GIDR WORKING PAPER SERIES

No. 239:December 2016

Effect of Rural Livelihoods Project on Adaptation Decision and Farmers' Wellbeing in Western Odisha, India:
Application of Endogenous Switching Regression

Unmesh Patnaik
Prasun Kumar Das
Chandra Sekhar Bahinipati

Gujarat Institute of Development Research

Working Paper No. 239

Effect of Rural Livelihoods Project on Adaptation Decision and Farmers' Wellbeing in Western Odisha, India: Application of Endogenous Switching Regression

Unmesh Patnaik
Prasun Kumar Das
Chandra Sekhar Bahinipati

December 2016

Gujarat Institute of Development Research
Ahmedabad

Abstracts of all GIDR Working Papers are available on the Institute's website.
Working Paper No. 121 onwards can be downloaded from the site.

First Published	: December 2016
ISBN	: 81-89023-97-7
Price	: Rs. 100.00

Abstract

Evidences suggest that developing countries, challenged as they are due to problems such as poverty, food insecurity, malnutrition and inequality are also highly vulnerable to current and future climatic shocks. While several projects have been undertaken in these countries over the years to address their development challenges, efforts to integrate climate change adaptation within development initiatives have virtually been absent. Also, empirical analyses that examine the causal relationship between such activities and agricultural adaptation decision by farmers or their overall wellbeing are scarce, particularly in the case of India. This paper seeks to address this gap by examining the effect of a rural livelihood project implemented in the drought prone western region of the state of Odisha in the last decade. The empirical analysis is based on a survey of 549 rural households. Employing the endogenous switching regression approach, the paper finds that the intervention did enhance the likelihood of undertaking farm-level adaptation measures. The other drivers are found to be access to technical education, formal and informal institutions, and agricultural extension services. It is also found that adaptations lead to significant gain in crop income of farmers. From a broader policy perspective, the paper emphasizes the significance of integrating climate change in development planning to reduce the possibility of mal-adaptation.

Keywords **:** Rural Livelihoods Project, Farm-level Adaptation, Crop Income, Endogenous Switching Regression, Western Odisha, India

JEL Classification **:** O13, Q12, Q54, C24

Acknowledgements

The data collection for this study was done through a research grant from South Asian Network for Development and Environmental Economics (SANDEE), Kathmandu, Nepal [SANDEE/2013-06]. We are thankful to Bijoy Satapathy, staffs of Odisha Watershed Development Mission and the Project Implementing Agencies of WORLP in Balangir for their support to conduct the field work. We acknowledge the support from Mr. Onkar Nath Tripathi who along with his team coordinated the household surveys. We are grateful to the respondent households for their participation in the survey. Thanks to Barun Deb Pal for providing comments and suggestions on a previous draft. Earlier versions were presented at the International Seminar on Poverty, Environment and Sustainable Development Goals (SDGs) in Asia Pacific', Institute for social and Economic Change, Bangalore and faculty seminar series at GIDR, Ahmedabad. We have benefited from discussions with R. Parthasarathy, Keshab Das, N. Lalitha and Tara Nair. Our sincere thanks to P.K. Viswanathan, Tara Nair and Itishree Pattnaik for their efforts to bring this paper as part of the GIDR working paper series. All views, interpretations, conclusions and recommendations made in this paper are those of the authors and not of those of the supporting or collaborating institutions. Usual disclaimers apply.

Contents

List of Tables

List of Figures

List of Appendix

Effect of Rural Livelihoods Project on Adaptation Decision and Farmers' Wellbeing in Western Odisha, India: Application of Endogenous Switching Regression

Unmesh Patnaik
Prasun Kumar Das
Chandra Sekhar Bahinipati

1. Introduction

At the core of the debate regarding the impact of climate variability and extreme events on agriculture in rural India lies the issue of adaptation. It has been widely recognised that the agriculture sector in developing nations, particularly India, has witnessed large negative externalities from climate variability and shocks (Mendelsohn et al., 2006; Porter et al., 2014;Jayaraman and Murari, 2014). Coupled with land degradation, loss of biodiversity and changes in hydrology, climatic patterns which characterize production tend to diminish agricultural yield at a micro-level, and in turn, amplify food insecurity on a macro scale (Ericksen et al., 2009). The short-term impact varies according to the extent of dependence on agriculture and diversification in income, while climatic risks are responsible for agricultural stagnation and rural poverty in the long run (Dorward and Kydd, 2002).The likelihood of increase in frequency and intensity of rapid- and slow-onset disasters, say, cyclonic storms, floods, droughts, sea-level rise, etc(Intergovernmental Panel on Climate Change, hereafter, IPCC, 2012), isa serious concern for farming households as their livelihood options are highly sensitive.

The contribution of agricultural sector to the Indian economy has been declining over the years, while it provides employment to 55% of the labour force as of Census 2011, mostly in rural areas (Bahinipati, 2015). It is noted that agriculture continues to be dominated by marginal (<1 ha) and small farmers (1-2 ha), and most of the areas are rain-fed (Pandey et al., 2007). Previous studies assert that agriculture is significantly affected by climate change (Kumar and Parikh, 2001; Kumar, 2011; Pattanayak and Kumar, 2014), and this could affect the wellbeing of a large number of farm households, particularly marginal and small farmers. Various planned adaptations need to be promoted to mitigate potential impacts, while farmers are already taking up both planned and autonomous adaptation options (Mishra, 2012; Panda et al., 2013; Bahinipati, 2015; Bahinipati and Venkatachalam, 2015).Though a host of studies have

Unmesh Patnaik (unmeshpatnaik@gmail.com) is with the Centre for Climate Change and Sustainability Studies, School of Habitat Studies, Tata Institute of Social Science, Mumbai; Prasun Kumar Das is withAsia Pacific Rural and Agricultural Credit Association, Bangkok,Thailand; andChandra Sekhar Bahinipati (csbahinipati@gmail.com) is with Gujarat Institute of DevelopmentResearch,Ahmedabad.

already focused on the determinants of adaptation, there is a dearth of studies that assess effectiveness of adaptations, particularly in India (Bahinipati and Patnaik, 2015a). On other hand, households are also encountering various developmental issues such as poverty, food security, malnutrition, inequality, etc.,which are likely to further enhance their vulnerability level (Patnaik and Narayanan, 2005, 2010; Bahinipati, 2014). Over the years, several rural livelihoods projects, therefore, have been undertaken to address these issues. Climate change literature has termed these interventions as generic adaptation measures (Sharma and Patwardhan, 2008; Bahinipati and Patnaik, 2015b). Studies have shown that socio-economic development plays a major role in the mitigation of the adverse impact of climate change (Bahinipati and Patnaik, 2015b), but its inter-linkages with the adaptation is explored less (Janetos et al., 2012). Of late, the international climate policy has been strongly recommending mainstreaming of adaptation into existing development planning and policies. However, gaps remain in understanding specific relationships, potential synergies and trade-offs in the integration process (Janetos et al., 2012). Indeed, the poverty reduction schemes could not always reduce the vulnerability to climate change (Sherman et al., 2016).

This study, therefore, aims to identify whether any synergies exist between developmental activities and adaptation decision, and also examines the effectiveness of taking up adaptation options. In particular, it explores the linkages between livelihood interventions, farm-level adaptation decision and farmers' welfare in western Odisha. The livelihood interventions we are referring here as Western Orissa Rural Livelihood Projects (WORLP) which was implemented in the last decade (the next section contains a detailed discussion on it; see Sharma et al., 2014; Patnaik et al., 2016a). While Odisha (spelt Orissa prior to 2011) is one of the poorest states in India and suffers from alarming levels of hunger and poverty, the situation is much worse in western Odisha where droughts and floods occur frequently (Swain, 2014; Panda, 2016). Some districts within this region, in fact, are found to be more vulnerable to cyclones and floods than other coastal districts (Bahinipati, 2014). This region has lower human development indicators, higher incidence of extreme poverty, a record of poor nutrient intake, more starvation deaths and higher infant mortality rate (WORLP, 1999; Rahman, 2016).Adopting an 'endogenous switching regression (ESR)' approach, the particular objective of this paper is to examine the possible influence of WORLP on adoption of farm-level adaptations and its impact on crop income. This is a novel approach from an econometric perspective as it accounts for sample selectivity bias while taking cognizance of the differential impact between adopters and non-adopters. ESR is being widely used for analyzing the impact of adaptation practices on crop production in diverse geographical settings (e.g., Teklewold et al., 2017; Ma and Abdulai, 2016; Coromaldi et al., 2015; Kassie et al., 2015; Di Falco and Veronesi, 2013; Di Falco et al., 2011), but no such analysis exists in the Indian context. Its uniqueness also lies in its attempt to establish synergies between livelihood interventions in general and the capacity of such programmes in reducing the impact on production systems in particular.

The remainder of this paper is organized as follows. While section two presents literature review, section three describes background and context. Fourth section provides empirical approach, and fifth section explains the survey instrument and data, and the sixthsection discusses the results. Finally, section sevenreports the concluding observations.

2. Review of Literature

Given the changing environment and increasing uncertainties regarding the scale and timing of natural disasters, the efficacy of adaptation mechanisms employed by farmers is of paramount importance. It is observed that Indian farmers deploy various farm-level measures to reduce the impact of climatic shocks (Bahinipati, 2015; Bahinipati and Venkatachalam, 2015; Panda et al., 2013; Mishra, 2012). According to the global studies, adaptation could reduce impact by 30% to 100%, which varies across agricultural crops and geographical locations (Bahinipati, 2011). However, there are limited micro-level studies to assess benefits of undertaking various farm-level adaptation mechanisms in the Indian context. A few studies looked at effectiveness of traditional coping measures, e.g., monetary transfer, relief, selling of livestock, borrowing, etc. (Patnaik and Narayanan, 2015a, b; Patnaik et al., 2016b).

There are two strands in literature that assess the potential benefits of undertaking adaptation options at micro-level. The traditional Ricardian approach, widely used in the Indian context, estimates potential impact from climate change on net revenue and agricultural output (Kumar, 2011; Sanghi and Mendelsohn, 2008; Kumar and Parikh, 2001). Presuming clairvoyant/optimal farmer hypotheses, this method implicitly models adaptation while calculating the impact. Adaptation is in-built in the model, and hence, it is a black box from a practical perspective (Seo and Mendelsohn, 2008). As a result, this model suffers not only from endogeneity and self-selection biases in the choice of adaptation measures (i.e., choice of irrigation frequency and heat-tolerant seeds are determined by climate itself), but also fails to identify adaptation mechanisms that could probably reduce the impact from the climate change (Di Falco et al., 2011). Analogous is the structural Ricardian approach which conjointly models the choices of adaptation measures and their potential capacity to reduce the impact (see Di Falco, 2014; Kurukulasuriya et al., 2011; Seo and Mendelsohn, 2008). Numerous studies have emerged based on this approach in the context of Africa, South America and Europe (Chatzopoulos and Lippert, 2015; Kurukulasuriya et al., 2011; Kurukulasuriya and Mendelsohn, 2008, 2007; Mendelsohn and Seo, 2007; Seo and Mendelsohn, 2007), but there are no studies on India.

Another burgeoning body of literature in recent years has attempted to identify determinants of adaptation and its impact on agricultural output based on ESR approach (Di Falco, 2014; Bahinipati and Patnaik, 2015a). For example, Di Falco et al.

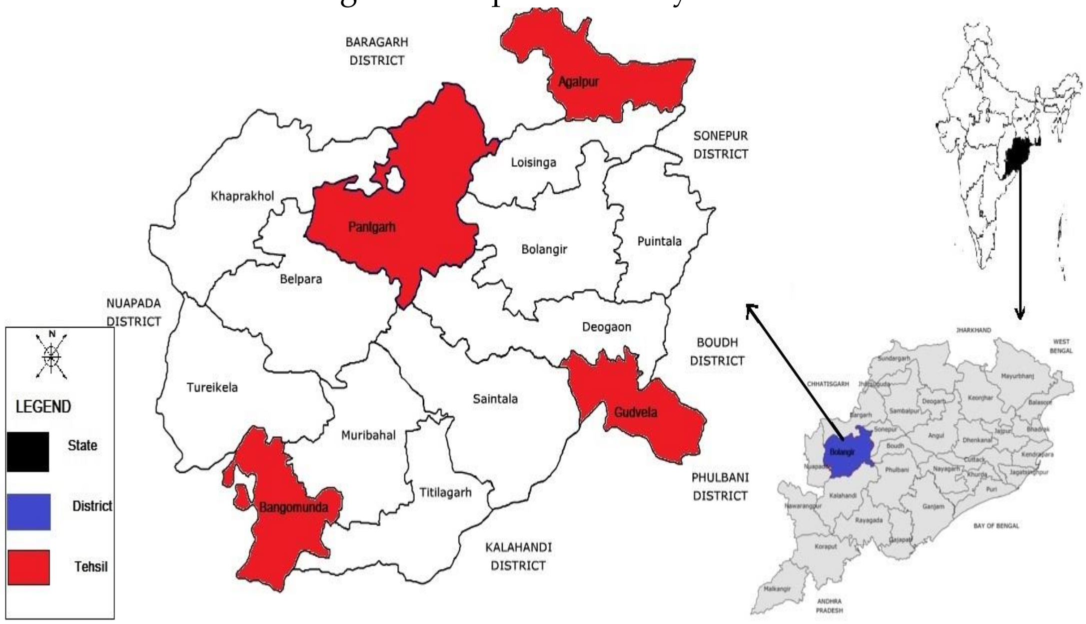
(2011), and Di Falco and Veronesi (2014) have estimated the benefits of undertaking adaptations in Ethiopia. While Di Falco et al. (2011) conclude that adaptation reduces the risk of crop failure, Di Falco and Veronesi (2014) and Teklewold et al. (2017) observe a higher economic benefit when the options are bundled. On similar lines, various studies have also looked at the impact of farm-level technological improvements, the impact of improved maize and wheat varieties, modern varieties, soil and water conservation technology and irrigation, and agricultural extension (cooperative membership) on various outcomes such as agricultural output, consumption expenditure, food security, biodiversity and household welfare (Ma and Abdulai, 2016; Kassie et al., 2015; Coromaldi et al., 2015; Khonje et al., 2015; Cunha et al., 2015; Abdulai and Huffman, 2014; Shiferaw et al., 2014). Here too, Indian studies are scanty.Hence, there is a scope to contribute to the region-specific literature.

3. Background and Context

The state of Odisha is susceptible to multiple climatic shocks such as cyclonic storms, floods, droughts, extreme temperature, etc. (Bahinipati, 2014), while the western Odisha frequently experiences recurrent droughts and deficient rainfall spells (Swain, 2014; Panda, 2016). Among the ten districts in western Odisha, Balangir (see Figure 1) is one of the highly drought-prone districts (Swain, 2014; Patnaik, 2012; Swain and Swain, 2011). It is a constituent of the erstwhile KBK (Kalahandi-Balangir-Koraput) region, one of the poorest and most underdeveloped regions of India. Between the years 1962 and 2002, the district has witnessed drought with varying intensities for 17 years, and the probability of occurrence of drought is approximately 34%, i.e., at least one drought-year in three, with the frequency increasing over time (Swain and Swain, 2011). Balangir experienced severe drought in the years 2002 and 2010, with moderate drought reported in years 1996, 1998 and 2000. As per the official estimates, the drought of 2002 imposed an economic loss of INR 1.7 billion (Patnaik, 2012). According to previous studies, households in these regions are taking up several adaptation strategies to shielding drought's impact such as insurance, migration, distress sale, credit, water conservation, shifting cultivation from rice to cotton, changing of planting dates and income diversification (Mishra, 2012; Panda et al., 2013).

A very high percentage of cultivated land is rain-fed (75%) which amplifies the risks in production systems. The HDI (Human Development Index) value, for the district is 0.546 and it is ranked 21st among the 30 districts in the state (Government of Odisha, 2013). According to Chaudhuri and Gupta (2009), around 66% of the rural households in the district fall in below the poverty line category. This further aggravates the vulnerability of majority of the rural households, particularly marginal and small farmers, to climatic shocks. Similar observations, i.e., the poorest households struggle the most with the impact of shocks that can trap them in an impoverished status from which they cannot escape, are also made by Carter et al. (2007) and Dercon (2002).

Figure 1: Map of the Study Area



In order to enhance the living standards of rural households, various livelihood interventions such as WORLP were implemented in Balangir during the last decade. It was funded by the United Kingdom's Department for International Development, and implemented over a period of ten years (2000-2011) by the Odisha Watershed Development Mission, an autonomous agency of the Government of Odisha. This project costs around INR (Indian rupees) 2.3 billion, and covered a total of 1,180 villages with 677 watersheds spread across four districts of western Odisha, namely Balangir, Nuapada, Bargarh and Kalahandi (Sharma et al., 2014). The overall goals were to reduce poverty in rain-fed areas and promote sustainable livelihoods, especially for the poor people (WORLP, 1999; Sharma et al., 2014). Following the 'Watershed-plus' approach, the major interventions were made in the land and water management activities, providing economic support to the poorest and in developing capacity building components (Sharma et al., 2014). While the first one was promoted through creation and development of watersheds which generally excludes the landless farmers, the latter two are the additional components to enhance the overall capacity of the poorest across all sections (Sharma et al., 2014).

Key activities were taken up in the construction of embankments, water storage ponds, and watershed supported irrigation channels.The capacity building component focused on the empowerment of communities through adoption of better practices in agriculture, natural resources management and providing support in terms of agricultural extension services. Specifically, the support received in terms of information, communication and advice for better management of production systems and diversification of agricultural practices could have translated into the reduction in fluctuations of agricultural output for the beneficiaries. Sharma et al. (2014) have well documented potential link of WORLP output and climate change adaptation. Further, Tiwari et al. (2011) and Esteves et al. (2013) find that land and water management activities undertaken through national rural employment guarantee scheme have potentially reduced household's vulnerability in rural India. However, there is little evidence of how revitalized ecosystems might improve households' resilience to climate change, particularly in India (Gray and Srinidhi, 2013). Indeed, examining the effects of WORLP interventions has larger policy implications, i.e., such activities can be scaled up in other regions of the country.

4. Empirical Approach

The causal relationship between farm-level adaptations to agricultural output could be examined through production function approach using Ordinary Least Squares (OLS) estimation. A binary independent variable depicting agricultural adaptation could be included in the model along with other covariates such as household- and farm-characteristics, climate change variables (temperature and rainfall), experience of shocks, and access to formal and informal institutions (Di Falco et al., 2011). Here adaptation is exogenously determined while it is potentially endogenous, i.e., the decision to adapt is voluntary and may be based on individual's selection. Farmers, for instance, might decide to adapt based on expected benefits and observed climatic patterns which makes it idiosyncratic (Di Falco et al., 2011). In addition, unobserved characteristics (e.g., farmer's technical abilities, land quality, social network and transaction costs involved in adaptation) could affect adaptation decision as well as net revenue, resulting in inconsistent estimates through OLS (Coromaldi et al., 2015; Abdulai and Huffman, 2014; Di Falco et al., 2011). Failing to control these variables may result in an upward bias in the estimated coefficients, a result which we also have observed and is presented in Appendix 1.

Without randomized control experiment, the use of cross sectional data to study the impact of a treatment (adaptation measures in the present study context) might suffer from sample selection and endogeneity biases (Coromaldi et al., 2015). Not distinguishing between the causal effect of farm level adaptation and the effect of unobserved heterogeneity could mislead policy-makers to formulate inappropriate or unwarranted policies. Addressing these issues, the present study employs ESR framework which controls for both sample selection and endogeneity biases (Coromaldi et al., 2015; Di Falco and Veronesi, 2014, 2013; Di Falco et al., 2011; see Lokshin and Sajaia, 2004). The ESR approach uses a two-stage framework to model adaptation decisions and its implications on crop production or crop failure (Di Falco and Veronesi, 2014, 2013; Di Falco et al., 2011). In the first stage, a selection model is analyzed which identifies determinants of the farm-level adaptation, and in the second stage, the impact of the adaptation on agricultural output is estimated, i.e., information stemming from the first step is used in a Ricardian model (Di Falco et al., 2011). A maximum likelihood ESR technique, originally developed as a generalization of Heckman's selection correction approach, is employed to account for endogeneity of the adaptation decision by estimating simultaneous equations model of farm-level adaptation and agricultural output in line with Di Falco and Veronesi (2014, 2013) and Di Falco et al. (2011). To distinguish between the two models, additional variables are used in the selection equation, but not in the outcome equation (these additional variables do not have any positive significant impact on the outcome variable; the results are presented in Appendix 2). While the selection model is estimated using probit regression, OLS with selectivity correction is used to examine the relationship between the outcome and a set of covariates conditional on the adaptation decision (Khonje et al., 2015).

4.1 Selection Model of Farm Level Adaptation

Farmers select an adaptation option that maximizes their expected benefit at the end of the production period, and therefore, the probability of an option being selected depends on its profitability (Bahinipati and Venkatachalam, 2015). Following Di Falco et al., (2011), let A^* be the latent variable that captures the expected net revenues from adaptation choice with respect to not adapting. While adaptation is a binary choice, the latent variable is:

$$A_i^* = Z_i\alpha + \eta_i \text{ with } \mathrm{A}_i = \begin{cases} 1 \; if \; A_i^* > 0 \\ 0 \; Otherwise \end{cases} \tag{1}$$

The deterministic component Z_i that influences the likelihood of adaptation includes household-and farm-specific characteristics, major livelihood interventions (e.g., WORLP in the present context), access to formal and informal institutions, experience of climatic shocks (whether drought was experienced during the last five years) and other selection instruments[1]. The selection instruments are access to agricultural extension, other livelihood support mechanisms (e.g., Mahatma Gandhi National Rural Employment Guarantee Scheme – MGNREGS), infant mortality, health expenditure and months of food scarcity experienced by the household.

1 These variables were taken to distinguish between the two equations, i.e., selection and outcome equations. On the other hand, it is also important that 'Z_i'should include a set of selection instruments in addition to those automatically generated by the non-linearity of the selection model of adoption, so that the ESR model could be identified (Khonje et al., 2015).

4.2 Endogenous Switching Regression Model

In the second stage, ESR is used to estimate impact of adaptation strategy on agricultural output (net revenue and value of production). Since adaptation is a binary variable a farmer faces two regimes: (i) to employ adaptation measures and (ii) not to adapt. The regression model is defined as (Di Falco et al., 2011),

$$\text{Regime1}: y_{1i} = X_{1i}\beta_1 + \varepsilon_{1i} \quad if \; A_i = 1 \tag{2a}$$

$$\text{Regime2}: y_{2i} = X_{2i}\beta_2 + \varepsilon_{2i} \quad if \; A_i = 0 \tag{2b}$$

Where y_i represents net revenue and value of agricultural output in regimes 1 and 2, and X_i depicts household and farm characteristics, major livelihood intervention and access to formal and informal institutions. While β_1 and β_2 are the vectors of parameters to be estimated, the error terms in both selection and outcome equations η_i *and* ε_i are assumed to have a trivariate normal distribution with zero mean and covariance matrix (Di Falco et al., 2011; Khonje et al., 2015):

$$\sum(\eta, \varepsilon_1, \varepsilon_2) = \begin{bmatrix} \sigma_\eta^2 & \sigma_{\eta 1} & \sigma_{\eta 1} \\ \sigma_{1\eta} & \sigma_1^2 & . \\ \sigma_{2\eta} & . & \sigma_2^2 \end{bmatrix} \tag{3}$$

Here σ_η^2 the variance of the error term in the selection equation (equation 1) equals 1 since coefficients are estimated till a scale factor (Coromaldi et al., 2015), and σ_1^2 and σ_2^2 are variances of the error term in the agricultural outcome equations (equations 2a and 2b). Both are observed separately, and therefore, covariance between them is not defined. The covariance of the error terms in the selection (η) and agricultural output (ε_1 and ε_2) equations are $\sigma_{1\eta}$ and $\sigma_{2\eta}$. If the following correlation coefficients turn significant, they indicate endogeneity of both the equations and provide validity to usage of ESR method with full information maximum likelihood (Coromaldi et al., 2015):

$$\rho_{1\eta} = \sigma_{1\eta} / \sigma_1 \sigma_\eta \quad , \; \rho_{2\eta} = \sigma_{2\eta} / \sigma_2 \sigma_\eta \tag{4}$$

As outlined by Khonje et al. (2015) the expected values of truncated errors (ε_1 and ε_2) conditional on the sample selection equal:

$$E\left(\varepsilon_{1i} \mid A_i = 1\right) = \sigma_{1\eta} \frac{\phi\left(Z_{i\alpha}\right)}{\Phi\left(Z_{i\alpha}\right)} = \sigma_{1\eta}\lambda_{1i} \qquad (5a)$$

$$E\left(\varepsilon_{2i} \mid A_i = 0\right) = -\sigma_{2\eta} \frac{\phi\left(Z_{i\alpha}\right)}{1-\Phi\left(Z_{i\alpha}\right)} = \sigma_{2\eta}\lambda_{2i} \qquad (5b)$$

While $\phi(.)$ is the standard normal probability density function, $\Phi(.)$ is the standard normal cumulative density function. Treatment effects are analyzed by estimating four variations of equation 6: expected agricultural output of (a) farmers that used agricultural adaptation, (b) farmers who did not use any adaptation measure, (c) if adopter farmers did use adaptation measure, and (d) if non-adapters would have employed any adaptation mechanism. Following Khonje et al., (2015) and Di Falco et al. (2011) the conditional expectations are:

$$E\left(y_{1i} \mid A_i = 1\right) = X_{1i}\beta_1 + \sigma_{1\eta}\lambda_{1i} \qquad (6a)$$

$$E\left(y_{2i} \mid A_i = 0\right) = X_{2i}\beta_2 + \sigma_{2\eta}\lambda_{2i} \qquad (6b)$$

$$E\left(y_{2i} \mid A_i = 1\right) = X_{1i}\beta_2 + \sigma_{2\eta}\lambda_{1i} \qquad (6c)$$

$$E\left(y_{1i} \mid A_i = 0\right) = X_{2i}\beta_1 + \sigma_{1\eta}\lambda_{2i} \qquad (6d)$$

Cases 'a' and 'b' in equation 6 represent actual expectation observed in the sample, whereas 'c' and 'd' represent the counterfactual. The effect of treatment (TT) for adopter households is the difference between (a) and (c) that indicates the effect of adaptation on agricultural productivity for farmers who actually adapted. This computes the average difference in outcomes of adopters with and without an adaptation:

$$\begin{aligned} TT &= E\left(y_{1i} \mid A_i = 1\right) - E\left(y_{2i} \mid A_i = 1\right) \\ &= X_{1i}\left(\beta_1 - \beta_2\right) + \left(\sigma_{1\eta} - \sigma_{2\eta}\right)\lambda_{1i} \qquad (7a) \end{aligned}$$

The effect of treatment in the case of non-adopter households (TU) is the difference between (d) and (b) which estimates the benefits of undertaking adaptation on agricultural productivity in the context of non-adopter households:

$$\begin{aligned} TU &= E\left(y_{1i} \mid A_i = 0\right) - E\left(y_{2i} \mid A_i = 0\right) \\ &= X_{2i}\left(\beta_1 - \beta_2\right) + \left(\sigma_{1\eta} - \sigma_{2\eta}\right)\lambda_{2i} \qquad (7b) \end{aligned}$$

Based on the above equations (a through d), heterogeneity effects is also estimated. Following Carter and Milon (2005), the effect of base heterogeneity for farmers who decided to adapt as the difference between (a) and (d):

$$\begin{aligned} BH_1 &= E\left(y_{1i} \mid A_i = 1\right) - E\left(y_{1i} \mid A_i = 0\right) \\ &= \left(X_{1i} - X_{2i}\right)\beta_{1i} + \sigma_{1\eta}\left(\lambda_{1i} - \lambda_{2i}\right) \end{aligned} \qquad (7c)$$

For farmers who did not adapt, the effect of base heterogeneity is the difference between (c) and (b):

$$\begin{aligned} BH_2 &= E\left(y_{2i} \mid A_i = 1\right) - E\left(y_{2i} \mid A_i = 0\right) \\ &= \left(X_{1i} - X_{2i}\right)\beta_{2i} + \sigma_{2\eta}\left(\lambda_{1i} - \lambda_{2i}\right) \end{aligned} \qquad (7d)$$

In addition, transitional heterogeneity (TH) could also be calculated to test the effect of employing farm adaptation measures i.e., the difference between TT and TU as outlined by Di Falco et al. (2011).

5. Data and Descriptive Statistics

The study uses data from a household survey conducted during late 2014 in four blocks (administrative divisions within a district) of Balangir district: (i) Agalpur, (ii) Bongamunda, (iii) Gudvela and (iv) Patnagarh where the WORLP interventions were carried out during the initial phase of implementation (Figure 1). While Agalpur is geographically located on the northern part of the district, Bongamunda is on the southern part. Gudvela and Patnagarh lie in the eastern and western parts of district, respectively. Stratified random sampling was used to select the villages for survey. Villages were selected from within the command area of watersheds and from outside. All households in the command area were WORLP beneficiaries while those outside were non-beneficiaries. In total, 800 households (600 beneficiaries) were surveyed randomly, out of which 549 households practiced agriculture and constituted the sample for the analysis of this paper. Information was elicited through a structured pre-tested interview schedule that included questions on household characteristics, land, crop and livestock details, consumption details, health and food security, household assets, loan, credit and savings, impact of climatic aberrations and adaptation measures.

Table 1 presents the variables used in the analysis along with definitions and descriptive statistics for the sample. In addition, Appendix 3 reports the descriptive statistics with results of tests for equality of means for adopters and non-adopters. Farm-level adaptation (AG_{ADAPT}) is quantified using a dummy that takes value 1 if the farmer adopts at least one farm-level adaptation option and 0 otherwise. Creation of field contour dams, use of drought-tolerant seeds and diversification of agricultural system were major forms of farm-level adaptation to climate change that were followed by 74% of the farmers. It was assumed that the surveyed farmers chose these options to mitigate the possible impact of climate variability and shocks.

While agricultural adaptation is the outcome variable in the selection equation, there are three dependent variables in the outcome equation: net revenue (N_{Rev}), value of agricultural output (VOP), and value of agricultural output per hectare (VOP_H). Net revenue was the difference between value of the total agricultural output produced by the household and total cost of production comprising input cost, labour cost, and expenditure for land preparation and harvesting. Value of production was arrived at by multiplying the total output of various agricultural products by their market price and adding them up. Household-specific characteristics were captured using the household size (SIZE), the age of the household head (AGE), years of education of the household head (EDU), technical education of the household head (EDU_T), value of agricultural assets owned (ASET), ownership of land (LAND) and migration (MIG). Based on the previous studies, it is expected that these variables positively influence adoption decision and outcome (Coromaldi et al., 2015; Bahinipati, 2015; Bahinipati and Venkatachalam, 2015; Cunha et al., 2015; Panda et al., 2013; Di Falco et al., 2011).

In the sample, 75% of the households were WORLP beneficiaries. A priori, this attribute is expected to display a positive relationship with both selection and outcome variables. Variables related to farm characteristics included the number of crops cultivated (CRP_N), the total value of agricultural input ($INPT_C$) and the number of livestock owned (LVST). There is a high likelihood that these variables positively influence farmers' adoption behaviour and crop income. Four variables were used to study the effects of formal and informal institutions: access to formal or informal credit (CRED), membership in a self-help group (SHG), owning a kisan credit card (KCC) and participation in employment guarantee scheme (EGS). Previous studies have found that farmers' adoption behaviour is influenced by access to formal and informal institutions (Bahinipati, 2015; Bahinipati and Venkatachalam, 2015; Coromaldi et al., 2015). Since the sample was drawn from a single district, it is assumed that significant variations in temperature and rainfall may not exist across the sample households. Moreover, the households had experienced droughts over the years, and they were specially asked to describe whether they had suffered a drought in the last five years (DRT). Earlier studies had also used climatic shocks variables in the model (Coromaldi et al., 2015; Di Falco et al., 2011).

Five selection instrument variables were included in the adaptation choice model to distinguish between selection and outcome equations. These were access to agricultural extension (EXTN) and other livelihood support schemes (SUP_{LV}), infant mortality reported during the past five years ($MORT_I$), household's health expenditure (EXP_H) and the number of months of food scarcity ($SCAR_F$) in the previous year. These are likely to have significant impact on farmers' decision to go for farm-level adaptation options. The t-value (presented in column 4, Appendix 3) suggests differences between the adopters and the non-adopters of adaptation mechanisms, with respect to household level characteristics, livelihood interventions, farm characteristics, and access to formal and informal institutions, negating the usage of non-adopters as control. The value of production significantly differs between adopters and non-adopters, indicating that the choice of adaptation has positively affected the agricultural output. Moreover, significant mean differences are observed for the age of household head; access to technical education and WORLP; livestock ownership; access to credit, SHGs, KCC, and extension; previous experience of drought and the number of months of food insufficiency.

Table 1: Summary of Variables and Descriptive Statistics for the Sample

Variable	Description of the Variable (Unit)	Mean (S.D.)
Outcome Variables		
AG_{ADAPT}	Dummy=1 if the household employs agricultural adaptation measures; 0 otherwise	0.74 (0.44)
LN_{Rev}	Net Revenue in natural log	8.94 (1.81)
LVOP	Value of agricultural output in natural log	9.96 (1.49)
$VOPT_{H}$	Value of agricultural output per hectare in natural log	10.17 (1.64)
N_{Rev}	Net Revenue (Rs.)	13,735.76 (11,663.79)
VOP	Value of agricultural output (Rs.)	30,079.6 (20,322.97)
VOP_{H}	Value of agricultural output per hectare (Rs./ha)	36,384.06 (20776.97)
Independent Variables		
Household and Household head characteristics		
SIZE	Total household members	5.32 (2.7)
AGE	Age of the household head	51.63 (11.79)
EDU	Number of years of education of the head of the household	3.31 (3.38)
EDU_{T}	Dummy =1 if the household head possesses technical education; 0 otherwise	0.05 (0.22)
ASET	Value of agricultural assets owned by the household in natural log	3.57 (3.68)
LAND	Agricultural land owned by the household in hectare	0.95 (0.81)
MIG	Dummy=1 if the household has migrant members; 0 otherwise	0.24 (0.43)

Major Livelihood Intervention		
WORLP	Dummy=1 if the household is beneficiary of WORLP; 0 otherwise	0.75 (0.43)
Farm characteristics		
CRP_N	Number of crops cultivated	1.32 (0.96)
$INPT_C$	Total value of all agricultural inputs used in natural log	9.46 (0.82)
$INPT_{CH}$	Total value of all agricultural inputs used per hectare in natural log	9.60 (1.52)
LVST	Number of big and small ruminants owned by the household	3.39 (4.6)
Formal and Informal Institutions		
CRED	Dummy=1 if the household has access to formal and informal credit; 0 Otherwise	0.38 (0.48)
SHG	Dummy=1 if the household has access to self-help group; 0 otherwise	0.39 (0.49)
KCC	Dummy=1 if the household has access to Kisan Credit Card; 0 otherwise	0.13 (0.34)
EGS	Dummy=1 if the household members have employment in MGNREGS; 0 otherwise	0.67 (0.47)
Experienced Climatic Shocks		
DRT	Dummy=1 if household is affected by drought during last 5 years; 0 otherwise	0.75 (0.43)
Selection Instruments		
EXTN	Dummy=1 if the household has access to agricultural extension; 0 otherwise	0.31 (0.46)
Variable	Description of the Variable (Unit)	Mean (S.D.)
SUP_{LV}	Dummy=1 if the household has benefited from various livelihood support schemes; 0 otherwise	0.25 (0.43)
$MORT_I$	Number of infant mortality recorded in the household during last 5 years	0.05 (0.29)
EXP_H	Health expenditure incurred by the household during the previous year in natural log	6.29 (3.24)
$SCAR_F$	Number of months of food scarcity faced by the household during the previous year	0.96 (1.29)

Source: Computed by the authors' from the primary data

6. Results and Discussion

The estimation results for ESR model are presented in Table 2. Estimations of the selection equations are depicted in columns (2), (5) and (8). In addition, the regime equations for adopters and non-adopters are shown respectively in columns (3) and (4) for net revenue, (6) and (7) for value of agricultural production, and (9) and (10) for value of agricultural production per ha. Robust standard error was used to control for heteroskedasticity, and the mean variance of inflation factor was 1.14, indicating the absence of multicollinearity among the independent variables. The estimates of σ_i and ρ_j account for endogenous switching in the agricultural outcome functions. It is found that correlation coefficients ρ_j (see equation 4) are significant, implying that the hypothesis of absence of sample selectivity bias may be rejected. This suggests self-selection in taking up farm-level adaptation, supporting the application of the ESR in the present manuscript. Correspondingly, farm-level adaptation may not have the same impact on the non-adopters, if they choose to adapt (Abdulai and Huffman, 2014). Moreover, the positive sign of ρ_j indicates a negative selection bias, suggesting that farmers with below average yields and net returns are more likely to adopt farm-level adaptation mechanisms in contrast to the findings of Abdulai and Huffman, (2014) and Di Falco et al. (2011).

In the selection equations (columns 2, 5 and 8), eight variables were found to be significant: being a WORLP beneficiary, age and technical education of the head of household, ownership of livestock, access to credit (formal and informal), past drought experience, infant mortality, and months of food scarcity during the previous year. In line with the findings of the earlier literature (Bahinipati, 2015; Bahinipati and Venkatachalam, 2015; Panda et al., 2013; Bryan et al., 2009; Hassan and Nhemachena, 2008), it is found that older and experienced farmers are more likely to employ adaptation options. Similarly, WORLP beneficiaries have a higher likelihood of adopting various adaptation measures as compared to non-beneficiaries. This indicates a positive spillover effect of the development-based programme: the programme influences the farmer to take up several adaptation measures. It should be noted here that a key activity in WORLP was agricultural extension support offered to beneficiaries such as promulgation of drought-tolerant seeds, technical support during cropping season and post-harvest, and water and land management activities. These activities seem to have contributed to building awareness about the effects of adopting various farm-level adaptation mechanisms on crop income among beneficiaries.

Table 2: Parameters Estimates of Household Adaptation at Farm Level to Climatic Aberrations and Change

Outcome Variable	Model 1			Model 2			Model 3		
	AG_{ADAPT}	HH_{ADAPT}	HH_{NADAPT}	AG_{ADAPT}	HH_{ADAPT}	HH_{NADAPT}	AG_{ADAPT}	HH_{ADAPT}	HH_{NADAPT}
		LN_{Rev}	LN_{Rev}		LVOP	LVOP		$LVOP_H$	$LOPT_H$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Household and Household head characteristics									
SIZE	-0.014 (0.025)	-0.011 (0.026)	0.130 (0.083)	-0.015 (0.025)	-0.008 (0.013)	0.088 (0.059)	-0.012 (0.024)	-0.015 (0.014)	0.087* (0.049)
AGE	0.019*** (0.006)	-0.007 (0.005)	0.006 (0.016)	0.018*** (0.006)	-0.003 (0.003)	0.009 (0.013)	0.019*** (0.006)	-0.001 (0.002)	0.013 (0.013)
EDU	-0.015 (0.021)	0.007 (0.020)	-0.058 (0.057)	-0.015 (0.021)	0.010 (0.009)	0.024 (0.034)	-0.018 (0.021)	0.007 (0.009)	0.041 (0.028)
EDU_T	0.697** (0.353)	-0.030 (0.235)	0.707 (1.063)	0.699** (0.352)	0.018 (0.097)	-0.356 (0.598)	0.667* (0.345)	-0.034 (0.096)	-0.475 (0.320)
ASET	-0.012 (0.020)	0.045** (0.019)	0.002 (0.045)	-0.013 (0.020)	0.022* (0.012)	-0.005 (0.042)	-0.009 (0.019)	0.013 (0.011)	0.022 (0.030)
LAND	-0.036 (0.082)	0.435*** (0.091)	0.867*** (0.320)	-0.058 (0.091)	0.178* (0.105)	0.340 (0.312)	-	-	-
MIG	0.195 (0.169)	-0.039 (0.170)	-0.038 (0.419)	0.206 (0.170)	-0.105 (0.122)	0.251 (0.252)	0.176 (0.167)	-0.067 (0.131)	0.166 (0.207)
Major Livelihood Intervention									
WORLP	0.970*** (0.170)	0.416*** (0.161)	-	0.965*** (0.169)	0.262* (0.146)	-	0.973*** (0.168)	0.269* (0.150)	-
Farm characteristics									
CRP_N	0.122 (0.076)	0.279*** (0.091)	0.715*** (0.223)	0.124 (0.075)	0.161*** (0.047)	0.385** (0.188)	-	-	-
INP_C / INP_{CH}	-	-	-	0.023 (0.092)	0.652*** (0.115)	0.860*** (0.090)	0.060 (0.042)	0.961*** (0.055)	0.969*** (0.032)
LVST	-0.033** (0.016)	-0.008 (0.023)	0.008 (0.029)	-0.035** (0.016)	0.007 (0.008)	-0.014 (0.031)	-0.033** (0.015)	0.017** (0.007)	0.005 (0.021)

Outcome Variable	Model 1			Model 2			Model 3		
	AG_{ADAPT}	HH_{ADAPT}	HH_{NADAPT}	AG_{ADAPT}	HH_{ADAPT}	HH_{NADAPT}	AG_{ADAPT}	HH_{ADAPT}	HH_{NADAPT}
		LN_{Rev}	LN_{Rev}		LVOP	LVOP	(8)	$LVOP_H$	$LOPT_H$
(1)	(2)	(3)	(4)	(5)	(6)	(7)		(9)	(10)
Formal and Informal Institutions									
CRED	0.758*** (0.152)	-0.116 (0.145)	0.035 (0.489)	0.768*** (0.154)	-0.135 (0.101)	0.077 (0.260)	0.755*** (0.150)	-0.052 (0.084)	0.081 (0.205)
SHG	0.212 (0.136)	0.046 (0.143)	-0.508 (0.421)	0.224 (0.137)	-0.007 (0.101)	-0.263 (0.339)	0.219 (0.135)	-0.013 (0.103)	-0.103 (0.308)
KCC	0.072 (0.213)	-0.092 (0.241)	0.773* (0.410)	0.095 (0.214)	-0.103 (0.178)	0.633** (0.301)	0.081 (0.213)	-0.144 (0.179)	0.556** (0.216)
EGS	0.153 (0.150)	-0.296** (0.131)	-0.103 (0.425)	0.151 (0.150)	-0.151** (0.059)	0.336 (0.429)	0.149 (0.147)	-0.124* (0.069)	0.215 (0.386)
Experienced Climatic Shocks									
DRT	0.441*** (0.152)	-0.244 (0.150)	1.074 (0.497)	0.444*** (0.153)	-0.200*** (0.061)	0.647 (0.441)	0.417*** (0.151)	-0.257*** (0.062)	0.105 (0.304)
Selection Instruments									
EXTN	-0.007 (0.168)	-	-	0.003 (0.166)	-	-	-0.035 (0.164)	-	-
SUP_{LV}	-0.274 (0.169)	-	-	-0.276 (0.170)	-	-	-0.216 (0.167)	-	-
$MORT_I$	0.694** (0.351)	-	-	0.738** (0.365)	-	-	0.749** (0.363	-	-
EXP_H	0.004 (0.021)	-	-	0.008 (0.021)	-	-	0.004 (0.020)	-	-
$SCAR_F$	-0.277*** (0.069)	-	-	-0.277*** (0.068)	-	-	-0.251*** (0.063)	-	-
Constant	-1.344*** (0.428)	8.526*** (0.299)	5.421*** (1.484)	-1.552* (0.892)	3.617*** (0.977)	-1.128 (1.471)	-1.808*** (0.588)	1.049** (0.527)	-1.130 (1.125)
σ_i	-	0.198*** (0.064)	-0.091 (0.278)	-	0.192*** (0.042)	-0.22 (0.214)	-	0.169*** (0.038)	-0.202 (0.218)

ρ_j	-	1.475*** (0.117)	2.035*** (0.122)	-	0.986 (0.221)	1.749*** (0.17)	-	0.956 (0.246)	1.509*** (0.237)
N	549			549			549		
Wald χ^2	79.93***			664.80***			731.21***		
Wald test	9.45***			21.20***			20.94***		

Source: Computed by the authors' from the primary data

Note: Estimation by full information maximum likelihood at the household level; robust standard errors in parentheses; σ_i represents variance of the error terms of the outcome equations; ρ_j denotes correlation between the error term in the selection equation and error terms in the outcome equations; *** p<0.01, ** p<0.05, * p<0.1

Households with access to credit (both formal and informal) are more likely to undertake adaptation mechanisms. Jodha (1981) states three ways in which credit helps farmers to reduce risks: (i) credit adds resources to agricultural system thus reducing vulnerability, (ii) it minimizes risks/losses, and (iii) it helps better loss management after a disaster. Whereas the first two directly govern farmer's behaviour, the last one indirectly influences their actions (Bahinipati and Venkatachalam, 2015). A possible reason for the negative relationship between the number of months of food insufficiency and adaptation to climatic shocks could be limited liquidity.

The results of the impact of farm-level adaptation on net revenue and value of agricultural production are presented for adopters and non-adopters respectively in columns (3), (4), (6), (7), (9) and (10) of Table 2. The differences in coefficients for outcome equations between farm households that adapted and those that did not, illustrate the presence of heterogeneity. Consistent with the economic theory, farm characteristics variables (i.e., number of crops and input costs) are found to be positive and significant in the case of both adopter and non-adopter equations. Moreover, these covariates have a higher impact in the case of non-adopter than adopter households which is in contrast with the findings of the previous studies, e.g., Di Falco et al. (2011) and Coromaldi et al. (2015). The other important factors in explaining higher net revenue and value of production among the farm households adapted are ownership of assets, landholding, and benefits from WORLP interventions (see Table 2).

The expected agricultural output, in terms of net revenue and value of production, under actual counterfactual conditions is presented in Table 3. While the values reported in cells (a) and (b) present expected agricultural output observed in the sample, cells (c) and (d) depict the counterfactual not observed from the sample. Column (6) of Table 3 derives the treatment effects of undertaking agricultural adaptation. Households that employed adaptation instruments display higher expected net revenue (INR 10,543) compared to non-adopters (INR 4,080) with a significant treatment effect of INR 6,462. On the other hand, the expected net revenue for farmers that did not adapt is INR 4,606, while they could have earned up to INR 38,042 had they taken up farm-adaptation translating to a significant mean difference to the tune of INR 33,436. These imply that farm level adaptation significantly enhances agricultural production, and in fact, adaptation benefits would have been more for the non-adopter households than those for the current adopters. The value for transitional heterogeneity is negative, which leads to the inference that the effects of adaptation are significantly smaller for the farm households that adapt than those did not adapt. This finding is similar to that of Di Falco et al. (2011). In addition, estimated heterogeneity effects suggest that the non-adopter farmers could be better off by taking farm level adaptation compared to the current adopters.

Similar trends also emerge for value of production per ha. The effect of treatment is significantly higher for both groups of households. While the difference is approximately INR 23,892 for farmers opting for adaptation, it stood at INR 12,589 for non-adopters. On the other hand, transitional heterogeneity is both positive and significant. This shows that the adapted households are better off by taking adaptation measure than non-adapted farmers. This is in contrast with the results reported for net revenue due to scale effects. The results obtained while considering the value of production per ha as an outcome also account for the intensity and nature of cropping besides land quality, and hence, are parsimonious. Therefore in absolute terms undertaking farm level adaptations have a positive impact on agricultural output, and in turn, could contribute towards enhancing food security in rural India. These are consistent with the findings of Di Falco et al. (2011), namely farm-level adaptation can improve agricultural income and food security.

Table 3: Treatment and Heterogeneity Effects for Average Expected Net Revenue, Value of Production and Value of Production per hectare

Decision Rule					
Sub Samples		To Adapt		Not to Adapt	Treatment Effects
(1)	(2)	(3)	(4)	(5)	(6)
N_{Rev}					
HH_{ADAPT}	(a)	10,543.04 (667.75)	(c)	4,080.73 (154.64)	6,462.31*** (715.65)
HH_{NADAPT}	(d)	38,042.86 (12,814.77)	(b)	4,606.63 (518.43)	33,436.24*** (13,448.5)
Heterogeneity Effects		-27,499.95*** (12,832.16)		-525.90 (540.99)	-26,973.93*** (657.98)
VOP					
HH_{ADAPT}	(a)	28,693.17 (1,242.98)	(c)	7,744.58 (644.37)	20,948.59*** (1,441.11)
HH_{NADAPT}	(d)	29,853.65 (4,213.17)	(b)	10,105.8 (1,065.90)	19,747.85*** (4,533.96)
Heterogeneity Effects		-1160.48 (4,392.70)		-2361.22** (1,245.54)	1,200.74*** (171.97)
VOP_H					
HH_{ADAPT}	(a)	34,257.8 (1,131.88)	(c)	10,365.81 (867.98)	23,891.99*** (1,447.09)
HH_{NADAPT}	(d)	24,239.47 (1,056.62)	(b)	11,650.75 (995.47)	12,588.72*** (1,459.08)
Heterogeneity Effects		10,018.34*** (1,548.41)		-1,284.93 (1,320.74)	11,303.27*** (72.65)

Source: Computation from the primary data
Note: Standard deviation in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All figures in Indian Rupees (INR)

7. Conclusion

This study has examined the inter-linkages between developmental interventions like WORLP, farm-level adaptation decision and farmers' wellbeing among the drought affected rural households in western Odisha. The objective of this study was twofold: (i) to explore the possible impact of WORLP on farmers' adaptation decision along with other covariates, and (ii) to estimate the effectiveness of adoption options. This has larger policy implications in the present situation since the literature advocates integration of adaptation to climate change into development planning. The empirical analysis is based on a cross sectional survey of 549 farm households in western Odisha. We have employed the ESR approach to account for sample selectivity bias and capture the differential impact of farm-level adaptations on the households that adapted and those that did not.

In sum, having technical education and experience of the head of the household, access to credit, previous experience of droughts, recorded infant mortality and months of food scarcity during the previous year are the major determinants of farm-level adaptation measures. It also emerges that WORLP had played a positive role in influencing farmers to seek adaptation measures. Government policies and investments, therefore, must promote access to these determinants to enhance adaptive capacity of farmers in vulnerable regions of rural India. This is in line with a few studies which observe that the employment guarantee scheme in rural India like MGNREGS has reduced the vulnerability of households (Esteves et al., 2013; Tiwari et al., 2011). Initiating developmental interventions based on the lines of WORLP would enhance farm-level adaptations, and in turn, reduce vulnerability of farmers. Availability and access to rural finance through development of credit markets will allow households to make investments in farm-level adaptations. The significant positive impact of farm-level adaptation on agricultural output reaffirms the potential role of adaptation in reducing production volatility, raising farm output and directly reducing rural poverty through higher income – similar to the finding of Abdulai and Huffman(2014). It also emerges that the non-adapters would receive higher net revenue by undertaking adaptation than received by the current adopters. Thus the beneficial effect of adaptation is found to be significantly high. These results are particularly important from policy perspectives while (i) designing effective adaptation strategies to withstand volatility in agricultural production and (ii) formulating management strategies for sustainable agriculture.

However, the results of this study need to be interpreted with caution. A key limitation has been the non-availability of detailed plot-level data which results in exclusion of many covariates related to farm and crop characteristics such as soil and input quality. The absence of key climate parameters like temperature and rainfall in the model is another limitation. However, since the study area is not geographically diverse and confined within a single agro-ecological zone, the possibility of confounding is limited. Future research could attempt to address these concerns by using panel data from multiple agro-ecological zones while also focusing on behavioral aspects to derive an inclusive policy.

Nonetheless, the findings suggest first, that developmental interventions in rural India enhance the likelihood of adopting various farm-level adaptation options to climate change, although these programmes are not specifically aimed to mitigate the impact of climatic aberrations and extremes. In fact, Government of India's recent guidelines on watershed development have not pointed out its inter-linkages with resilience and adaptation to climate change (Gray and Srinidhi, 2013). Secondly, additional focus of such interventions on livelihood security promotes access to formal institutions like credit availability which is a crucial determinant of adaptation decision. This study recommends that such developmental interventions in rural India be scaled up in order to extend the adoption of various farm-level adaptation mechanisms, so that we can avoid potential adverse impact of climate change in the foreseeable future, particularly in rural India.

References

Abdulai, A., and W. Huffman (2014). 'The adoption and impact of soil and water conservation technology: an endogenous switching regression application', *Land Economics*, 90(1), pp. 26-43.

Bahinipati, C. S. (2014). 'Assessment of vulnerability to cyclones and floods in Odisha, India: A District-level analysis', *Current Science*, 107(12), pp. 1997-2007.

Bahinipati, C.S. (2011). 'Economics of adaptation to climate change: learning from impact and vulnerability literature'. *MIDS Working Paper No. 213*, Madras Institute of Development Studies, Chennai, India.

Bahinipati, C.S. (2015). 'Determinants of farm-level adaptation diversity to cyclone and flood: insights from a farm household-level survey in Eastern India', *Water Policy*, 17(4), pp. 742-761.

Bahinipati, C.S., and L. Venkatachalam (2015). 'What drives farmers to adopt farm-level adaptation practices to climate extremes: empirical evidence from Odisha, India', *International Journal of Disaster Risk Reduction*, 14(4), pp. 347-356.

Bahinipati, C.S., and U. Patnaik (2015a). 'Climate change economics: a review on theoretical understanding and controversies', *GIDR Working Paper Series No. 226*, Gujarat Institute of Development Research, Ahmedabad, India.

Bahinipati, C.S., and U. Patnaik (2015b). 'The damages from climate extremes in India: do disaster specific and generic adaptation measures matter?', *Environmental Economics and Policy Studies*, 17(1), pp. 157-177.

Bryan, E., T. Deressa, G.A. Gbetibouo, C. Ringler, (2009). 'Adaptation to climate change in Ethiopia and South Africa: options and constraints', *Environmental Science and Policy*, 12(4), pp. 413–426.

Carter, D.W., and J.W. Milon (2005). 'Price knowledge in household demand for utility services', *Land Economics*, 81(2), pp. 265–283.

Carter, M. R., P.D. Little, T. Mogues, and W. Negatu (2007). 'Poverty traps and natural disasters in Ethiopia and Honduras', *World Development*, 35(5), pp. 835-856.

Chatzopoulos, T., and C. Lippert (2015). 'Adaptation and climate change impacts: a structural Ricardian analysis of farm types in Germany', *Journal of Agricultural Economics*, 66(2), pp. 537-554.

Chaudhuri, S., and N. Gupta (2009). 'Levels of living and poverty patterns: a district-wise analysis for India', *Economic and Political Weekly*, 44(9), pp. 94-110.

Coromaldi, M., G. Pallante, and S. Savastano, (2015). 'Adoption of modern varieties, farmers' welfare and crop biodiversity: evidence from Uganda', *Ecological Economics*, 119, pp. 346-358.

Cunha, D. A., A.B. Coelho, J.G. Feres (2015). 'Irrigation as an adaptive strategy to climate change: an economic perspective on Brazilian agriculture', *Environment and Development Economics*, 20(1), pp. 57-79.

Dercon, S. (2002). 'Income risk, coping strategies and safety nets', *World Bank Research Observer*, 17(2), pp. 141–166.

Dercon, S. (2013). 'Agriculture and development: revisiting the policy narratives', *Agricultural Economics*, 44(s1), pp. 183-187.

Devereux, S. (2007). 'The impact of droughts and floods on food security and policy options to alleviate negative effects', *Agricultural Economics*, 37, pp. 47-58.

Di Falco, S. (2014). 'Adaptation to climate change in Sub-Saharan agriculture: assessing the evidence and rethinking the drivers', *European Review of Agricultural Economics*, 41(3), pp. 405-430.

Di Falco, S., and M. Veronesi (2013). 'How African agriculture can adapt to climate change? a counterfactual analysis from Ethiopia', *Land Economics*, 89(4), pp. 743-766.

Di Falco, S., and M. Veronesi (2014). 'Managing environmental risk in presence of climate change: the role of adaptation in the Nile Basin of Ethiopia', *Environment and Resource Economics*, 57, pp. 553-577.

Di Falco, S., M. Veronesi, and M. Yesuf (2011). 'Does adaptation to climate change provide food security? a micro-perspective from Ethiopia', *American Journal of Agricultural Economics*, 93(3), pp. 829–846.

Dorward, A., and J. Kydd (2002). '*The Malawi 2002 food crisis: the rural development challenge*', Imperial College, Wye.

Ericksen, P. J., J.S.I. Ingram, D.M. Liverman (2009). 'Food security and global environmental change: emerging challenges', *Environmental Science and Policy*, 12, pp. 373-377.

Esteves, T. *et al.* (2013). 'Agricultural and Livelihood Vulnerability Reduction through the MGNREGA', *Economic and Political Weekly*, XLVIII(52), pp. 94-103.

Government of Odisha (2013). '*Economic Survey 2013*', Planning and Coordination Department, Government of Odisha, Bhubaneswar, India.

Gray, E., and A. Srindhi (2013). 'Watershed development in India: economic valuation and adaptation considerations', *Working Paper*, World Resource Institute, Washington D.C. Retrieved from https://www.wri.org/sites/default/files/watershed_development_india.pdf; accessed on April 13, 2017.

Haen, H.D., and G. Hemrich (2007). 'The economics of natural disasters: implications and challenges for food security', *Agricultural Economics*, 37, pp. 31-45.

Hassan, R., and C. Nhemachena (2008). 'Determinants of African farmer's strategies for adapting to climate change: multinomial choice analysis', *African Journal of Agriculture and Resource Economics*, 2(1), pp. 83–104.

IPCC (Intergovernmental Panel on Climate Change) (2012). '*Managing the risks of extreme events and disasters to advance climate change adaptation*', A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. New York: Cambridge University Press.

Jayaraman, T., and K. Murari (2014). 'Climate change and agriculture: current and future trends, and implications for India', *Review of Agrarian Studies*, 4(1), pp. 1-49.

Jodha, N.S. (1981). 'Role of credit in farmers' adjustment against risk in arid and semi-arid tropical areas of India', *Economic and Political Weekly*, 26(42–43), pp. 1696–1709.

Kassie, M., H. Teklewold, P. Marenya, M. Jaleta, O. Erenstein, (2015). 'Production risks and food security under alternative technology choices in Malawi: application of a multinomial endogenous switching regression', *Journal of Agricultural Economics*, 66(3), pp. 640-659.

Khonje, M., J. Manda, A.D. Alene, and M. Kassie, (2015). 'Analysis of adoption and impacts of improved Maize varieties in Eastern Zambia', *World Development*, 66, pp. 695-706.

Kumar, K.S.K. (2011). 'Climate sensitivity of Indian agriculture: do spatial effects matter?', *Cambridge Journal of Regions, Economy and Society*, 4(2), pp. 221-235.

Kumar, K.S.K., and J. Parikh, (2001). 'Indian agriculture and climate sensitivity', *Global Environmental Change*, 11(2), pp. 147-154.

Kurukulasuriya, P., and R. Mendelsohn (2007). 'Modeling endogenous irrigation: the impact of climate change on farmers in Africa', *World Bank Policy Research Working Paper 4278*, Washington D.C.

Kurukulasuriya, P., and R. Mendelsohn (2008). 'Crop switching as an adaptation strategy to climate change', *African Journal Agriculture and Resource Economics*, 2, pp. 105–126.

Kurukulasuriya, P., N. Kala, and R. Mendelsohn, (2011). 'Adaptation and climate change impacts: a structural Ricardian model of irrigation and farm income in Africa', *Climate Change Economics*, 2(2), pp. 149-174.

Lokshin, M., and Z. Sajaia (2004). 'Maximum likelihood estimation of endogenous switching regression models', *Stata Journal*, 4(3), pp. 282–289.

Ma, W., and A. Abdulai (2016). 'Does cooperative membership improve household welfare? evidence from apple farmers in China', *Food Policy*, 58, pp. 94-102.

Macours, K. (2013). 'Volatility, agricultural risk, and household poverty: micro- evidence from randomized control trials', *Agricultural Economics*, 44, pp. 79-84.

Mendelsohn, R., A. Dinar and L. Williams, (2006). 'The distributional impacts of climate change on rich and poor countries', *Environment and Development Economics*, 11(2), pp. 159-178.

Mendelsohn, R., and S.N. Seo, (2007). 'Changing farm types and irrigation as an adaptation to climate change in South America', *World Bank Policy Research Series Working Paper 4161*, Washington D.C.

Mishra, S. (2012). 'Coping mechanisms of people in drought prone areas of rural Orissa' *Journal of Rural Development*, 31(1), pp. 61-83.

Panda, A. (2016). 'Vulnerability to climate variability and drought among small and marginal farmers: a case study in Odisha, India', *Climate and Development*, doi:10.1080/17565529.2016.1184606.

Panda, A., U. Sharma, K. Ninan, and A. Patt (2013). 'Adaptive capacity contributing to improved agricultural productivity at the household level: Empirical findings highlighting the importance of crop insurance', *Global Environmental Change*, 23(4), pp. 782–790.

Pandey, S., H. Bhandari, and B. Hardy (2007). '*Economic costs of drought and rice farmers' coping mechanisms: a cross-country comparative analysis*', International Rice Research Institute, Los Baños, Philippines.

Patnaik, U., and K. Narayanan (2005). '*Vulnerability and climate change: an analysis of the Eastern coastal districts of India*', Presented at the GECHS International Workshop on Human Security and Climate Change. Oslo, Norway, June 21–23.

Patnaik, U., and K. Narayanan (2010). 'Vulnerability of household to disaster risks: evidence from rural India', *Artha Vijnana*, 52(3), pp. 261-273.

Patnaik, U., and K. Narayanan (2015b). 'Are traditional coping mechanisms effective in managing the risk against extreme events? evidences from flood prone region in rural India', *Water Policy*, 17(4), pp. 724-741.

Patnaik, U., and K. Narayanan, (2015a). 'How effective are coping mechanisms in securing livelihoods against climatic aberrations? evidences from rural India', *International Journal of Climate Change Strategies and Management*, 7(3), pp. 359-374.

Patnaik, U., P. K. Das, and C. S. Bahinipati (2016b). 'Coping with climatic shocks: empirical evidence from rural coastal Odisha, India', *Global Business Review*, 17(1), pp. 161-175.

Patnaik, U., P. K. Das, C. S. Bahinipati and O. Tripathy (2016a). 'Can developmental interventions reduce households' vulnerability? empirical evidence from Western Odisha, India', *GIDR Working Paper Series No. 235*, Gujarat Institute of Development Research (GIDR), Ahmedabad, India

Pattanayak, A., and K.S.K. Kumar (2014), 'Weather sensitivity of rice yield: evidence from India', *Climate Change Economics*, 5(4), DOI: 10.1142/S2010007814500110.

Pattnaik, I. (2012). 'Livelihood pattern and coping mechanisms during drought: a study of two villages in Odisha', *RULNR working paper no. 17*, Research Unit for Livelihoods and Natural Resources, Centre for Economic and Social Studies, Hyderabad, India.

Sanghi, A., and R. Mendelsohn (2008). 'The impacts of global warming on farmers in Brazil and India', *Global Environmental Change*, 18, pp. 655-665.

Seo, S.N., and R. Mendelsohn (2007). 'Measuring impacts and adaptations to climate change: a structural Ricardian model of African livestock management', *Agricultural Economics*, 38(2), pp. 151-165.

Seo, S.N., and R. Mendelsohn (2008). 'An analysis of crop choice: adapting to climate change in South American farms', *Ecological Economics*, 67(1), pp. 109–116.

Sharma, V., B. Reddy, N. Sahu (2014). 'Sustainable rural livelihoods approach for climate change adaptation in Western Odisha, Eastern India', *Development in Practice*, 24(4), pp. 591-604.

Shiferaw, B., M. Kassie, M. Jaleta, and C. Yirga, (2014). 'Adoption of improved wheat varieties and impact of household food security in Ethiopia', *Food Policy*, 44, pp. 272-284.

Swain, M. (2014). 'Sources of growth and instability in agricultural production in Western Odisha, India', *Asian Journal of Agriculture and Development*, 11(2), pp. 51-70.

Swain, M., and M. Swain, (2011). 'Drought vulnerability, coping capacity and residual risk: evidence from Balangir district in Odisha, India', *Asian Journal of Environment and Disaster Management*, 3(4), pp. 453-473.

Teklewold, H., A. Mekonnen, G. Kohlin, and S. Di Falco (2017),'"Does adoption of multiple climate smart practices improve farmers' climate resilience? Empirical evidence from the Nile basin of Ethiopia', *Climate Change Economics*, 8(1), DOI: 10.1142/S2010007817500014.

Tiwari, R. *et al.* (2011). 'MGNREGA for environmental service enhancement and vulnerability reduction: Rapid appraisal in Chitradurga district, Karnataka', *Economic and Political Weekly*, XLVI(20), pp. 39-47.

WORLP (Western Orissa Rural Livelihood Programme), (1999). '*Project memorandum. Western Odisha rural livelihoods project*', Odisha Watershed Development Mission, Government of Odisha, Bhubaneswar, mimeo.

Appendix 1: Parameter Estimates for OLS Regression

Variables	Full Sample			Sub Sample: Beneficiaries			Sub Sample: Non-Beneficiaries		
	Coefficients (S.E.)	Coefficients (S.E.)	Coefficients (S.E.)	Coefficients (S.E.)	Coefficients (S.E.)	Coefficients (S.E.)	Coefficients (S.E.)	Coefficients (S.E.)	Coefficients (S.E.)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AG_{ADAPT}	0.241 (0.194)	0.194 (0.138)	0.095 (0.117)	0.163 (0.223)	0.145 (0.166)	0.023 (0.132)	0.600 (0.400)	0.307 (0.289)	0.254 (0.217)
Household and Household head characteristics									
SIZE	0.025 (0.025)	0.014 (0.015)	0.006 (0.014)	0.021 (0.029)	0.022 (0.016)	0.010 (0.015)	0.058 (0.064)	-0.015 (0.059)	0.014 (0.051)
AGE	-0.007 (0.005)	-0.002 (0.004)	0.001 (0.003)	-0.011* (0.006)	-0.006* (0.004)	-0.003 (0.002)	0.010 (0.013)	0.015 (0.013)	0.017 (0.015)
EDU	-0.014 (0.021)	0.007 (0.012)	0.010 (0.009)	-0.001 (0.023)	0.013 (0.010)	0.007 (0.009)	-0.033 (0.046)	0.005 (0.039)	0.033 (0.032)
EDU_T	0.079 (0.236)	0.058 (0.091)	-0.032 (0.080)	0.041 (0.272)	0.009 (0.095)	-0.070 (0.110)	0.119 (0.292)	0.241 (0.265)	0.020 (0.158)
ASET	0.030 (0.019)	0.012 (0.015)	0.014 (0.011)	0.028 (0.021)	0.011 (0.012)	0.002 (0.009)	0.049 (0.043)	0.025 (0.044)	0.051* (0.031)
LAND	0.495*** (0.104)	0.169* (0.101)	-	0.419*** (0.108)	0.076 (0.098)	-	0.747*** (0.267)	0.515* (0.309)	-
MIG	0.008 (0.175)	0.048 (0.118)	0.024 (0.114)	0.230 (0.175)	0.145 (0.117)	0.125 (0.109)	-0.871* (0.471)	-0.414 (0.325)	-0.467 (0.352)
Major Livelihood Intervention									
WORLP	0.298* (0.172)	0.234 (0.147)	0.282** (0.138)	-	-	-	-	-	-
Farm characteristics									
CRP_N	0.349*** (0.087)	0.205*** (0.055)	-	0.401*** (0.103)	0.224*** (0.059)	-	0.112 (0.172)	0.204 (0.161)	-
INPC /INPCH	-	0.781*** (0.102)	0.979*** (0.036)	-	0.812*** (0.107)	0.993*** (0.034)	-	0.659** (0.300)	0.914*** (0.116)

Variables	Full Sample			Sub Sample: Beneficiaries			Sub Sample: Non-Beneficiaries		
	Coefficients (S.E.)	Coefficients (S.E.)	Coefficients (S.E.)	Coefficients (S.E.)	Coefficients (S.E.)	Coefficients (S.E.)	Coefficients (S.E.)	Coefficients (S.E.)	Coefficients (S.E.)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LVST	0.009 (0.018)	0.007 (0.008)	0.018*** (0.007)	0.001 (0.018)	0.007 (0.008)	0.020*** (0.006)	0.091 (0.058)	0.052 (0.042)	0.042 (0.039)
Formal and Informal Institutions									
CRED	-0.087 (0.145)	-0.060 (0.102)	-0.022 (0.078)	0.045 (0.161)	-0.056 (0.106)	0.019 (0.069)	-0.194 (0.316)	0.149 (0.250)	0.089 (0.182)
KCC	-0.019 (0.212)	-0.052 (0.159)	-0.065 (0.156)	-0.128 (0.253)	-0.078 (0.193)	-0.127 (0.186)	0.346 (0.301)	0.195 (0.258)	0.161 (0.217)
EGS	-0.278* (0.155)	-0.032 (0.127)	-0.038 (0.110)	-0.511*** (0.158)	-0.286*** (0.107)	-0.201** (0.096)	0.455 (0.437)	0.733 (0.447)	0.561 (0.385)
Experienced Climatic Shocks									
DRT	0.132 (0.196)	-0.001 (0.131)	-0.168* (0.095)	0.216 (0.227)	0.055 (0.135)	-0.088 (0.105)	0.098 (0.365)	-0.078 (0.258)	-0.230 (0.178)
Constant	7.913*** (0.485)	1.800* (1.055)	0.390 (0.526)	8.452*** (0.438)	2.130** (1.002)	0.811** (0.391)	6.404*** (1.410)	1.324 (3.488)	-0.345 (1.841)
N	549	549	549	413	413	413	136	136	136
F value	89.32***	17.75***	5.19***	4.33***	21.21***	127.0***	2.98***	8.33***	6.22***
R^2	0.525	0.292	0.131	0.140	0.362	0.647	0.214	0.250	0.291
Dependent Variable	LN_{Rev}	LVOP	$LVOP_H$	LN_{Rev}	LVOP	$LVOP_H$	LN_{Rev}	LVOP	$LVOP_H$

Source: Computation from the primary data

Note: Robust standard errors in parentheses; Mean Variance Inflation Factor (VIF) = 1.14; *** p<0.01, ** p<0.05, * p<0.1

Appendix 2: Parameter Estimates for Test on the Validity of the Selection Instruments

Outcome Variable	AGADAPT	NRev	VOP	VOP_H
(1)	(2)	(3)	(4)	(5)
MORTI	0.403* (0.216)	0.813 (1.002)	0.468 (0.946)	0.263 (0.925)
EXPH	0.013 (0.019)	-0.005 (0.052)	0.017 (0.049)	0.015 (0.047)
SCARF	-0.201** (0.047)	0.028 (0.139)	-0.04 (0.131)	-0.121 (0.128)
EXTN	0.239* (0.138)	-	-	-
SUP_{LV}	0.105 (0.142)	-	-	-
Constant	-0.681* (0.140)	8.619*** (0.354)	9.648*** (0.334)	9.959*** (0.327)
N	549	136	136	136
Wald χ^2 / F value	25.36***	0.861	0.14	0.31
Pseudo R^2 / R^2	0.021	0.005	0.003	0.006
Model	Probit	OLS	OLS	OLS

Source: Computation from the primary data

Note: robust standard errors in parentheses; OLS- Ordinary Least Squares; *** p<0.01, ** p<0.05, * p<0.1

Appendix 3: Summary Statistics of Adopters and Non-adopters of Agricultural Adaptation

Variable	Adopters Mean (S.D.)	Non-adopters Mean (S.D.)	Mean Difference
(1)	(2)	(3)	(4)
Dependent Variables			
LN_{Rev}	9.01 (1.59)	8.72 (2.34)	0.29
LVOP	10.02 (1.20)	9.76 (2.13)	0.26*
$LVOP_{H}$	10.24 (1.42)	9.98 (2.17)	0.27*
Independent Variables			
Household and Household Head's Characteristics			
SIZE	5.33 (2.74)	5.32 (2.59)	0.004
AGE	52.52 (11.71)	49.04 (11.69)	3.48***
EDU	3.27 (3.23)	3.44 (3.81)	-0.17
EDU_{T}	0.06 (0.24)	0.02 (0.15)	0.04*
ASET	3.64 (3.72)	3.37 (3.56)	0.28
LAND	0.96 (0.87)	0.92 (0.58)	0.04
MIG	0.24 (0.43)	0.22 (0.42)	0.02
Major Livelihood Intervention			
WORLP	0.81 (0.39)	0.57 (0.50)	0.24***
Farm Characteristics			
CRP_{N}	1.33 (0.99)	1.31 (0.86)	0.016
$INPT_{C}$	9.47 (0.73)	9.43 (1.03)	0.04
$INPT_{CH}$	9.68 (1.08)	9.53 (1.53)	0.15
LVST	3.17 (4.28)	4.03 (5.40)	-0.86*
Access to Formal and Informal Institutions			
CRED	0.44 (0.50)	0.20 (0.40)	0.24***
SHG	0.41 (0.49)	0.33 (0.47)	0.08*
KCC	0.15 (0.35)	0.09 (0.28)	0.06*
EGS	0.69 (0.46)	0.62 (0.49)	0.07
Experienced Climatic Shocks			
DRT	0.78 (0.42)	0.67 (0.47)	0.11**
Selection Instruments			
EXTN	0.35 (0.48)	0.21 (0.41)	0.14***
SUP_{LV}	0.27 (0.44)	0.21 (0.41)	0.05
$MORT_{I}$	0.06 (0.33)	0.02 (0.15)	0.04
EXP_{H}	6.23 (3.33)	6.49 (2.99)	-0.26
$SCAR_{F}$	0.81 (1.21)	1.40 (1.40)	-0.59***
N	409	140	-

Source: Computation from the primary data

Note: *** p<0.01, ** p<0.05, * p<0.1