	-0.00	0.12	0.19**	0.09
Media exposure	0.23**	0.09	0.23***	0.08
Owns livestock	0.28**	0.11	0.13*	0.07
Number of observation	166		264	
Pseudo R square	0.1519***		0.1232	

*Source: Author's estimation using household survey data. Note: asterisks denote the following: *** = significant at 1% level, ** =significant at 5% level, *= significant at 10% level.*

6.4.2.3 Impact of LP on Household VtP

Table 6.4 reports the average effects of participation in LP on household VtP, estimated using the PSM approach. We estimated the effect of LP on both monetary vulnerable as well as multidimensional vulnerable households. The results indicate that participation in LP has a positive and significant effect on reducing household VtP, but non-significant results are observed for the case of VDMP. The results from the matching methods show that all three estimators yield similar results (Table 6.4). We check the satisfaction of the balancing test and the balancing tests show that the differences after matching are statistically insignificant, which is a desired property for a good matching algorithm and which shows that the results are reliable (Table A6.1). Further, Bootstrap standard errors based on 1000 replications are reported, given the cross-sectional nature of data. For three matching methods, the propensity score graphs are shown in Figure 6.3 (6.3.1, 6.3.2, and 6.3.3, respectively) and Figure A6.1.

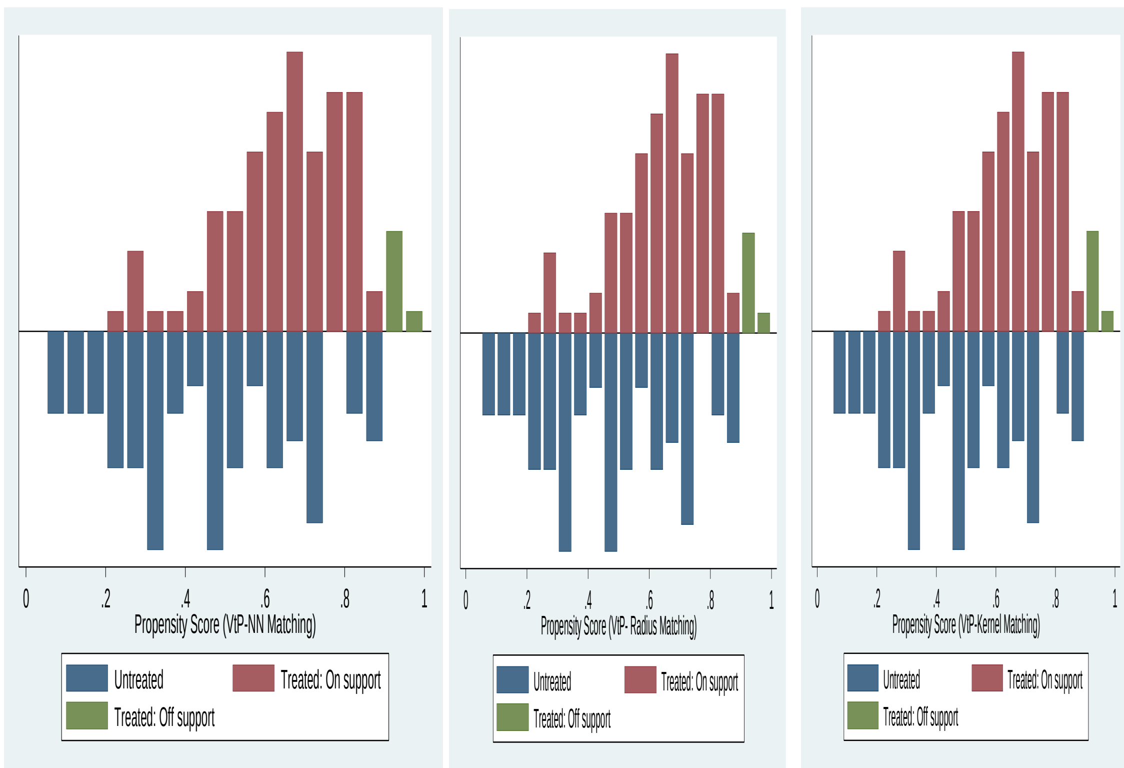

Figure 6.3 (6.3.1, 6.3.2, 6.3.3): Common Support; Nearest Neighbor (5), Kernel, and Radius matching method

After verifying that the treatment and control group are properly balanced and ensuring common support, we estimated the program impact as the average treatment effect on the treated. The PSM results imply that LP has a positive and significant impact on reducing household VtP. The analysis demonstrates that households with access to LP can better cope with the situation than are households without it. More importantly, depending on the specific algorithm used, the estimated impact of LP participation on the VtP measured by vulnerability score, it is estimated that the vulnerability decrease ranges are from 3% to 4% (Table 6.4). The findings are consistent with the previous limited studies on the impact of social protection on VtP. For instance, Vo and Van (2019) have shown that social protection (health insurance) reduces VtP by 16% in Vietnam. Azeem et al. (2019) found out that social protection (welfare programs) reduces idiosyncratic VtP by 18% and covariate VtP by 14% in Pakistan. The study further analyzed what would have happened to the VMDP households that participated in LP in the absence of LP. All the three matching methods confirm the negative impacts, and the mean difference in vulnerability to poverty estimated is -0.01 for all three algorithms; however, they are not statistically significant.

Table 6.4: Impact of LP on Household VtP and VMDP, PSM Results

Outcome variable	Matching estimator	Rural Odisha			
		Impact of LP on VtP households		Impact of LP on VMDP households	
		ATT	t-test	ATT	t-test
Vulnerability to poverty score	Nearest neighbors	-0.04	-2.20**	-0.01	-0.78
	Kernel matching	-0.03	-2.02**	-0.01	-1.31
	Radius matching	-0.03	-1.97**	-0.01	-1.37
	Observations	166		264	

*Source: Authors' estimation using household survey data. Note: asterisks denote the following: ***= significant at 1% level, **=significant at 5% level, *= significant at 10% level. Bootstrap replication of 1000 is used.*

6.4.2.4 Sensitivity Analysis

To assess our results' sensitivity to hidden bias, we conducted a sensitivity analysis, following Rosenbaum's (2002) bounding approach (Table 6.5). The present study analyzed the sensitivity analysis at the margin of the 0.1 scale. The sensitivity analysis results show that the treatment effect remains significant at a higher level of gamma (Γ=1.7); the lower bound is statistically significant at 10%. Overall, the sensitivity analysis suggests that unobserved heterogeneity does not influence the qualitative meaning of our results.

Table 6.5: Rosenbaum Bounds Sensitivity Analysis for LP Policy Treatment Effects

	Γ	sig+	sig-	t-hat+	t-hat-	CI+	CI-
LP Impact on household VtP	1	0	0.00	-0.05	-0.05	-0.07	-0.03
	1.1	0	0.00	-0.06	-0.05	-0.08	-0.02
	1.2	0	0.00	-0.06	-0.04	-0.08	-0.01
	1.3	0	0.01	-0.06	-0.04	-0.08	-0.01
	1.4	0	0.02	-0.06	-0.04	-0.09	-0.00
	1.5	0	0.04	-0.07	-0.03	-0.09	-0.00
	1.6	0	0.06	-0.07	-0.03	-0.09	0.01
	1.7	0	0.09	-0.08	-0.02	-0.09	0.01
	1.8	0	0.14	-0.08	-0.02	-0.10	0.01
	1.9	0	0.19	-0.08	-0.02	-0.10	0.02
	2	0	0.25	-0.08	-0.01	-0.10	0.03

Source: Authors Estimation using Rosenbaum Bound sensitivity analysis.

Note: * gamma - log odds of differential assignment due to unobserved factors.

upper bound significance level (sig+)

lower bound significance level (sig-)

upper bound Hodges-Lehmann point estimate (t-hat+)

lower bound Hodges-Lehmann point estimate (t-hat-)

upper bound confidence interval (a= .95) (CI+)

lower bound confidence interval (a= .95) (CI-)

6.4.2.5 Results from ESR Model

As the results of the PSM model may be biased due to unobserved factors, the ESR model was used to check the robustness of the estimated effects obtained from the PSM model. The advantage of the ESR model over the PSM model is that it can estimate the potential gain for non-participants had they participated in LP. The second stage estimation of ESR is presented in Table A6.2. The ATT and ATU of LP estimated from the ESR model on the monetary vulnerable households are presented in Table 6.6. These estimates corroborate the PSM model findings and show that the ESR-based ATT is close to PSM-based estimates. There is a negative and statistically significant ATT of LP on household monetary VtP. More specifically, the VtP effect for the LP participants is -0.03, suggesting that LP reduces their probability of falling below the poverty line by 3%. Similarly, the ATU for the non-participants is 2%, which means had the former decided to participate in the LPs, their household VtP would have declined by 2%.

Similarly, in the case of multidimensional vulnerability to poverty, the ATT and ATU of LP estimated from the ESR models on the vulnerable households are presented in Table 6.6. The impact estimates were found to be quite similar to the impact estimates yielded by the PSM approach. There is a negative but statistically not significant ATT of LP on household VtP, which suggests that participation of multidimensional vulnerable households in LP has not reduced their probability of falling below the poverty line. ESR result is essentially a comparison between the actual and counterfactual scenarios of a regime. So, the not significant average treatment effect of actual and counterfactual effects provides the household that program participation for the multidimensional vulnerable household did not enhance the risk reduction capacity. This could be due to the fact that policies are implemented based on monetary poverty. Therefore, more research on the impact of LP on VMDP is needed to explore the underlying causes or pathways that explain the result presented in this study.

Overall, households who have participated in LP would have had 3% (ATT=-0.03) higher chances of falling below the poverty line had they not participated in LP. The negative impacts of the LP on vulnerable households are associated with the direct and indirect benefits from the programs. The direct benefit reflects income received, training, and micro-credit to improve the livelihoods (Figure 6.1). The indirect benefits are in terms of building rural infrastructure in the tribal areas through various activities such as providing sanitation facilities, clean drinking water, and irrigation facilities.

A past study observed a negative relationship between rural development and poverty reduction (Charlery et al., 2016). Since rural households are largely dependent on agriculture for livelihoods, the result indicates that LP improves rural households' resilience against climate change. As the program helped promote water in the agricultural lands through watersheds and irrigation facilities, climatic shocks are mitigated during drought shocks. Other studies also found out that the employment generation scheme in rural areas also built the infrastructure that results in mitigating climatic shocks (Godfrey-Wood and Flower, 2018).

Micro credits play a major role in rural areas through small business promotion, which enabled contribute to improving livelihood and reducing poverty by increasing income and reducing the risk (Swain and Floro, 2012). Many government and non-government organizations are actively working on rural development by providing microcredit to households through SHG groups. Past contributions by world bank groups have observed that the livelihoods program 'TRIPTI' helped households in mitigating the negative impacts of adverse events (Christian et al., 2018). Similarly, Datta (2015) evaluated the livelihood program 'Jeevika' and its implications for rural poverty through SHG and found out that the program does result in women empowerment and asset building in rural areas.

Developing countries are extremely vulnerable to external shock, as a large section of the population depends on agriculture and casual daily wage employment for livelihood. Hence livelihood diversification is a viable strategy as it provides access to employment opportunities and sustainable incomes. The number of workdays available per year to a household in Odisha is 36 days, indicating that more employment opportunities need to be generated (Breitkreuz et al., 2017). Therefore, additional work in livelihood improvement significantly impacts rural household VtP.

In general, it is observed that social protection has a capacity to reduce households from falling into poverty, but the efforts crucially depend on the design, objective, and performance of the program. Azeem et al. (2019) also confirm that program impact depends on the nature of the program and suggest designing issue-related programs. Christian et al. (2018) echo similar views in their impact analysis of “TRIPTI” on household resilience capacity in Odisha, India.

Table 6.6: Impact of LP on Household VtP, ESR Results

Outcome variable	Category	Impact of LP on Monetary VtP households			Impact of LP on Multidimensional VtP households		
		To participate	Not to participate	Average Treatment Effect	To participate	Not to participate	Average Treatment Effect
Vulnerability to poverty score	ATT	(a) 0.60 (.01)	(c) 0.63 (.01)	-0.03***(.01)	(a) 0.53(.00)	(c) 0.54(.00)	-0.01.00)
	ATU	(d) 0.60 (.01)	(b) 0.62 (.01)	-0.02** (.01)	(d) 0.54(.00)	(b) 0.55(.00)	-0.01(.00)

Source: Authors' estimation using household survey data. Standard errors in parenthesis.
*Note: asterisks denote the following: ***= significant at 1% level, **=significant at 5% level, *= significant at 10% level.*

ATT is average treatment effect on treated (LP participant) [(a)-(c)]
ATU is average treatment effect on untreated (non-participant) [(d)-(b)]
(a)= receiver with participation (real scenario)
(b) = non-receiver with non-participation (real scenario)
(c) = receiver with no participation (counterfactual scenario)
(d) = non-receiver with no participation (counterfactual scenario)

6.5 Conclusion

This chapter presents an assessment of the impact of rural livelihoods program on household vulnerability to monetary and multidimensional poverty. The available quantitative evidence on the impact of social protection on reducing vulnerability to poverty is scant. Therefore, filling the gap by estimating the impact of livelihoods program on vulnerability is an important contribution to the literature on VtP, particularly to the literature that discusses the impact of social protection on household VtP. Using a cross-sectional household survey data of 479 in the tribal zone of Odisha, India, this study contributes empirical evidence for the impact of livelihoods program on reducing monetary and multidimensional vulnerability to poverty.

The estimated vulnerability to poverty score from chapter 5 has been used as the outcome variable to estimate the welfare effects of LP. Given the observational data, this study used the PSM and the ESR methods to address the observed and unobserved selection bias. Corresponding to monetary VtP, the PSM results show that engaging in livelihoods program has a negative and significant impact on VtP households, indicating that households participating in LP have a lower likelihood of falling into consumption poverty than their counterfactual. More specifically, the household's VtP is reduced between 3% and 4% for the households who participated in LP. This suggests that households who participated in LP would have had 4% higher chances of falling below the poverty line if they had not participated in LP. On the other hand, The ATT for the vulnerability to multidimensional poverty is negative for all three matching methods, but they are statistically not significant.

The ESR results are similar to the impact estimates yielded by the PSM approach. The empirical findings show a negative and statistically significant impact of LP on household VtP. More specifically, the VtP effect for the participant is -0.03, suggesting that LP reduces their probability of falling below the poverty line by 3%. In the case of VMDP, the ATT is negative but statistically not significant. This implies that the participation of multidimensional vulnerable households in LP has not reduced their probability of falling below the poverty line.

The empirical analysis has been conducted using cross-sectional data. Panel data would undoubtedly increase the precision of the estimated values and enhance the reliability of the findings. Therefore, we recommend further research, using panel data, on the impact of LP on VtP in developing countries.

CHAPTER 7
CONCLUSION

7.1 Overview

Reducing poverty is a key priority among developing countries worldwide. In the past two decades, several nations have managed to reduce the percentage of poor households (United Nations, 2015). However, the continuous rise in idiosyncratic and community shocks will cause a large proportion of households to fall back into poverty (CRED, 2020). The two most affected regions in the world are South Asia and Sub-Saharan Africa. The former is recognized for possessing the world's greatest population of poor people, while the latter has the world's highest poverty rate (Tsehay and Bauer, 2012). Specifically, 31% and 51% of households are living below the monetary poverty line in South Asia and Sub-Saharan Africa, respectively. The multidimensional poverty rate is even higher than the monetary poverty rate, which is 53.4% and 59.6% for South Asia and Sub-Saharan Africa, respectively (United Nations, 2015; UNDP, 2014). The comprehensive review of literature in chapter 2 revealed that the share of households at risk of falling into poverty is higher than the currently classified headcount poverty rate. The most important challenge for policymakers is thus to prevent households from falling into poverty since typical ex-post poverty measures do not identify the households that have a risk of falling into poverty (Jha and Dang, 2010; Mahanta and Das, 2017). As a result, it is widely accepted that poverty-reduction interventions should go beyond dealing with issues of ex-post poverty to the risk of future poverty or vulnerability to poverty (VtP).

Despite this recognition, most academic research on poverty assessment seems to be dominated by conventional ex-post poverty measures. The prevalence and sources of ex-ante VtP in various countries are little understood. Quantitative research on the impacts of social protection (SP) on reducing VtP in literature is much harder to find. Particularly in the case of India, limited studies have examined the impact of SP in reducing VtP, despite the fact that SP expenditures have increased in many folds (Patnaik et al., 2017; Swain and Floro, 2012; Jha et al., 2009).

India has been successful in reducing the proportion of rural poor households from 26.1% to 21.92% during the first decade of the new millennium (Government of India, 2015). However, the reduction of poverty is based on the official classification, which defines poverty solely in terms of monetary expenditures. As discussed in chapters 1 and 2, poverty is much more complex than income deprivation alone. There is a growing consensus that poverty is not solely defined by a household's income constraints; it also encompasses other facets of poverty, such as sanitation, child mortality, health, and education (Sen, 1982; Alkire and Foster, 2011a, 2011b; Azeem et al., 2018). Past assessments of poverty and VtP have given far less attention to these multiple indicators of poverty. Further, levels of poverty vary considerably, however, not just across regions and countries but within the country (Tsehay and Bauer, 2012). As a result, it is likely that the success story of poverty reduction in India may change if alternative measures of poverty, such as multidimensional poverty and vulnerability to multidimensional poverty, are consistently applied. Most of the previous empirical studies in the country tried to analyse observed (ex-post) poverty and do not give sufficient attention to vulnerability to poverty (Dutta and Kumar, 2016).

Measuring vulnerability to poverty is important, since it enables the identification of people who are not poor but may become poor, as well as those who will remain poor. Once identified, appropriate policies can be designed to prevent the former from falling into poverty and to help the latter to escape poverty. Clearly, measures that are focused on the current profile of poverty may be ineffective for those vulnerable individuals and households. By obtaining a vulnerability profile, both existing and future poverty can be targeted. As is usually accepted, prevention is better than cure, and prevention of poverty necessitates accurate measurement of vulnerability to poverty.

Given the risks and shocks and lack of coping mechanisms, the government has undertaken a number of policy actions and interventions to either reduce or alleviate poverty. Particularly, the policy is designed to help both the poor and vulnerable groups through food security, employment, credit facility, insurances, and other provisions. Since vulnerability is associated with shocks and lack of coping measures, research in link with social protection and vulnerability is needed to design policies that are appropriate for both the poor and vulnerable (Azeem et al., 2018).

This thesis aims to investigate the changes in household poverty status, VtP, and effectiveness of social protection in rural Odisha, India. The study sites are known for their poor living standard, food insecurity, and lower literacy rate (Rahman, 2016; World Bank, 2016). The households in the region are largely relying on agriculture and forest resources for their livelihood, and the region is also prone to climatic shocks (GoO, 2017; 2018; 2019). Firstly, the thesis contributes towards examining the policy implications of changes in poverty status measurement using expenditure-based (monetary poverty) indicators of poverty. Second, it lies in investigating the sources of VtP, that is, VtP related to covariate shocks and idiosyncratic shocks. This thesis goes beyond measuring ex-post one-dimensional poverty and measures the ex-ante monetary as well as multidimensional vulnerability to poverty. The third and most significant contribution lies in evaluating the impact of SP on household monetary and multidimensional vulnerability to poverty. Using a household survey data set of 479 households collected during 2018-2019, this study reduces knowledge gaps on the causes of poverty and VtP. This is expected to help policymakers in Odisha, India, to better address the issues of poverty and VtP as highlighted in the post-2015 global development agenda.

The purpose of the thesis was addressed through three research objectives. The remaining sections of this chapter discuss the main findings and policy implications that correspond to each of the three research objectives. We close this dissertation with an evaluation of the limitations of our study and suggestions for further avenues of research.

7.2 Research Findings

7.2.1 Research Objective 1: To Estimate the Changes in Poverty Status and the Factors Determine It.

Chapter 4 has attempted to examine the role of livelihood diversification and social capital on poverty dynamics in rural Odisha. Using panel data of 1353 households for the period between 2004-05 and 2011-12, the study has found out that at the state level, 25.26% of the households have been into chronic poor, 45.24% of the households have been transient poor, and remaining 29.50% of households have been non-poor during the phases mentioned above. Further, it has also been discovered that, out of the transient poor, 8.2% of the households have descended into poverty and 37% of households have ascended out of poverty during the same period. In geographical divisions analysed, chronic poverty in the northern area is the largest, escape from poverty in the coastal region and descended into poverty in the southern region is highest.

The findings from the livelihood approach show that there is a positive relationship between non-farm activities and escaping poverty. They indicate that diversified non-farm activities assures income and thereby enables the household to escape poverty. It is further observed that households that escaped poverty are characterized by smaller family size, households with higher educated heads, households participated more in the non-farm sector, and possess more assets than the chronic and transient poor households.

The results from Multinomial Logistic Regression indicate that social capital in the form of group membership in different saving schemes and social groups could help escape poverty traps. Social group membership supports poor households in obtaining vital information circulated within the group. It works as a pledged asset by eliminating the barriers to getting credit from the banks for the households who do not have enough social security. The illiterate and unskilled people and households lacking financial support also benefit greatly from social capital. Awareness and women empowerment is also shown to be achieved through social capital. However, NGOs working on poverty reduction in various parts of the remote areas require more social capital to be successful. Therefore, it can be surmised that creating more social capital through NGOs, expanding microfinance in remote areas, providing regular training, and educating people through social capital reduces poverty in rural areas.

It has also been found out that households are less likely to remain as ‘chronic poor’ if they have access to higher education, asset, and ownership of land. Besides, household members engaged in the salaried and business sector and being a part of social groups, are also unlikely to stay chronic poor. On the other side, households with large family sizes, a higher proportion of dependency ratio, members engaged in the farming sector and the daily wage jobs are more likely to remain as ‘chronic poor’.

7.2.2 Research Objective 2: To Measure Household Vulnerability to Poverty Using Both the Monetary and Multidimensional Approaches.

Households in developing nations are often hit by risks and shocks, which have a significant negative effect on poor and vulnerable households' livelihoods due to their lack of resistance to these incidents. Further, the nature of shock and coping strategies differs from place to place and region to region, meaning, a common (universal) policy may not be successful across the state or country. Understanding household’s experienced dominant risks and shocks, as well as their coping mechanisms, will facilitate the development of forward-looking policies, including the implementation of preventive measures to reduce damages from risk events that reduce the household's chance of falling into poverty. Further, past literature on VtP estimation is largely available on monetary measures. Given the importance of multidimensional measures, as prioritized in SDGs 2030, vulnerability to poverty estimation should also be based on a multidimensional approach. This study adds considerable value to the vulnerability literature by estimating VtP for both monetary and multidimensional measures.

The main findings from the FGLS estimation for the monetary VtP show that about 35% of the total sample are at the risk of becoming poor in the near future. The empirical analysis also reveals that factors such as gender, landholding, years of schooling of the head, access to productive and durable assets, SHG, and saving groups have a significant positive association with the likelihood of increasing household consumption. On the other hand, factors like household engaged in the farm, wage, household size, dependency ratio, flood, sold livestock have a significant inverse association with the likelihood of reducing household consumption. From the VtP categories, approximately 13% of the total sample is identified as chronic poor, with the possibility of remaining poor, whereas 21.29% of non-poor households have a high risk of falling into poverty. These findings demonstrate that monetary poverty in rural Odisha is determined by the risks and lack of coping mechanisms. It was also observed that chronic and transient poor are mostly experienced shocks, which is in line with the theoretical explanation of VtP.

With regard to the MDP estimation, the empirical findings show that 47% of the total sample are identified to be MDP, which is higher than the 29% monetary poverty rate. There is heterogeneity in the MDP rate observed for the households among the occupation and districts. In the context of livelihood categories, the proportion of households living in MDP is found to be highest for the households depending on the agriculture sector, followed by the wage earners in non-farm and self-employed in non-farm sectors. In the district-wise analysis, approximately 58% of the total sample households are identified as MDP in the Koraput districts. In contrast, it was observed 36% for Kandhamal and 42% for Nabarangpur districts.

On the other hand, the FGLS estimate for multidimensional poverty shows that about 55% of households are more likely to fall into multidimensional poverty (MDP). The factors influencing VMDP demonstrate that years of schooling of the household head, household size, household possessing durable assets, households belonging to a saving group, and household members attending public meetings reduce the deprivation. On the other hand, illness of the household member, flood, and borrowed from informal money lender increases the deprivation of households. From the VtP categories, it was further observed that about 36% of currently identified MDP households are likely to remain MDP, and about 20% of non-poor households are identified to be at the risk of falling into MDP. The overall conclusion from these approaches (monetary and multidimensional) is that the rate of households having a risk of falling into poverty is higher than the currently classified poverty rate. Among the districts analyzed, the proportion of households that are at high risk of falling into poverty is highest in the Koraput district, followed by Kandhamal and Nabarangpur districts. Further, households engaged in farming are observed to be most vulnerable, followed by those engaged in wages in non-farm and self-employed in the non-farm sector. In general, poverty is determined by the risk and shocks for both the monetary and multidimensional measures, where many households are likely to fall into or remain poverty. Particularly, the VtP categories in the multidimensional measure are higher than the monetary measure. Unlike many other studies, we do have a fair amount of information on shocks actually experienced by the households. The aggregate impact of observed shocks substantially impacts poor and vulnerable households, as observed both from quantitative and qualitative assessments.

7.2.3 Research Objective 3: To Investigate the Impact of the Welfare Program on Household Vulnerability to Monetary and Multidimensional Poverty.

Chapter 6 presents an assessment of the impact of livelihoods program on household vulnerability to monetary as well as multidimensional poverty. The available quantitative evidence on the impact of welfare program on reducing vulnerability to poverty is scant. Therefore, filling this gap by estimating the impact of livelihoods program on vulnerability is an important contribution to the literature on VtP, particularly to the literature that discusses the impact of social protection on household VtP. Using a cross-sectional household survey data of 479 in the tribal zone of Odisha, this study contributes empirical evidence for the impact of livelihoods program on reducing monetary and multidimensional vulnerability to poverty.

The estimated vulnerability to poverty score using the FGLS estimation has been used as the outcome variable for both monetary and multidimensional VtP. Given the observational nature of data, this study used the PSM and the ESR methods to address the observed and unobserved selection bias. Corresponding to monetary VtP, the PSM results show that engaging in a welfare program (rural livelihoods program) has a positive and significant impact on VtP households, indicating that households participating in livelihoods program have a lower likelihood of falling into monetary poverty than their counterfactual. However, it was observed to be statistically not significant for the vulnerability to multidimensional poverty.

The ATT and ATU estimated from the ESR models corroborate the findings from the PSM model. There is a negative and statistically significant ATT of livelihoods program on monetary VtP. More specifically, the VtP effect for the livelihoods program participants is -0.03, suggesting that their probability of falling below the poverty line is reduced by 3%. Similarly, the ATU for the non-participants is 2%, meaning, had the former decided to participate in the livelihoods program, their household VtP would have declined by 2%. The positive impact of the program on vulnerable households is associated with the direct and indirect benefits from the program. The direct benefit reflects income received, training, and micro-credit to improve their livelihoods. The indirect benefits are in terms of building rural infrastructure in the tribal areas through various activities such as providing sanitation facilities, clean drinking water and irrigation facilities.

On the other hand, there is a negative but statistically not significant ATT of livelihoods program on vulnerability to MDP. This suggests that the livelihoods program does not have any noticeable effect on multidimensional vulnerable households which is in non-expected lines. This could be due to the fact that policies are implemented based on monetary poverty. Therefore, more research on the impact of livelihoods program on vulnerability to MDP is needed so as to explore the underlying causes or pathways that explain the result presented in this study.

7.3 Concluding Remarks and Policy Implications

The emerging evidence from the analysis revealed that over time, households move in and out of poverty. It is also observed that poverty in rural Odisha is pervasive because many households are at risk of falling into poverty. This suggests that enhancing household coping mechanisms through welfare program can protect these vulnerable households from falling into poverty. In this regard, it is observed that households that have participated in the welfare program are able to overcome the adverse events better when compared with their counterfactuals. While we acknowledge that the program helped participants, we also admit that other initiatives in the study regions may have had an impact on households. Overall, anti-poverty policy should include vulnerable households in order to achieve the objective of ending poverty everywhere.

The study suggests a number of policy implications pertaining to the specific research issues addressed from the empirical findings. Firstly, social capital in the form of group membership has a positive association with escaping poverty. Given the large share of livelihood depending on agriculture, the farmer organizations in cooperatives can also help farmers conduct themselves in an inclusive decision-making system to support each other. As per the literature, different farmer organizations exist, such as members in agricultural, milk, or co-operative and other common farmer groups in the state (Desai and Vanneman, 2012; Khosla and Jena, 2020). Therefore, the government should involve and prioritize such social capital to strengthen the farmer organisation. This should function as a 'bottom up' strategy in which farmers make key decisions through consensus or majority principle. Additionally, such farmer associations facilitate support for smallholder farmers by the government and external financing sources. For instance, Fairtrade certification, which attempts to assist smallholder farmers by guaranteeing a minimum 'price floor' during times of market price crisis, requires member farmers to form a formal cooperative.

Further, livelihood diversification has a positive association with escaping poverty and reducing falling into poverty. According to the Odisha government official report, 20.5% of households are self-employed, 2.6% of households engaged in regular salaried jobs, and 57% participated in the MGNREGA (GoO, 2012). This shows the importance of non-farm livelihood activities in rural areas. Since, the majority of the households in the study area are farmers and wage earners in the non-farm sector, credit facilities for non-farm enterprises will benefit the most households. Given the importance and success of microfinance in rural areas, non-farm jobs such as livestock rearing and small business enterprises should be prioritized. In this line of suggestion, it is also observed that additional public work programs reduce household VtP. Additional public work benefits the most vulnerable because the vast majority are seasonal migrants with limited work opportunities (household in Odisha work 36 days per year) (Breitkreuz et al., 2017, GoO, 2012). This suggests creating new employment opportunities through promoting income-job-generating practices which in turn will move people out of poverty and help the vulnerable households to remain non-poor. Because of this, the budget outlay for rural development should increase. This is because the annualized change for 2019-20 to 2021-22 is just 4% increased (GoO, 2021). However, it is not to neglect the farming sector and as far as income and employment prospects in rural areas are concerned, the agriculture sector would supply much of them. Interventions in this sector could include agricultural development advice and assistance with marketing, educational seminars on resource conservation, and assistance with the formation of cooperatives.

The findings also suggest that improvement in education, access to health care, and infrastructure development for a better standard of living should be prioritized for the southern region of Odisha. Therefore, the study suggests that increasing investments in education, particularly skill-based training and vocational training (training in hairdressing, embroidery, masonry, weaving, and cabinet making) will enhance the potential of the labor force. The skill improvement will equip the rural population to engage in diversified income streams. Building rural infrastructure will improve transportability and will create job opportunities for poor households. On the other hand, job creation through social projects such as tree plantations and tourism development at the village level that result in a significant number of jobs should be supported and promoted by the government. More importantly, it would be helpful to have a job market monitoring center to support others who are looking for jobs. Furthermore, the data from this center would provide information on skill sets needed for future jobs. Thus, this will enable the government and authorities to upgrade, improve, and design training programs for the people who want to obtain jobs.

Secondly, the current study has observed that risks and shocks negatively impact rural household’s well-being, where a significant proportion of households are likely to remain and fall into poverty. This has grave concerns for poverty reduction in general. In accordance with these findings, the study's findings indicate that ex-ante preventive strategies are the most effective way to fight poverty. Therefore, the findings suggest that a forward-looking measure of poverty policies should be taken into account when designing poverty alleviation policies, covering those who are already fallen to poverty presently and those at risk of becoming poor in the near future. This can be done through a data-driven approach in which precise data regarding shocks, livelihood choices, assets, income, and consumption is collated to identify vulnerable households. Finally, the major reason for policy failure is that the needy households fail to receive national or international benefits and the poor receive less benefit than the non-poor (Ravalion, 2009, p. 220). The selection of the right beneficiaries remains a challenge even now. Previous studies have observed several anomalies in the inclusion and exclusion of beneficiaries in the scheme, where most deserving beneficiaries are often excluded from the list in almost every state in various social protection programs (Balani, 2013;

Boyanagari and Boyanagari, 2019). To solve these issues, proper identification of deserving households is important. In this context, the analysis proposed in the current study contributes to determining the poor and vulnerable households that need support.

Further, given the objective of LP outreach and improving household wellbeing, the findings show there is no noticeable impact on vulnerability to MDP. Therefore, policy design should be targeted to the multidimensional vulnerable households. Given the significant contribution of idiosyncratic shocks on VtP, which is largely related to health shocks, insurance policies should be scaled up and cover the right beneficiaries. This is important because previous studies, particularly on health insurance, have reported that public investment in health in India is grossly inadequate, with public spending hovering around 1% of GDP for decades. Further, the health insurance scheme-RBSY has not been able to reduce the out-of-pocket expenditure for poor households (Rout and Mahapatra, 2019; Rout and Choudhury, 2018). In case of severe health issues, for instance, the incident of an accident or chronic illness, requires a huge amount of money to recover from the diseases/accidents. Rs. 30000 support per year for a household is not sufficient, given the severe health issues. It will further worsen the household situation by forcing them to borrow or sell the productive assets if more family members are affected by any diseases. Although the new health insurance policy, namely Ayushman Bharat Pradhan Mantri Jan Arogya Yojana (AB-PMJAY) has increased the budget per household, studies are yet to find out its impact. Besides, the irrigation and drainage systems must be strengthened in view of the prevalence of climate shocks in the study region to enhance the household's capacity to tackle droughts, floods, and cyclones.

Finally, raising awareness about family planning, growing smallholders' involvement in non-farm activities, diversifying their crop production, allowing targeted and timely transfers, and improving credit facilities will dramatically reduce the region's vulnerable households. Therefore, for effective intervention, policies aimed at reducing poverty must take into account the factors that contribute to household vulnerability to poverty in a given context in order to lift rural households out of poverty and sustain pro-poor development.

7.4 Research Limitations and Future Directions

Although the research for the thesis was carefully planned and prepared, there were some unavoidable limitations. The poverty dynamics estimated in Chapter 4 are based on two-wave panel data sets, future research is required to extend the estimation using lengthier panel data. Chapter 5 estimated VtP for monetary and multidimensional measures using the VEP approach. Further investigation of this could be done using Gunther and Hartgen's (2009) multilevel modeling and the asset-based approach by Carter and Barrette (2006) to explicitly estimate for idiosyncratic and covariate shocks. The impact evaluation performed in Chapter 6 is based on PSM and ESR models, however, using panel data and difference-in-difference (DID) model can further be estimated.

There is also scope for future research on several aspects that can be further investigated with respect to vulnerability to poverty and policy evaluation. A district-level in-depth analysis of vulnerability to poverty can be carried out at the country level to gain information on specific needs for each region. In the present study, we have included coping strategies that are adopted by the households. However, a coping strategy for each shock would provide more insight into the household coping measures. Since VtP is linked with shocks and lack of coping measures, and as the government has implemented social protections to enhance household coping strategies through insurance, food security, employment program, and access to credit so as to reduce poverty and vulnerability. Therefore, analyzing the impact of different social protections on reducing vulnerability will provide more effective ways of ending poverty. More specifically, given the importance of SP and VtP in SDGs, the detailed impact evaluation of other major regular policies such as Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA), Pradhan Mantri Jan Arogya Yojana (PM-JAY), Public Distribution System (PDS), and Indira Awas Yojana (IAY) on household vulnerability to poverty is left as a subject of future research.

Ultimately our analysis provides just a glimpse of what is available with the household survey data. The empirical analysis has been conducted for VtP and impact evaluation using cross-sectional data. Panel data would undoubtedly increase the precision of the estimated values and enhance the reliability of the findings. In future studies, estimation based on panel data can provide more insight into the dynamics of VtP and VMDP, particularly to the literature that focuses on shock and vulnerability. Therefore, we recommend further research, using panel data, on the impact of SP on VtP in developing countries.

To recap, despite the government of India's efforts at the national and state levels through numerous intervention programs, the reduction in both monetary and multidimensional poverty remains a challenge. This thesis has investigated the impact of livelihoods program on household VtP using cross-sectional household survey data. Based on the empirical analysis, policy implications have been suggested with the hope of improving the standard of living and fighting against poverty.

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APPENDICES

APPENDIX I: QUESTIONNAIRE

Schedule No

CONFIDENTIAL FOR RESEARCH PURPOSE ONLY

School of Management
National Institute of Technology Karnataka, Surathkal
Mangalore, Karnataka, PIN- 575025

Sunil Khosla **Dr. Pradyot Ranjan Jena**
Research Scholar Supervisor

Section 1: Survey Information

Village Name		Ward	
Panchayat		Block	
District		Name of the Household Head	
Name of the respondent		Sex	Male/Female
Category	GEN/OBC/SC/ST	Religion	Hindu/Christian/Muslim/Others

Section 2: Household Details

Sl. No	Names of the Family Member including Head	Relationship to head of the family	Sex (M F)	Age	Marital status	Main Occupation	Sub-Occupation
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1							
2							
3							
4							
5							
6							
7							
8	HH Siblings		NR	NR	HH	HH father's	

(3) 1. Head 2- wife/husband, 3- son/daughter, 4- son/daughter in law, 5- grandson/daughter, 6- great grandchild, 7- parent (mother), 8 – parent (father), 9- brother/sister, 10- brother/sister-in-law, 11- niece/nephew, 12- adopted/step child, 13- other relative
(6) 1- married, 2- widow, 3- divorced, 4- separated, 5- unmarried
(7) 0. Unemployed 1. Farmer 3. Tenant 4. Casual agricultural labor 5. Private service 6. Govt employee 7. Banking 8. Wage earner 9. Clerical grade 10. IT 11. Industrial regular worker 12. Business 13. Small trader 14. Street vendor 15. Student 16. Housewife 11. Other

Section 3: Health status

Sl. No.	Names of the Family Member including Head	Health status							
		How healthy is?	Does feel healthier than last year	Does feel healthier than last 5 years	No of death in the last 5 years	Reasons for death	Medical attention	Whether suffered by any of the following diseases of the household	If you have, did you use RSBY card for the major health issue
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1									
2									
3									
4									
5									
6									
7									
8									

(3) 1. Not at all 2. Yes, a bit 3. Yes, a lot
(4) 1. Yes 2. No (1. Somehow 2. Better 3. Normal 4. Worst)
(5) 1. Yes 2. No (1. Somehow 2. Better 3. Normal 4. Worst)
(7) 1. Natural 2. Accident 3. Illness 4. Could not admit hospital
(8) 0. Nothing 1. Government 2. Private 3. Pharmacy 4. Health worker 5. Traditional healer
(9) 1. Disability (specify) 2. Injury 3. Acute Illness 4. Chronic Illness 5. Childhood diseases 6. Surgery 7. Other (specify)
10. 1. Yes 2. No 3. Not availed

Section 4: Education status

Sl. No.	Names of the Family Member including Head	Education (Year of schooling)	Institution type	Place of Institution	Reason for not continuing	Source of fund
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1						
2						
3						
4						
5						
6						
7						
8		HH father's				

(3) 0. Illiterate 1. Primary (class 1to class 5) 2. Upper primary (class 6 to 7) 3. Secondary (class 8 to 10) 4. Higher secondary (class 11th to 12th) 5. Graduation 6. Post-graduation 7. vocational 8. Technical education 9. Others
(4) 1. Govt. 2. Private 3. Trust (Aided)
(5) 1. Village 2. Block Headquarter 3. District Headquarter 4. Another city 5. Other state
(6) 1. Economic condition 2. Parents decision 3. Did not get admission 4. Not interested 5. Other
(7) 1. Home 2. Relatives 3. Borrowing 4. Govt. 5. Scholarship

Section 5: Standard of living indicators

5.1: Housing condition

1. House ownership (Owned/Rent): Value/rent:
2. Made house by govt scheme IAY (1. Yes 2. No)
3. Types of house (1. Hut 2. Kutcha 3. Tiled 4. Semi-Pucca 5. Concrete), Rooms:
4. The Primary source of drinking water (1. Well 2. Govt supply 3. Borewell 4. Pond 5. Stream 6. Others)
5. Do you have toilet facilities? (1. Yes 2. No)
6. Ownership of land (1. Yes 2. No) if yes, Hector………. The value (Rs.)
7. Whether the irrigation facility is available (Yes/No)
8. Do you have a Ration Card? (1. Yes 2. No) (1. BPL 2. APL 3. Antadoya 4. other)

5.2: Fuel & energy use

Do have electricity facility? (1. Yes 2. No) Does your household use…….

Firewood /Twigs? For what purpose it is used? 1. Fuel not used 2. Mainly cooking 3. Mainly lighting 4. Mainly heating 5. Combinations

Dung cake? For what purpose it is used? 1. Fuel not used 2. Mainly cooking 3. Mainly lighting 4. Mainly heating 5. Combinations

Crop residue/by-product for what purpose it is used? 1. Fuel not used 2. Mainly cooking 3. Mainly lighting 4. Mainly heating 5. Combinations

Kerosene? For what purpose it is used? 1. Fuel not used 2. Mainly cooking 3. Mainly lighting 4. Mainly heating 5. Combinations

LPG? For what purpose it is used? 1. Fuel not used 2. Mainly cooking 3. Mainly lighting 4. Mainly heating 5. Combinations

Coal/Charcoal? For what purpose it is used? 1. Fuel not used 2. Mainly cooking 3. Mainly lighting 4. Mainly heating 5. Combinations

Electricity? For what purpose it is used? 1. Fuel not used 2. Mainly cooking 3. Mainly lighting 4. Mainly heating 5. Combinations

Gobar gas? For what purpose it is used? 1. Fuel not used 2. Mainly cooking 3. Mainly lighting 4. Mainly heating 5. Combinations

Separate room for cooking (1. Yes 2. No)

Where do you get most of?		If purchased, how much did you pay for what you used in the last 30 days	
Firewood/Twigs	1. Purchase 2. Collect from own land 3. Collect from village/other places 4. Both 5. Govt supply	Firewood/Twigs	Rs.
Dung cake	1. Purchase 2. Collect from own land 3. Collect from village/other places 4. Both 5. Govt supply	Dung cake	Rs.
Crop residue/by-product	1. Purchase 2. Collect from own land 3. Collect from village/other places 4. Both 5. Govt supply	Crop residue/by-product	Rs.
Kerosene	1. Purchase 2. Collect from own land 3. Collect from village/other places 4. Both 5. Govt supply	Kerosene	Rs.
LPG	1. Purchase 2. Collect from own land 3. Collect from village/other places 4. Both 5. Govt supply	LPG	Rs.
Coal/Charcoal	1. Purchase 2. Collect from own land 3. Collect from village/other places 4. Both 5. Govt supply	Coal/Charcoal	Rs.
Electricity	1. Purchase 2. Collect from own land 3. Collect from village/other places 4. Both 5. Govt supply	Electricity	Rs.
Gobar gas	1. Purchase 2. Collect from own land 3. Collect from village/other places 4. Both 5. Govt supply	Gobar gas	Rs.

1. Adult women older than 15 years of age spend collecting fuel? 1. Daily 2. Weekly 3. Monthly 4. Quarterly 5. Half yearly 5. Yearly
2. Adult men older than 15 years of age spend collecting fuel? 1. Daily 2. Weekly 3. Monthly 4. Quarterly 5. Half yearly 5. Yearly
3. Girls under 15 years of age spend collecting fuel? 1. Daily 2. Weekly 3. Monthly 4. Quarterly 5. Half yearly 5. Yearly
4. Boys under 15 years of age spend collecting fuel? 1. Daily 2. Weekly 3. Monthly 4. Quarterly 5. Half yearly 5. Yearly

Section 6: Household Assets & monthly expenditure

6. 1: Durable household goods

Tube-wells	Electric Pumps	Diesel pumps	Bullock carts/Dunlop carts	Tractors/Tillers	Threshers	Hand/Power Sprayer	Chaff cutter	Drip irrigation
Sprinkler set	Seed drill	Other farm tools	Rice mill	Threshing machine	Boat	Fishing Net (s) (respective)	Fishing Traps	Water pumps
Water pumps	Water tank	Car	Truck/Pick up	Two Wheeler	Bicycle	Refrigerator	T.V	Washing Machine
Computer/Laptop	DVD	Satellite Dish	Jewelry	Mobile phone	Sofa Sets	Credit card	Furniture	Sewing machine
Landline	Cookers	Chairs, tables	Stereo sets	Water heater	Iron box	Grinder	Watches and clocks	Bed
Vacuum cleaner	Air conditioner	Matters	Gas	Radio	Fan	Chaff cutter		

6. 2: Livestock:

Do you Own Livestock (Yes/No) if yes

Bullock:	Sheep:	Cow:	Poultry:	Buffalo:	Goat:	Pig:

6.3: Monthly Income:

Crop (FI)	Livestock (FI)	Forest (FI)	Ot. forest (FI)	Business (NF)	Salary (NF)	Wage (NF)	Remit (NF)	Other (NF)

6. 4: Monthly expenditure

Food	Clothing	Health	Education	Loan repayment	Agriculture expenses	Personal expenses	Consumption of electricity	Ceremony (marriages)
Festival	SHG	Savings	Travel	Others	Insurance	Relatives	Consumption of fuel for cooking	Funeral/family program

Section 7: Shocks

7a) What were the major shocks that affected your household in the past 5 years?

Type of event	(1)	
When did the event occur?	(2)	
Estimated severity of the event in your household?	(3)	
Estimated loss of income due to the event in the year of occurrences?	(4)	
Estimated loss of assets	(5)	
What was your major coping activity to deal with the event?	(6)	
2nd & 3rd activity	(7)	
Did the household still have to reduce household consumption expenditures because of the event?	(8)	
Whether Asset helped to reduce the severity	(9)	
How many years did it take to recover from the event?	(10)	

(1. **Types of events**) **(Demographic)** 1. Illness of household member 2. The death of Household member 3. Household member left the household 4. Person joined the household 5. Money spent for the ceremony in the household **Social** 6. Household damage 7. Theft 8. Conflict with neighbor in the village 9. Relatives/Friends stopped sending money (**Natural/agriculture)** 10 Flooding 11. Drought 12. Famine 13. Unusually heavy rain 14. Crop pests 15. Storage pests 16. Livestock disease 17. Landslide, Erosion (**Economics)** 18. Job loss 19. The collapse of business 20. Unable to pay back loan 21. The Strong increase of interest rate on loans 22. The Strong decrease of prices for outputs 23. The Strong

increase of prices for input 24. Change in market regulation

(3) 1. High 2. Moderate 3. Low 4. No impact 5. Other, specify

(6. **Coping strategies**) 1. Did nothing **Economics** 2. Took up additional occupation 3. Diversify agricultural portfolio 4. Substitute crops 5. Reduced production units **Demographics** 6. Took children out of school 7. Sent children to relatives/friends 8. Adult migrated to look for job 9. Adult migrated to live with relatives 10 adults migrated to marry **Sale** 11. Sold livestock 12. Sold land 13. Sold storage 14. Sold other assets **Borrowing & savings** 15. Used savings 16. Used insurance 17. Borrowed from relatives 18 Borrowed from friends/neighbour 19. Borrowed from informal money lender 20. Borrowed from village funds 21. Borrowed from commercial bank 22. Borrowed from Govt. saving banks (SBI) **Grants** 23. Help from Govt. 24. Help from NGOs 25. Help from relatives 26. Help from friends/neighbours 27. Other, specify (Reduced consumption).

(8) 1. Yes, 2. No

(9) 1. Not at all 2. Yes, a bit 3. Yes a lot 4. The same

(10) 0. Less than 1 year 1. 1 year 2. More than 1 year, but now recovered 3. Not yet recovered

7b) During experiencing shock, was there a time when:

a) You were worried you would run out of food because of a lack of money or other resources? 1. Yes 2. No
b) You were unable to eat healthy and nutritious food because of a lack of money or other resources? 1. Yes 2. No
c) You ate only a few kinds of foods because of a lack of money or other resources? 1. Yes 2. No
d) You had to skip a meal because there was not enough money or other resources to get food? 1. Yes 2. No
e) You ate less than you thought you should because of a lack of money or other resources? 1. Yes 2. No
f) Your household ran out of food because of a lack of money or other resources? 1. Yes 2. No
g) You were hungry but did not eat because there was not enough money or other resources for food? 1. Yes 2. No
h) You went without eating for a whole day because of a lack of money or other resources? 1. Yes 2. No

Section 8: Government programs to reduce vulnerability (in last 5 years)

8.1: Demographic **(**Old: 1. disability 2. pension (MPY) Child: 3. Anganwadi 4. other: 5. maternity 6. widow) 1= Yes

Programs	**1**	**n**	**2**	**n**	**3**	**n**	**4**	**n**	**5**	**n**	**6**	**n**
Enrolled year & Number												
Still benefiting												
Reason for stopped												

Do you feel, without the support it would have reduced your living standard/consumption? 1. Mostly 2. Some extent 3. No
RFS: 1. Govt stopped 2. Escaped poverty 6. Don't know

8.2: Social

a. Education (1. Scholarship 2. Loan 3. Private loan 4. Other)

Programs	1	2	3	4
Amount				
Year				

Was it helpful to continue your education? 1. Greatly 2. Medium 3. No

b. Health (free health service at village, Avail RSBY)

Did you get support in case of major health issue (Operation/accident?) 1. Govt 2. Relative 3. Private loan

Do you have health insurance? 1. Yes 2. No

c. Household damage in last 5 years and received support (1. Cyclone, 2. Flood, 3. Heavy wind, 4. Other)

Affected by	1	2	3	4
Amount				
Year				

Did you get support from govt? 1. Yes 2. No 3. How much?

8.3: Economics

a. Employment (1. MGNREGA, 2. Other)

Programs	**1**	**n**	**2**	**n**	**3**	**n**	**4**	**n**	**5**	**n**
Enrolled year & Number										
Still benefiting										
Reason for stopped										

Benefit ways: 1. Work 2. Days 3. Didn’t get work 4. Received work safety 5. Other support 6. Delay in payment

Whether the scheme has increased your living standard? 1. Greatly 2. Somehow 3. Not at all

Do you feel, without the support it would have reduced your consumption/lS? 1. Mostly 2. Some extent 3. No

Do you get any training to increase your skill? 1. Yes 2. No

RFS: 1. Govt stopped 2. Migrated 3. Engaged in other job 4. Not interested 6. Don’t know

3. Direct benefit (1. TPDS, 2.AAY, 3.MDM, 4.SNP 5. other)

Programs	**1**	**n**	**2**	**n**	**3**	**n**	**4**	**n**	**5**	**n**
Enrolled year & Number										
Still benefiting										
Reason for stopped										

Whether the scheme has increased your living standard? 1. Greatly 2. Somehow 3. Not at all

Do you feel, without the support it would have reduced your consumption/lS? 1. Mostly 2. Some extent 3. No

RFS: 1. Govt stopped 2. Escaped poverty 6. Don’t know

Do you feel, without the support it would have reduced your consumption/lS? 1. Mostly 2. Some extent 3. No

8.4: Livelihood support (OTELP, JEEVIKA/NRLP)

Programs	**1**	**n**	**2**	**n**	**3**	**n**
Enrolled year & Number						
Still benefiting						
Reason for stopped						

Benefit ways: 1. Work 2. Loan 3. Instrument 4. Training 5. Other support
Whether it has increased the livelihood of your household? 1. Greatly 2. Somehow 3. not at all
Do you feel, without the support it would have reduced your consumption/lS? 1. Mostly 2. Some extent 3. No
RFS: 1. Govt stopped 2. Migrated 3. Escaped poverty 4. Engaged in other job 5. Not interested 6. Don’t know

Whether you get the information of adverse events for agricultural damages? 1. Yes 2. No
How you get the information? 1. Govt officials 2. TV 3. Friends 4. Relatives 5. Others, specify
What kind of support you get during the crop failure? 1. Nothing 2. Loan waive 3. Money 4. Other, specify
Do you get information about the HHY seeds and other information? 1. Yes 2. No
Do you get training for the farming? 1. Yes 2. No
Do you get the knowledge to avoid the crop pest? 1. Yes 2. No
SRF: 1. Govt stopped 2. Migrated 3. Engaged in other job 4. 6. Don’t know

Section 8. 2 Capitals

Community characteristics (KM) (Yes=0km)	Social capital (Member) Yes, year	Institutional capital
D-Bus stop	Member in Mahila Mandal	Microfinance (often, S Time, never)
D-Hospital	Member in SHG	Veterinary hospitals (often, S Time, never)
D-Market	Member in social group	Credit cooperative societies (often, S Time, never)
D-Bank	Member in saving group	Direct Benefit scheme (distribution of seeds) (often, S Time, never)
D-Fertilizer	Member in NGO	Warehousing (often, S Time, never)
D-Community road	Relative send information from town	Network availability
D-State road	Member in religion group	
D-Secondary school	Member in Agricultural, milk, or other co-operative	
D-Higher secondary school	Member Lions/Youth/Rotary club & Other	
D-Industry	Attend public meeting	Reads newspaper daily
	Panchayat member/official close to household	Watches news daily on TV

Appendix II: MULTICOLLINEARITY TEST AND CORRELATION MATRIX FOR RESEARCH OBJECTIVE 1

Table A3.1: VIF for Poverty Dynamics

Variable	VIF	1/VIF
Farming	2.04	0.491236
Dummy coastal region	1.91	0.524014
Owns livestock	1.79	0.558849
Dummy northern	1.67	0.598861
Household size	1.46	0.686048
Wage earner in non-farm	1.32	0.757670
Area cultivated	1.31	0.762228
Self-employed in non-farm	1.30	0.767167
Member in caste	1.29	0.774284
Member in development	1.26	0.795650
Years of schooling	1.24	0.808713
Proportion of dependency	1.18	0.847541
Age of head	1.14	0.873572
Head gender	1.12	0.894688
Market distance	1.10	0.909567
Income remittance	1.05	0.948870
Member credit	1.04	0.960344
Member cooperative	1.03	0.974929
Mean VIF	1.35	

Table A3.2: Correlation Matrix for Poverty Dynamics Groups

Variables	Head gender	Age of the household head	Household head's years of schooling	Log income remittances	Cultivated land in acre	Household size	Northern region	Coastal region	member engaged in farming sector	member engaged in service sector
Head gender	1.0000									
Age of the household head	-0.0463	1.0000								
Household head's years of schooling	0.2176	-0.2131	1.0000							
Log income remittances	-0.0816	0.0524	0.0095	1.0000						
Cultivated land in acre	0.1137	0.0843	0.0673	0.0213	1.0000					
Household size	0.1542	0.0075	0.0108	-0.0327	0.2616	1.0000				
Northern region	-0.0336	-0.0683	0.0824	-0.0519	-0.1307	-0.0427	1.0000			
Coastal region	0.0526	0.1241	0.0950	0.0972	0.1946	0.1620	-0.4855	1.0000		
member engaged in farming sector	0.1364	0.0085	-0.1150	-0.0340	0.3634	0.3270	0.0404	0.0523	1.0000	
member engaged in service sector	-0.0038	0.0414	0.1472	0.0314	-0.0244	0.1761	0.0798	0.0187	-0.1884	1.0000

Table A3.2: Correlation Matrix for Poverty Dynamics Groups Cont.

Variables	member engaged in daily wage sector	Member in credit or savings	Member in caste association	Member in development/NGO	Member in cooperative	Market distance	Owns livestock
member engaged in daily wage sector	1.0000						
Member in credit or savings	-0.0821	1.0000					
Member in caste association	-0.0485	0.0759	1.0000				
Member in development/ NGO	0.0784	0.0402	0.4130	1.0000			
Member in cooperative	-0.0500	0.0836	0.0242	0.0334	1.0000		
Market distance	0.0171	0.0755	-0.1115	0.0068	-0.0311	1.0000	
Owns livestock	-0.0366	0.0136	-0.0774	-0.0952	-0.0109	0.1576	1.0000

APPENDIX III: STATISTICAL TEST FOR RESEARCH OBJECTIVE 2

Table A5.1: Different Indicators used Under Health Dimension

Journal/Authors	Health Dimension	
Oxford development studies (2017)	Food security: Frequently or always not enough food	Access to health care: No access to doctor, clinic, pharmacy or NGO
World Bank (2017)	food consumption: If per capita food consumption < 4/5 of food poverty line	Illness: If more than 50% of household members report illness or injury over the past month (past 6 months for 2013).
Oxford Poverty and Human Development Index (OPHI) (2010)	Nutrition: If any adult or child in the family is malnourished	Mortality: If any child has died in the family
World Development (2015)	Nutrition: Any adult to child for whom there is nutritional information is malnourished	Mortality: Any child has died in the family
Journal of economic inequality	Nutrition: If any adult or child in the family is malnourished	Mortality: If any child has died in the family
Journal of Public Economics (2011)	Nutrition: If any adult or child in the family is malnourished	Mortality: If any child has died in the family
The Journal of Economic Inequality (2011b)	Nutrition: If any adult or child in the family is malnourished	Mortality: If any child has died in the family
Soc Indic Res (2013)	Body Mass Index (BMI): At least one adult member of the household with BMI less than 18.5 kg/m2	Social Security: No any household member has access to any kind of medical insurance
The Quarterly Review of Economics and Finance (2015) And Quality & quantity And Soc Indic Res	Immunization: If not immunized then D = 1, and 0 otherwise:	Safe drinking water facility: Pre-natal consultation: If did not go for any pre-natal consultation then D = 1, and 0 otherwise
Soc Indic Res	Occurrence of diseases in respondent’s Household: >=3 common diseases	
Child Indicators Research	Access to healthcare (0.05)	Child mortality (0.05)
The Journal of Development Studies (2016)	Child Mortality (1/6): A child has died within the house	Nutrition: Any adult or child for whom there is nutritional information is malnourished
Development Southern Africa (2018)	Child mortality: at least a child died in the last year (0-4)	Disability: At least one household member is disabled

Soc Indic Res (2018)	Health Status: Deprived if the health of any member of the household aged 70 years or younger was poor or very poor	Health care: Deprived if health care was not affordable or only met by borrowing or with much difficulty

Source: Based on author’s literature review

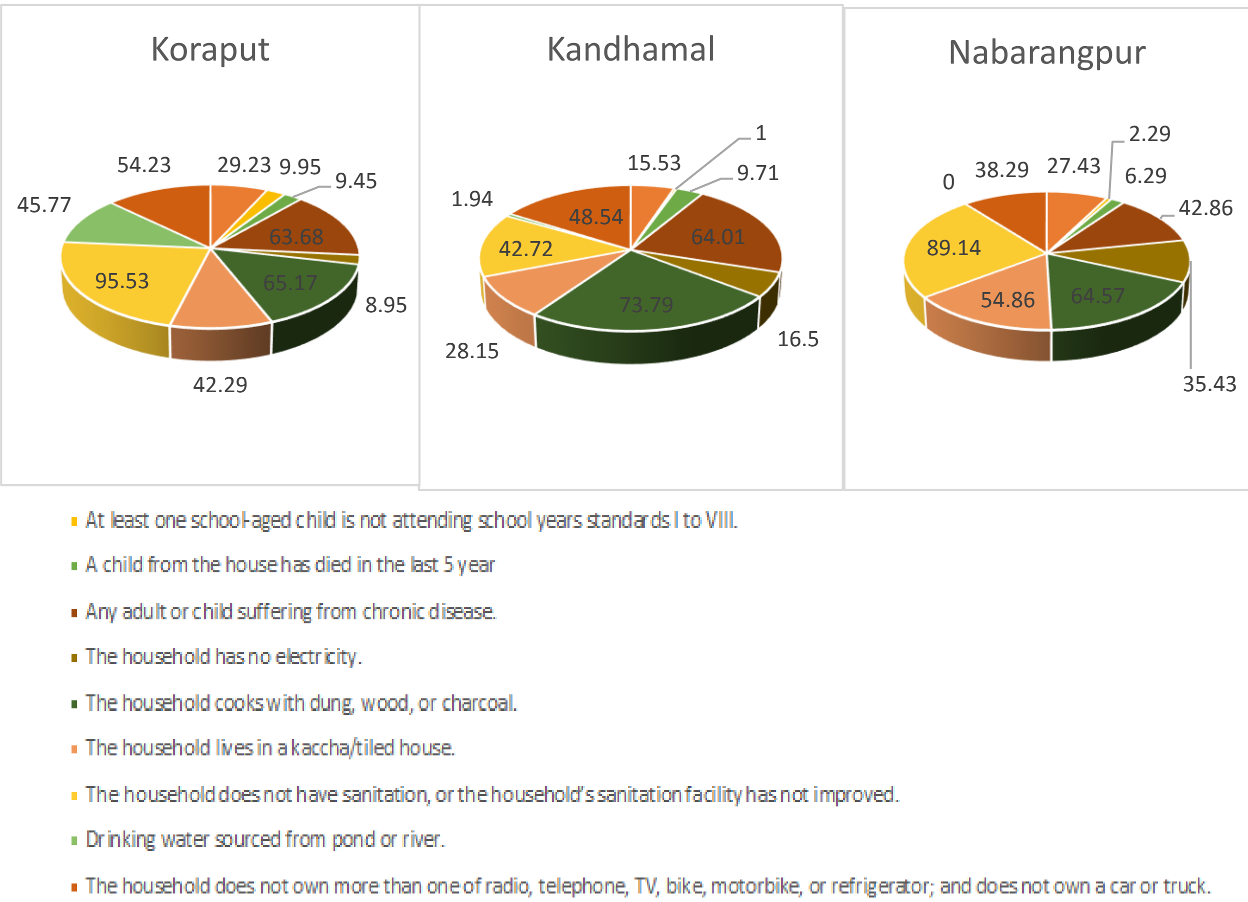

Figure A5.1: Dimensional Decomposition of Multidimensional Poverty Indicators at District Levels (%)

Figure A5.2: Dimensional Decomposition of Multidimensional Poverty Indicators at Livelihood Levels (%)
Source: Authors' estimation using survey data.

Table A5.2: Decomposition of VtP Based on Shocks (%)

Variable	Monetary VtP					Multidimensional VtP				
	Flood	Drought	Cyclone	Illness	Death	Flood	Drought	Cyclone	Illness	Death
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Chronic poor	54.69	73.44	71.87	93.75	25	47.65	73.53	70.59	97.65	22.35
Transient poor	47.06	84.31	67.65	92.16	22.55	30.85	58.51	71.27	94.68	8.51
Non-poor	29.17	60.42	67.92	82.92	13.33	30.81	66.04	66.67	74.84	17.61
Escaped poverty	28.77	68.49	76.71	91.78	13.70	26.71	76.78	73.21	82.14	12.5

Source: Authors estimation using survey data

Table A5.3: Decomposition of VtP Based on Coping Strategies (%)

Variable	Monetary VtP					Multidimensional VtP				
	Money lender	Relatives	Sold land	Sold live stock	Sold gold	oney lender	Relatives	Sold land	Sold live stock	Sold gold
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Chronic poor	28.12	31.25	12.5	40.62	3.12	54.12	43.53	12.35	25.88	0.6
Transient poor	38.23	46.08	14.71	41.18	12.74	38.30	46.81	7.45	20.21	4.25
Non-poor	42.5	55	6.25	14.58	2.08	26.41	54.01	6.29	25.16	8.8
Escaped poverty	30.14	63.01	6.85	19.18	0	16.64	73.21	8.93	25	1.8

Source: Authors estimation using survey data

Table A5.4: VIF for VtP/VMDP

Variable	VIF	1/VIF
Durable assets	2.04	0.491375
Years of schooling of head	1.58	0.631020
Farm employed	1.57	0.638614
Own land	1.50	0.666705
Flood	1.41	0.708573
Drought	1.41	0.711222
Sold land	1.36	0.735563
Attending public meeting (gram sabha)	1.34	0.743624
Borrowed from informal money lender	1.34	0.743845
Age of head	1.34	0.747082
Member in saving group (credit/chit fund)	1.33	0.750306
Productive assets	1.30	0.770030
Sold livestock	1.30	0.770819
Gender	1.25	0.798275
Household size	1.25	0.798487
Wage earner in non-farm	1.25	0.802997
Cyclone	1.20	0.832332
Member in SHG	1.19	0.842964
Dependency ratio	1.17	0.853288
Sold gold	1.12	0.890435
Death of income earner	1.11	0.898434
Borrowed from relatives	1.11	0.899161
Illness	1.10	0.911163
Mean VIF	1.33	

Table A5.5: Correlation Matrix for Research Objective 2

Variables	Gender	Farm employed	Wage in non-farm	Household size	Dependency ratio	Age of head	Years of schooling	Own land	Durable assets	Illness	Cyclone	Death of income earner	Flood
Gender	1.0000												
Farm employed	0.1667	1.0000											
Wage in non-farm	0.0137	-0.3313	1.0000										
Household size	0.2643	0.0936	0.1131	1.0000									
Dependency ratio	-0.0329	0.0772	-0.0655	-0.0288	1.0000								
Age of head	-0.1840	0.0410	-0.0828	-0.1089	0.1201	1.0000							
Years of	0.1876	-0.1743	0.1957	0.0059	-0.0725	-0.3825	1.0000						
Own land	0.0955	0.4183	-0.1819	0.1359	0.1304	-0.0501	-0.1238	1.0000					
Durable assets	0.1069	-0.1974	0.2908	0.2466	-0.2334	-0.0077	0.3804	-0.0548	1.0000				
Illness	0.0175	-0.0211	0.0332	-0.0155	0.1071	0.1180	-0.0886	-0.0601	-0.0498	1.0000			
Cyclone	0.1317	0.0292	-0.0669	-0.0213	-0.0760	0.0232	-0.0401	-0.1602	-0.1604	0.1125	1.0000		
Death of income earner	-0.1010	0.0610	-0.0023	0.0079	-0.0375	0.0539	-0.0825	0.0647	0.0192	-0.0004	-0.0786	1.0000	
Flood	0.0165	0.2120	-0.0908	0.0657	0.0395	0.1214	-0.0666	0.2035	0.0838	0.0189	-0.2015	0.1572	1.0000

Table A5.5: Correlation Matrix for Research Objective 2 Cont.

Variable	Drought	Sold livestock	Sold land	Sold gold	Borrowed from informal money lender	Borrowed from relatives	Productive assets	Member in SHG	Member in saving	Attending public
Drought	1.0000									
Sold livestock	0.2393	1.0000								
Sold land	0.0873	0.3144	1.0000							
Sold gold	0.0068	0.1000	0.1170	1.0000						
Borrowed from informal money lender	0.1210	0.0881	0.2674	0.0526	1.0000					
Borrowed from relatives	0.1369	-0.0082	-0.1606	-0.0048	-0.0136	1.0000				
Productive assets	0.2038	0.0542	0.1566	-0.0491	0.2596	-0.1176	1.0000			
Member in SHG	-0.0592	0.1348	0.0372	-0.0182	-0.1079	-0.0532	-0.0071	1.0000		
Member in saving group (credit/chit fund)	-0.1183	-0.0118	0.0168	0.1224	0.2076	-0.0867	0.1126	0.0979	1.0000	
Attending public meeting (gram sabha)	-0.1569	-0.0495	-0.0889	0.0152	-0.1375	0.0683	-0.0434	0.2223	0.1732	1.0000

APPENDIX IV: STATISTICAL TEST FOR RESEARCH OBJECTIVE 3

Table A6.1: Statistical Significance of Explanatory Variables used in the PSM Before and After Matching

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	% reduct |bias|	t-test t	t-test p>|t|
Schedule caste	U	0.35	0.37	-3.6		-0.23	0.82
	M	0.32	0.33	-2.8	22.8	-0.19	0.85
Schedule Tribe	U	0.44	0.37	13.4		0.85	0.40
	M	0.45	0.39	12.6	5.8	0.84	0.40
Gender	U	0.92	0.94	-10.2		-0.64	0.52
	M	0.92	0.97	-18.2	-78.2	-1.38	0.17
Income earner	U**	1.68	2.04	-42.0		-2.72	0.01
	M	1.72	1.65	7.6	81.8	0.60	0.55
Member in social group	U	0.44	0.314	25.5		1.61	0.11
	M	0.4	0.40	0.5	98.2	0.03	0.98
Member in saving group	U**	0.031	0.14	-40.1		-2.68	0.01
	M	0.033	0.02	4.8	88.1	0.55	0.58
Media exposure	U*	0.40	0.27	26.5		1.67	0.10
	M	0.37	0.32	10.4	60.7	0.69	0.49
Age of head	U	40.40	41.21	-6.7		-0.43	0.67
	M	40.29	40.65	-3.0	55.7	-0.22	0.83
Household size	U	6.10	6.39	-15.4		-0.99	0.32
	M	6.15	6.02	6.4	58.1	0.49	0.62
Own land	U	0.78	0.8	-7.1		-0.45	0.65
	M	0.78	0.83	-13.5	-90.5	-0.94	0.35
Years of schooling of head	U	2.11	2.27	-4.8		-0.30	0.76
	M	2.13	1.98	4.6	3.7	0.33	0.74

Attending public meeting	U	0.44	0.4	7.6		0.48	0.63
	M	0.42	0.34	15.7	-107.4	1.07	0.29
Owns livestock	U**	0.83	0.69	34.8		2.26	0.02
	M	0.82	0.82	-0.00	100.0	-0.00	1.00

*Note: asterisks denote the following: *** = significant at 1% level, ** =significant at 5% level, *= significant at 10% level*

Table A6.2: ESR Second Stage Estimation

Variable	Monetary VtP				Multidimensional VtP			
	Participated households		Non-participated households		Participated households		Non-participated households	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Gender	-0.08**	0.04	0.01	0.04	-0.005	0.01	0.01	0.02
Income earner	-0.03	0.04	0.04	0.03	-0.004	0.01	0.01	0.01
Member in social group	-0.003	0.07	-0.02	0.06	0.03	0.04	-0.0004	0.04
Member in saving group	-0.03	0.19	0.10	0.12	.0.03	0.04	0.05	0.04
Member in attends public meeting	-0.06**	0.03	-0.06**	0.03	-0.002	0.01	-0.02	0.01
Age of head	0.0002	0.001	-0.002	0.001	0.001**	0.001	0.002***	0.0005
Household size	0.02***	0.01	0.02***	0.01	-0.003	0.004	0.004	0.004
Own land	-0.00	0.04	-0.00	0.04	-0.003	0.01	-0.03*	0.02
Years of schooling of head	-0.01*	0.03	-0.005	0.003	0.002	0.003	0.005	0.003
Schedule caste	0.002	0.03	0.03	0.02	0.02**	0.01	-0.02	0.01
Schedule tribe	-0.01	0.03	0.01	0.02	0.02	0.03	-0.02	0.04
Media exposure	0.04	0.06	-0.07	0.06	0.01	0.04	-0.05	0.04
Owns livestock	0.07	0.08	-0.02	0.06	0.004	0.02	-0.02	0.02
Mills1	0.06	0.21			0.06	0.11		
Mills2			-0.16	0.14			-0.04	0.12
Constant	0.52***	0.11	0.32*	0.18	0.41***	0.08	0.40	0.10
Number of observation	96		70		124		140	
R square	0.34		0.39		0.37		0.36	

Source: Author's estimation using household survey data. Note: asterisks denote the following:

**** = significant at 1% level, ** =significant at 5% level, *= significant at 10% level*

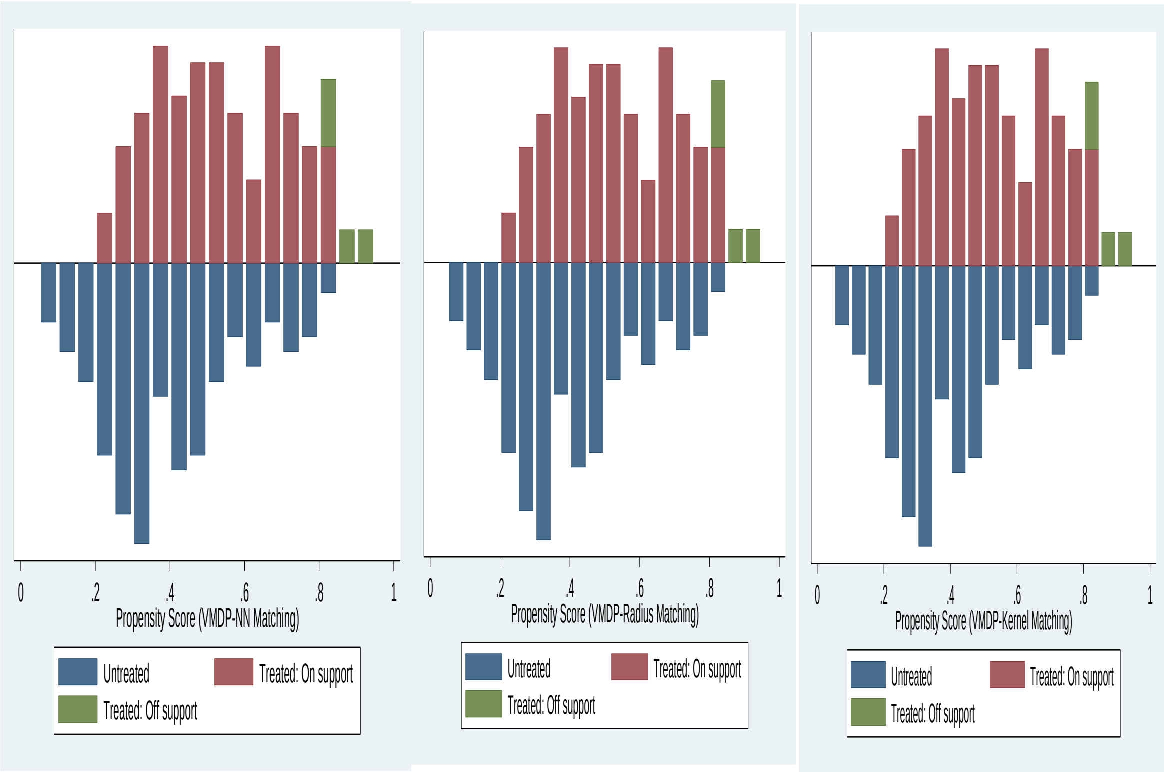

Figure A6.1: Propensity Score Graph for VMDP

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- Khosla, S. and Jena, P. R. (2019). Switch in Livelihood Strategies and Social Capital Have a Role to Play in Deciding Rural Poverty Dynamics: Evidence from Panel Data Analysis from Eastern India. Journal of Asian and African Studies, 55 (1), 76-94. https://doi.org/10.1177/0021909619868243 (Scopus indexed) (**Published**).
- Khosla, S. and Jena, P. R (2022). Analyzing Vulnerability to Poverty and Assessing the Role of Universal Public Works and Food Security Programs to Reduce it: Evidence from an Eastern Indian State (**Accepted for publication** at Review of Development Economics).
- Khosla, S. and Jena, P. R. Rural Livelihood Program and Household Vulnerability to Poverty: Empirical Evidence from a Tribal Region of Eastern India (**Minor Revision Submitted** at Economic Analysis and Policy).
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