Report on
the Dynamics of Climate Variability, Occupational Diversification and Household Welfare: Insights from Rural Bangladesh

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Abstract

Households in developing countries are often subject to various shocks, such as climate variability and natural disasters, which can arguably influence the occupational choices of households. Using a household-level panel data set, we investigate the over-time change in occupations and examine the impact of climate-induced shocks on occupational diversification in rural Bangladesh. Furthermore, using an instrumental variable approach, we exploit the exogenous variation in rainfall to isolate the effect of occupational diversification on household welfare. Our analysis indicates that excessive monsoon rainfall prompts unemployed household members to seek employment, primarily in agriculture. We also observe a preference for the agriculture sector over non-agriculture, possibly due to familiarity and perceived benefits of natural rainfall in achieving a better harvest and/or a lack of employment opportunities in the non-agriculture sector. In terms of welfare, occupational diversification towards agriculture induced by rainfall variability is found to have a positive effect on food expenditure with no significant effect on non-food expenditure. Therefore, households adapting to climate uncertainties through occupational changes may struggle to meet non-food consumption needs. Our findings therefore indicate the importance of targeted policies to support households affected by variable rainfall, particularly those experiencing challenges in maintaining a minimum level of welfare.

1 Introduction

In developing countries, households are often prone to different types of shock that could shape their individual as well as household decision-making processes. The most common types of shock are those associated with climate variability and natural calamities. For rural households, such climate-induced idiosyncratic shocks can affect production processes and thereby can shape the occupational choices of individuals within a household. In the case of occupational choices, while household members in rural areas often tend to specialize in a particular sector or type of occupation, and thereby help to share knowledge and gain productivity, climate-induced shocks and uncertainty in this context can act as 'push' factors for such decisions (Bandyopadhyay & Skoufias, 2015).

In the absence of a well-functioning marketing system and credit market, contrary to the specialization of household members in similar types of activities, such a shock-induced diversification in occupational choices within households can have negative implications for an individual's labour productivity and household income. As a result, the welfare of households can be affected by this diversification with a wide range of implications for household consumption. Climate variability can therefore not only have a direct effect on agricultural production in rural households, but can also shape the occupational choices of its members. With the increasing threat of global warming and climate variability, further uncertainty and concerns have emerged about the welfare of already vulnerable rural households (Skoufias & Vinha, 2013). It should also be considered that the consequences of climate variability can be more intense on the disadvantaged groups like those of female-headed households (Flatø, Muttarak, & Pelser, 2017). These households are argued to bear a 'triple burden' as they are not only low in resource endowment, but also have to bear the responsibility as the sole earner in most cases, and are additionally obligated to carry out domestic chores (Flatø et al., 2017; Rosenhouse, 1989). Given their limited resources and employment opportunities along with the prevailing patriarchy in most developing countries, female-headed households are argued to be the worst-sufferer in case of climate-induced shocks (Flatø et al., 2017; World Bank, 2012).

Bangladesh is considered one of the most vulnerable countries in terms of natural disasters and climate-induced shocks, such as drought, floods, river erosion, etc. Due to its location in the Gangetic Delta, hundreds of rivers crisscross the country, which soar up during the monsoon and cause regular flooding (Bandyopadhyay & Skoufias, 2015; Islam, Samreth, Islam, & Sato, 2022; Yu et al., 2016). In case of a heavy monsoon, these floods can take a serious shape and can affect the lives and livelihoods of millions. Consequently, such climate variability can have important implications on the choice of employment of Bangladeshi households. Bandyopadhyay and Skoufias (2015) argue that the choices of the household members (excluding the household head) are made on the basis of a number of pull and push factors. In the context of Bangladesh, the two most crucial push factors are flood and variability in rainfall- these factors tend to influence non-head members of the household to choose occupations in sectors different from that of the household head or to engage in different types of employment.

The choice of diversification of the occupation as opposed to specialization can affect the welfare of households through the change of consumption, and the diversification of the occupation in this sense can be induced by rainfall variability (Bandyopadhyay & Skoufias, 2015; Skoufias, Bandyopadhyay, & Olivieri, 2016). For Bangladesh, such variability in rainfall can be substantial, which is likely to result in a greater possibility of occupational diversification within household members. Therefore, it is crucial to understand whether the variation in rainfall is linked to occupational diversification and whether such diversification affects household welfare in terms of consumption. Besides, given the conservative and patriarchal socioeconomic structure of Bangladesh, in case of climate-induced shocks, female-headed households can be deemed vulnerable compared to their male counterparts.

This paper aims to empirically determine whether households change their current occupational engagements when faced with climatic shocks where climatic shocks can be defined as deviations from historical averages in specific climate parameters, such as rainfall variability. We attempt to understand the corresponding consequences on the welfare level of households that diversify their occupational activities and those that do not. Bandyopadhyay and Skoufias (2015) argue that households forced to change their activities due to increased risk face a lower level of welfare compared to those who willingly diversify their activities. Given the endogenous nature of occupational transitions, which can be influenced by numerous observed and unobserved factors, we adopt an instrumental variable approach to isolate the exogenous variation in occupation choice due to climate variability.

Although there are studies on climate variability and occupational choice, our research is unique in several ways. Firstly, we use a panel data set to understand the change in the welfare of households; panel data in this context not only controls unobserved heterogeneity, but also enables us to analyze changes in welfare over time. Secondly, from a methodological point of view, this research applies an instrumental variable approach, which allows us to draw a causal link between the change in occupations and household welfare. Third, we define occupational diversification in a more robust way compared to those used in cross-sectional studies. Lastly, we attempt to examine whether occupational diversification due to climate variability is heterogeneous between males and females. To our knowledge, this paper is the first of its kind to analyze the differing effect of climate variability on occupational diversification between male- and female-headed households and their collective effect on the welfare of the households.

2 Literature Review

Bangladesh mainly comprises low plains, most of which lie in the Ganges-Brahmaputra-Meghna delta. More than 230 rivers traverse the country, which cause heavy flooding in every monsoon; it is also highly vulnerable to tropical cyclones due to its proximity to the Bay of Bengal (World Bank Group, 2021). It ranks 29th in the world on the INFORM Risk Index 2023, and it is placed in the high-risk category by the European Commission.[1] Higher temperatures, induced by global warming, increase evaporation and atmospheric moisture and are likely to result in more intense and extreme monsoons in South Asian countries (Jayasankar, Surendran, & Rajendran, 2015; World Bank Group, 2021). Bangladesh is also at risk of facing two types

[1]Retrieved from https://drmkc.jrc.ec.europa.eu/inform-index/

of droughts: meteorological and hydrological; meteorological droughts are associated with low rainfall, and hydrological droughts are associated with a depletion in surface and sub-surface water flow (World Bank Group, 2021). Hydrological droughts can occur due to purely political deadlocks that bar river water-sharing mechanisms. Although Bangladesh faces a low probability of meteorological droughts, less severe droughts tend to occur more frequently (Rahman & Lateh, 2016). Naumann et al. (2018) predict that if the global temperature increases by 1.5°C–2°C, the occurrence of meteorological droughts can increase from 1 in 100 years to 1 in 40-50 years. Warming up to 3°C may lead to severe drought every 20 years.

In such uncertain weather conditions induced by climate change, households look for ways to adapt and prevail. Households try to employ coping strategies related to the diversification of livelihoods to reduce the adverse effects of climate variability (Antwi-Agyei, Stringer, & Dougill, 2014). In regions experiencing rainfall variability, farm-based households tend to sell livestock, diversify crops, and engage in casual employment to hedge the possibility of unfavorable events; at the same time, they tend to reduce their consumption (Alemayehu & Bewket, 2017; Trærup & Mertz, 2011). They may be inclined to move to non-agricultural activities in areas prone to climate shocks, making it challenging to carry out agricultural activities without adequate insurance mechanisms (Barrett, Reardon, & Webb, 2001; Reardon, Berdegué, Barrett, & Stamoulis, 2006). In addition, household members tend to diversify their employment differently from the household heads and seek secondary income sources (Bandyopadhyay & Skoufias, 2015; Skoufias et al., 2016; Zheng & Byg, 2014).

It is not surprising that variable weather conditions adversely affect household consumption behavior (Skoufias & Vinha, 2013). The effects vary depending on the household setting; for example, households headed by a single male tend to be more vulnerable compared to households operated jointly by two adult members (Flatø et al., 2017). In Bangladesh, Islam et al. (2022) find that climate variability negatively affects a household's primary food consumption; moreover, welfare (in terms of consumption expenditure) tends to be lower when households are forced to change their occupational activities due to increased risk compared to those who willingly diversify their activities (Bandyopadhyay & Skoufias, 2015).

Extreme weather conditions can reduce household welfare through multiple channels and households often opt for numerous coping strategies at the same time. Access to formal social security programs and non-farm employment can jointly reduce the adverse effects of rainfall and temperature shocks (Gao & Mills, 2018). Households facing health issues try to cope by choosing medications without expert advice or opting for poorly equipped and unqualified medical practitioners (Haque et al., 2013). Small-scale farmers may opt for on-farm and off-farm options, such as sale of household assets, change in dietary patterns, migration of the entire family, selection of extreme weather tolerant variety, soil conservation, etc. (Aniah, Kaunza-Nu-Dem, & Ayembilla, 2019).

3 Data

3.1 Data Source

We use the Bangladesh Integrated Household Survey (BIHS) longitudinal survey dataset combined with the BIHS Harmonized Dataset. Compared to other nationally representative household datasets, the BIHS is a relatively newer dataset with a panel dimension. Although focused on rural areas, it fits the purpose of our research objectives. The BIHS sample design, nationally representative of rural Bangladesh, follows a two-stage stratified sampling based on the Bangladesh Population and Housing Census 2001. In the first stage, 275 primary sampling units (PSUs) are selected at the village level from seven strata (administrative divisions). In the second stage, households are selected from within each PSU. Since the dataset consists of individual and household-level information, population and household survey weights are provided by IFPRI (2020). The BIHS Harmonized Dataset contains biophysical data corresponding to the BIHS sample households from multiple sources, including the International Soil Reference and Information Centre (ISRIC) World Soil Information, NASA MODIS vegetation indices and land surface temperature data, and the HarvestChoice spatially-disaggregated database (IFPRI, 2017). To identify climatic shocks such as excessive rainfall, we match the rainfall experienced by the sample households with the historical monthly rainfall data from 1981 to 2010 obtained by the Bangladesh Meteorological Department from 35 stations around the country.[2]

3.2 Data Description

Table 1 provides an overview of sample household characteristics over 2011/12 and 2015. While the average age of household heads increased slightly from 43.84 years to 45.87 years, there was a notable rise in household size from 4.16 to 4.80 individuals. There was a decrease in the proportion of household heads without formal education, dropping from 49% to 46%. However, the percentage of households where the head does not earn saw a slight increase by around 2 percentage points. Notably, there was a decline in the proportion of household heads engaged in agriculture, which decreased from 42% to 37%, while those in the non-agricultural sector remained relatively stable. Furthermore, there were significant improvements in access to amenities such as electricity and communication devices, with notable increases in phone ownership (from 73%

[2]For our analysis, we use BIHS 2011/12 and 2015 datasets only as BIHS Harmonized Dataset is only available for those years.

to 88%) and TV ownership (from 25% to 31%). However, the proportion of households with a separate toilet decreased substantially from 94% to 70%.

Table 1: Summary statistics on sample households

	2011/12	2015
HH head age	43.84 (13.83)	45.87 (13.68)
HH size	4.16 (1.56)	4.80 (1.82)
Female HH head	0.18 (0.38)	0.20 (0.40)
HH head no formal education	0.49 (0.50)	0.46 (0.50)
HH head does not earn	0.13 (0.33)	0.15 (0.36)
HH head in agriculture sector	0.42 (0.49)	0.37 (0.48)
HH head in non-agriculture sector	0.46 (0.50)	0.47 (0.50)
Land owned (decimals)	89.84 (143.63)	95.48 (155.67)
Dependency ratio	0.36 (0.22)	0.33 (0.21)
Receives remittance	0.25 (0.43)	0.33 (0.47)
House in good condition	0.11 (0.31)	0.16 (0.36)
Has electricity	0.48 (0.50)	0.59 (0.49)
Owns a phone	0.73 (0.44)	0.88 (0.33)
Owns a TV	0.25 (0.44)	0.31 (0.46)
Has separate toilet	0.94 (0.23)	0.70 (0.46)
Experienced adverse event	0.53 (0.50)	0.40 (0.49)
Distance to nearest marketplace (km)	0.61 (0.69)	0.48 (0.56)

Note: Mean values reported. Standard deviation in parentheses. A house is said to be in good condition if the wall and roof are made of durable material such as tin or concrete and the floor is not made of mud.

4 Methodology

4.1 Climate Variability and Occupational Choice

In areas where weather conditions are uncertain, household members are expected to choose the non-agricultural sector over agriculture. Bandyopadhyay and Skoufias (2015) argue that household members typically employ themselves in economic sectors different from household heads. In addition, in villages where rainfall varies widely, household heads and other members are likely to diversify between economic sectors. Such diversification can, more commonly, be assumed to be driven by push factors such as rainfall variability. However, rural Bangladesh is dominated by the agricultural sector, with the majority of the population relying on it for their livelihood (Miah, Hasan, & Uddin, 2020). Whether earners can switch from the agriculture sector is also contingent upon the scope and opportunities created by the non-farm sector. Regardless of the uncertainty caused by climate change, individuals committed to the farming sector are likely to experience inertia while considering a change in occupation. Moreover, a lack of skills and infrastructure in villages may also contribute to the preference for agricultural work over non-agricultural options (Salam & Bauer, 2022). In certain cases, non-agriculture sector jobs might be associated with specific skills required for those jobs, discouraging individual members from switching to those. We test these scenarios in the following intra-household occupational choice model:

$$Y_{ijv} = \beta_0 + \beta_1 X_{1ijv} + \beta_2 X_{2jv} + \beta_3 X_{3v} + \beta_4 R_{jv} + \beta_5 CVR_{jv} + \varepsilon_{ijv}, \quad (1)$$

Here, the variables X are exogenous, where X_{1ijv} represents individual characteristics, such as age, sex and education, X_{2jv} represents household characteristics, such as land ownership, education of the household head and other members, access to electricity and mobile phones, and whether the household receives remittances from a migrant member, and X_{3v} represents village infrastructure, which is proxied by distance to the nearest facilities.[3] R_{jv} is the dummy variable of interest that represents rainfall variability. It takes the value of 1 if household j residing in village v experienced excess monsoon rainfall in 2011 compared to the 30-year average annual monsoon rainfall, and 0 if otherwise. Occupational change can also be driven by past experience of rainfall, which is accounted for by CVR_{jv}. It is an ex-ante measure of climate variability in the form of the coefficient of variation of annual monsoon rain in the last 30 years in village v. We also include a variable for mean summer temperature to control for other weather phenomena. The dependent variable Y_{ijv} is binary in nature and can be specified in two ways: it takes the value of 1 if a member i in household j in village v takes up work (either in the agriculture or non-agriculture sector) in period $t+1$ and 0 if s/he remain non-earning in periods t and $t+1$; and it takes the value of 1 if the member is engaged in a different occupational sector in period $t+1$ than s/he was in period t and 0 if otherwise. Assuming that the risk of rainfall variability is a driver of occupational diversification, we expect β_4 and β_5 to be statistically significant. We estimate Equation 1 in three ways: first, with the whole sample. Second, with a sub-sample of household members excluding the household head; and third, with only the household heads.

[3]Occupational diversification may also be driven by pull factors that are controlled for by these variables.

4.2 Welfare Effects of Occupational Change

In the next stage, we evaluate the welfare effects of occupational change by households experiencing climate variability. Islam et al. (2022) employ Difference-in-Differences (DiD) to evaluate the adverse consequences of extreme climatic events on food consumption, where households facing climatic shocks can be considered the treatment group. Since we are interested in examining the effect of occupational change induced by rainfall variation, we cannot consider households that changed occupational sector as treatment group due to potential endogeneity. Numerous observed and unobserved factors can be responsible for switching between sectors, which makes the causal estimation biased and inconsistent. For this purpsose, we employ an instrumental variable method.

We take per capita household expenditure (total/food/non-food) and household dietary diversity score (DDS) as indicators of a household's welfare level. The relationship between occupational change and household welfare can thus be modeled as follows:

$$W_{j,t} = \delta_0 + \delta_1 X_{1ijv} + \delta_2 X_{2jv} + \delta_3 OC_{ijv} + \varepsilon_{j,v}, \tag{2}$$

where the dependent variable, $W_{j,t}$, can be specified in four ways: per capita household expenditure (log), per capita food expenditure (log), per capita non-food expenditure (log), and DDS. X_{1ijv} represents the set of household head characteristics and X_{2jv} is the set of household traits. OC_{ijv} is the dummy variable of interest that represents occupational change; it can be specified in two ways. In the first model, it takes the value of 1 if the head i of household j in village v switches to the non-agriculture sector in 2015, and 0 if s/he remains in the agriculture sector in 2011 and 2015. In the second, it takes the value of 1 if the head switches to the agriculture sector in 2015, and 0 if s/he remains in the non-agriculture sector in 2011 and 2015. ε_{jv} is the idiosyncratic error term.

While we are interested in δ_3, its estimates are likely to be inconsistent due to non-randomness. A household head's decision to switch occupational sectors may depend on a number of confounding observable and unobservable factors, leading to a correlation with the error term;

$$Cov(OC_{ijv},\ \varepsilon_{jv}) \neq 0$$

There may also be a reverse causality problem, in which a household's increased expenditures or dietary demands may require the household head to switch occupations. We thus exploit the exogenous nature of rainfall variation data and use an IV in place of OC_{ijv}: dummy R_{jv}, representing whether household j in village v experienced excess monsoon rain in 2011.

We estimate the causal effect of occupational change on household welfare with the two-stage least squares (2SLS) method. In the first stage, we regress the endogenous variable, OC_{ijv}, on the exogenous IVs and the set of control variables included in Equation 2:

$$OC_{ijv} = \gamma_0 + \gamma_1 X_{1ijv} + \gamma_2 X_{2jv} + \gamma_3 R_{jv} + \gamma_4 CVR_{jv} + \eta_{j,v} \tag{3}$$

We use the predicted values from Equation 3 in the second stage in place of the endogenous variable. Thus, the second stage equation can be specified as follows:

$$W_{j,t} = \alpha_0 + \alpha_1 X_{1ijv} + \alpha_2 X_{2jv} + \alpha_3 \widehat{OC}_{ijv} + \rho_{j,v}, \tag{4}$$

The α_3 estimates of the second stage equation show the local average treatment effects (LATE) (Imbens & Angrist, 1994). It shows the causal effect of occupational change on household welfare for households whose occupational change is induced by exogenous rainfall variation. More specifically, it indicates the average change in household welfare that can be attributed to occupational change for households whose decision to change occupations is affected by variation in rainfall patterns. This effect is localized to households whose decisions to switch occupations are influenced by variations in rainfall, as captured by the instrumental variables.

5 Empirical Findings

5.1 Change in Occupation

Using annual monsoon rainfall data from the Bangladesh Meteorological Department, spanning from 1981 to 2010 and covering 35 weather stations, we calculate the amount of rainfall experienced by each household over the past 30 years. This calculation is done through the inverse distance weighted average of the three nearest stations. We then compare these estimates with the actual monsoon rainfall experienced by households in 2011, using data from the BIHS Harmonized Dataset. As shown in Table 2, we identify households and populations that experienced excess monsoon rainfall in 2011 compared to the 30-year historic average.[4] Around 90% of the households and populations residing in the Sylhet and Khulna divisions experienced excess monsoon rainfall. Sylhet borders the state of Meghalaya in India, which is known as the wettest place on Earth due to the severity of annual rainfall.[5] Khulna is a coastal division that consists of the Sundarbans and is subject to seasonal cyclones at regular intervals. Rangpur, the northernmost and driest division, comprises the lowest proportion of households and people who ex excessive rainfall. It is also the

[4]Households are said to have experienced excesses rainfall if the monsoon rainfall in 2011 exceeds the 30-year average plus 5%.

[5]See https://www.theatlantic.com/photo/2014/08/meghalaya-the-wettest-place-on-earth/100797/

only division with a lower mean monsoon rainfall in 2011 compared to the 30-year historic mean. Evidently, rainfall fluctuated widely across households in 2011 compared to the standard deviation of the past 30 years. This suggests more diverse rainfall experiences compared to previous trends, and thus the plausibility of varying household welfare primarily through occupational change by household members.

Table 2: Percentage of households/population in each division who experienced excess monsoon rainfall in 2011

Division	% of Households	% of Population	Annual Monsoon Rainfall (mm)			
			Historic Mean	SD	2011 Mean	SD
Dhaka	59.26	58.26	1373.1	119.4	1487.7	379.8
Barishal	65.22	65.61	1716.5	227.1	1928.2	510.1
Chittagong	70.25	70.76	1870.8	429.7	2143.0	807.9
Sylhet	89.68	90.06	1915.4	245.7	2506.8	906.7
Khulna	93.02	92.93	1222.6	116.9	1357.3	265.2
Rajshahi	76.52	77.67	1170.3	71.3	1237.2	249.4
Rangpur	40.18	40.58	1575.0	53.3	1510.7	384.3

Regarding occupational diversification, we consider two aspects: whether a non-earning individual in 2011 started earning in 2015, and whether an earning individual in 2011 switched their occupational sector in 2015. Although both of these changes can have implications on household welfare, the impact of the latter could be quite different from the former, where the former can be termed as 'added worker effect.' In Table 3, we observe that among the household heads who did not earn in 2011, approximately 30% started earning in 2015; 24% of the non-earners began working in the agriculture sector and 10% in the non-agriculture sector. However, the number is at least 68% lower for the rest of the household members, with only 11% of the previously non-earners engaging in income-earning activities in 2015. The effect of climate change, therefore, might have a greater impact on the occupational choices of household heads. Besides, approximately 20% of the household heads who previously worked in the agriculture sector switched to the non-agriculture sector, but the number is around 7 percentage points lower in the case of switching to the non-agriculture sector. The percentage of switching to the agriculture sector is also higher among the rest of the household members compared to switching to the non-agriculture sector. A higher preference for the agriculture sector is observed for the non-earns and those who want to switch sectors. This could be due to inadequate opportunities or a lack of required infrastructure in the non-agriculture sector (Salam & Bauer, 2022). In addition, a lack of necessary skills of the household heads/members for non-agriculture based occupations might be a contributing factor too.

Table 3: Change in occupational sectors between 2011 and 2015

	% HH head	% HH member
Started earning in 2015	29.77	11.28
Started earning in the agriculture sector in 2015	23.97	7.62
Started earning in the non-agriculture sector in 2015	9.79	4.27
Switched occupation between 2011 and 2015	24.24	21.32
Switched to agriculture sector in 2015	20.43	17.96
Switched to non-agriculture sector in 2015	13.91	12.86

5.1.1 Entering the Workforce as a New Member

We estimate Equation 1 to understand the relationship between excessive rainfall experienced by households and the change in occupations of their members as a coping strategy (Table 4). According to our estimates, if a household experiences excessive rainfall in period t, all members are two percentage points more likely to take up work (in any sector) in period t+1. Segregating the sample into two groups, we see that the probability increases by almost one percentage point for the household heads, and by slightly more than one percentage point for non-head household members. The positive effect of excessive rainfall on taking up work across all household members is found to be statistically significant precise at 5% level with the fluctuation of monsoon rainfall in the past 30 years, captured by the coefficient of variation (CV), has a negative relationship with taking up work for all household members but no statistically significant effect on the household heads. This indicates that historical variation in rainfall negatively affects all household members in taking up income-earning activities as a coping strategy but the effect is nullified for the household heads. Regardless of the long-term experience of fluctuating rainfall (notwithstanding the direction), household heads respond to the more recent occurrences of excessive rainfall and cope by taking up employment.

Given the possibility that household coping strategies might be shaped by the sex of the relevant member, Table A.1 shows whether the effect varies heterogenous between males and females. We observe that the coefficients for the excessive monsoon rain dummy have become statistically insignificant, indicating that the effect is heterogeneous across sexes. The interaction between excessive monsoon rainfall and females is statistically significant for household heads only, which suggests that only female household heads are more likely to engage in income-generating activities when faced with excessive rainfall. Besides, although females, in general, are less likely to work for an income (possibly due to barriers to entering the labour market), when faced with climate variability, female household heads carry out the extra responsibility of earning for the family.

Table 5 presents the estimates of Equation 1 where the dependent variable indicates whether an unemployed individual in 2011 took up work in the agriculture sector in 2015. Across all members, the likelihood of taking up work in the agriculture sector in period t+1 increases by approximately three percentage points when a household experiences excessive monsoon rain in period t. But the likelihood increases by as much as 11 percentage points for household heads and only two percentage points for non-head members. Historical fluctuation in rainfall is observed to have no significant impact on the decision to work in the agriculture sector. Regardless of past experience of rainfall variation, in response to recent experience of excess rainfall, unemployed household heads are more inclined to work in the agriculture sector compared to other members. This finding could be indicative of two things: either the household heads have more willingness to carry out agricultural activities, or they have better access to the agriculture labour market and know-how to penetrate the farm-based market.

If we consider sex of household heads in this decision-making process then, as shown in Table A.2, when faced with excessive rainfall, female non-head members are found to be two percentage points more likely to take up agricultural income-earning activities. The effect is similar across all household members in general, but there is no differential impact due to sex of the household heads. The excessive monsoon rainfall dummy has positive and statistically significant coefficients, suggesting a differential impact for male non-head members in taking up agricultural work. However, in the case of household heads, there is no heterogeneity across sexes.

We, however, do not see any statistically significant impact of excessive monsoon rainfall on taking up work in the non-agriculture sector in period t+1 among those who were unemployed in period t (Table 6). But past fluctuations in rainfall tend to have a negative association with non-head members engaging in non-agricultural activities. Table 6 shows that there is no differential impact across the sexes either. Regardless of sex, excessive rainfall does not induce non-employed household heads and non-head members to engage in non-agricultural work. This may stem from insufficient infrastructure or a lack of necessary skills for engaging in non-agricultural businesses. Additionally, households experiencing precarious climate variability may exhibit reluctance to undertake further business ventures that they may consider unfamiliar and uncertain. The decision to not pursue non-agricultural activities could serve as an indicator of risk aversion among households.

Table 4: Relationship between heavier rainfall in period t and taking up work in period t+1

	(1)	(2)	(3)
Heavier monsoon rain in 2011	0.024*	0.019	0.117**
	(0.0129)	(0.0121)	(0.0591)
Monsoon rainfall CV	−0.002	−0.003	0.004
	(0.0037)	(0.0032)	(0.0192)
Mean summer temperature in 2011	0.003	0.002	0.023
	(0.0040)	(0.0037)	(0.0198)
Age	0.017***	0.015***	0.031***
	(0.0011)	(0.0010)	(0.0091)
Age squared	−0.000***	−0.000***	−0.000***
	(0.0000)	(0.0000)	(0.0001)
Female	−0.062***	−0.062***	−0.191**
	(0.0059)	(0.0054)	(0.0823)
Completed years of education	0.006*	0.003	0.006
	(0.0031)	(0.0031)	(0.0083)
HH averages years of education	−0.002	−0.001	−0.017
	(0.0028)	(0.0027)	(0.0127)
Married	0.134***	0.152***	−0.007
	(0.0179)	(0.0195)	(0.0688)
Land owned	−0.000	−0.000	0.000
	(0.0000)	(0.0000)	(0.0001)
Female HH head	0.008	0.001	
	(0.0106)	(0.0097)	
HH head primary education	−0.035***	−0.023*	
	(0.0126)	(0.0129)	
HH head secondary education	−0.066***	−0.041*	
	(0.0249)	(0.0242)	
HH head higher secondary education	−0.083**	−0.052	
	(0.0371)	(0.0358)	
HH head tertiary/above education	−0.136***	−0.100**	
	(0.0474)	(0.0470)	
Has electricity	−0.015*	−0.014*	−0.010
	(0.0086)	(0.0083)	(0.0486)
Owns a phone	−0.005	−0.002	−0.071
	(0.0073)	(0.0072)	(0.0618)
Receives remittance	−0.033***	−0.028***	−0.071
	(0.0096)	(0.0093)	(0.0569)
Distance to nearest marketplace	0.000	0.000	−0.002
	(0.0019)	(0.0018)	(0.0128)
Distance to nearest public transport	0.000	0.000	0.006
	(0.0008)	(0.0008)	(0.0056)
Distance to nearest hospital	−0.000	0.000	−0.001
	(0.0007)	(0.0007)	(0.0030)
Observations	10993	10483	510
Location fixed effects	*Yes*	*Yes*	*Yes*

Standard errors in parentheses clustered at village level
Sample: All members in col. 1, all but HH head in col. 2, and HH head in col. 3
Dependent variable: Dummy = 1 if non-earning in 2011 and earning in 2015, and 0 if non-earning in 2011 and 2015.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Relationship between heavier rainfall in period t and taking up work in the agricultural sector in period t+1

	(1)	(2)	(3)
Heavier monsoon rain in 2011	0.030**	0.025**	0.150**
	(0.0128)	(0.0117)	(0.0636)
Monsoon rainfall CV	0.000	0.000	−0.003
	(0.0033)	(0.0029)	(0.0189)
Mean summer temperature in 2011	0.006	0.005	0.027
	(0.0038)	(0.0035)	(0.0202)
Age	0.009***	0.007***	0.025***
	(0.0008)	(0.0008)	(0.0086)
Age squared	−0.000***	−0.000***	−0.000***
	(0.0000)	(0.0000)	(0.0001)
Female	−0.005	−0.009**	−0.074
	(0.0045)	(0.0038)	(0.0840)
Completed years of education	0.007**	0.004	−0.002
	(0.0027)	(0.0027)	(0.0087)
HH averages years of education	−0.003	−0.003	−0.008
	(0.0024)	(0.0024)	(0.0128)
Married	0.189***	0.214***	0.034
	(0.0174)	(0.0194)	(0.0651)
Land owned	0.000***	0.000***	0.000
	(0.0000)	(0.0000)	(0.0001)
Female HH head	0.004	−0.006	
	(0.0091)	(0.0075)	
HH head primary education	−0.028**	−0.016	
	(0.0113)	(0.0113)	
HH head secondary education	−0.061***	−0.036*	
	(0.0223)	(0.0214)	
HH head higher secondary education	−0.087**	−0.050	
	(0.0338)	(0.0324)	
HH head tertiary/above education	−0.132***	−0.086**	
	(0.0419)	(0.0409)	
Has electricity	−0.007	−0.007	−0.024
	(0.0076)	(0.0073)	(0.0483)
Owns a phone	0.003	0.002	0.014
	(0.0063)	(0.0059)	(0.0593)
Receives remittance	−0.015*	−0.007	−0.054
	(0.0088)	(0.0081)	(0.0558)
Distance to nearest marketplace	−0.000	−0.000	−0.002
	(0.0018)	(0.0017)	(0.0130)
Distance to nearest public transport	0.001	0.001	0.005
	(0.0008)	(0.0008)	(0.0059)
Distance to nearest hospital	0.000	0.000	0.003
	(0.0007)	(0.0007)	(0.0032)
Observations	10532	10066	466
Location fixed effects	*Yes*	*Yes*	*Yes*

Standard errors in parentheses clustered at village level
Sample: All members in col. 1, all but HH head in col. 2, and HH head in col. 3
Dependent variable: Dummy = 1 if non-earning in 2011 and earning in agricultural sector 2015, and 0 if non-earning in 2011 and 2015.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Relationship between heavier rainfall in period t and taking up work in the non-agricultural sector in period t+1

	(1)	(2)	(3)
Heavier monsoon rain in 2011	−0.004	−0.004	−0.003
	(0.0052)	(0.0052)	(0.0382)
Monsoon rainfall CV	−0.002	−0.003**	0.007
	(0.0015)	(0.0014)	(0.0115)
Mean summer temperature in 2011	−0.003*	−0.003*	−0.006
	(0.0015)	(0.0015)	(0.0116)
Age	0.009***	0.009***	0.016**
	(0.0007)	(0.0007)	(0.0065)
Age squared	−0.000***	−0.000***	−0.000***
	(0.0000)	(0.0000)	(0.0001)
Female	−0.063***	−0.058***	−0.241***
	(0.0046)	(0.0044)	(0.0712)
Completed years of education	0.000	−0.000	0.014**
	(0.0020)	(0.0020)	(0.0063)
HH averages years of education	−0.000	0.001	−0.021**
	(0.0017)	(0.0018)	(0.0086)
Married	−0.037***	−0.043***	−0.077
	(0.0099)	(0.0100)	(0.0504)
Land owned	−0.000***	−0.000***	−0.000*
	(0.0000)	(0.0000)	(0.0001)
Female HH head	0.006	0.008	
	(0.0073)	(0.0076)	
HH head primary education	−0.013	−0.011	
	(0.0093)	(0.0091)	
HH head secondary education	−0.015	−0.012	
	(0.0163)	(0.0156)	
HH head higher secondary education	−0.009	−0.012	
	(0.0261)	(0.0251)	
HH head tertiary/above education	−0.023	−0.029	
	(0.0313)	(0.0306)	
Has electricity	−0.010**	−0.010**	0.005
	(0.0047)	(0.0047)	(0.0360)
Owns a phone	−0.009*	−0.005	−0.110**
	(0.0052)	(0.0052)	(0.0512)
Receives remittance	−0.024***	−0.026***	−0.059
	(0.0058)	(0.0059)	(0.0407)
Distance to nearest marketplace	0.000	0.000	−0.000
	(0.0010)	(0.0010)	(0.0088)
Distance to nearest public transport	−0.000	−0.000	0.002
	(0.0004)	(0.0003)	(0.0047)
Distance to nearest hospital	−0.000	0.000	−0.006***
	(0.0003)	(0.0003)	(0.0016)
Observations	10093	9703	390
Location fixed effects	*Yes*	*Yes*	*Yes*

Standard errors in parentheses clustered at village level
Sample: All members in col. 1, all but HH head in col. 2, and HH head in col. 3
Dependent variable: Dummy = 1 if non-earning in 2011 and earning in non-agricultural sector 2015, and 0 if non-earning in 2011 and 2015.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.1.2 Switching Sectors

The transition between sectors in period t+1—whether from agriculture to non-agriculture or vice versa—is significantly influenced by excessive monsoon rainfall in period t, impacting all household members, including the household heads. As shown in Table 7, although the household heads are five percentage points more likely to switch sectors, non-head members remain unaffected and they either do not have the tendency or the capability to implement the transition. Household heads carry out the responsibility to help the family cope with climatic uncertainty through occupational diversification. Past experience of rainfall fluctuation remains statistically insignificant across all household members. Moreover, excessive rainfall does not induce a significant switch to the agriculture sector among females, but the effect is positively channeled through male household heads (Table A.4).

Contrary to expectations based on prior literature, Table 8 shows that excessive rainfall induces a shift to the agriculture sector from the non-agriculture sector across all members, including household heads. The latter have a four percentage points higher probability of moving to agriculture, whereas all household members on average are two percentage points more likely. Whereas, historic fluctuations in rainfall do not influence the switch to the agriculture sector. Moreover, female household members are not likely to shift to agriculture due to excessive rainfall in period t; the entire effect is channelled through male members (Table A.5). Male members are more likely to take on the responsibility of helping the family cope with rainfall variation by switching to a sector that they are familiar with and that they can rely on despite climatic uncertainties. It is also possible that they perceive excessive rainfall as a factor driving a better harvest; natural occurrences of rainfall save fuel and electricity costs for artificial irrigation.

However, excessive rainfall in period t has a statistically significant and negative effect on switching to the non-agriculture sector from agriculture in period t+1 on non-head household members only (Table 9). Household heads opt against switching to the non-agriculture sector due to their past experience of monsoon rainfall fluctuation. This tendency is generally observed among all household members but is more precise among household heads. Moreover, the shift to the non-agriculture sector due to excessive rainfall is not very significant between males and females (Table A.6). While the effect is insignificant for males (heads/non-heads), female members in general are less likely to switch from agriculture to non-agriculture. Although the effect is only significant at a 90% confidence interval, the disinclination of females toward non-farm activities could be due to existing labour market barriers, an unsuitable work environment, a lack of opportunities, etc.

Table 7: Relationship between heavier rainfall in period t and switching occupational sectors in period t+1

	(1)	(2)	(3)
Heavier monsoon rain in 2011	0.004	−0.027	0.021
	(0.0136)	(0.0251)	(0.0154)
Monsoon rainfall CV	−0.002	0.002	−0.004
	(0.0047)	(0.0079)	(0.0057)
Mean summer temperature in 2011	0.002	0.003	0.002
	(0.0041)	(0.0064)	(0.0049)
Age	−0.000	−0.005	0.007**
	(0.0020)	(0.0038)	(0.0032)
Age squared	−0.000	0.000	−0.000**
	(0.0000)	(0.0000)	(0.0000)
Female	−0.038***	−0.014	−0.058**
	(0.0136)	(0.0257)	(0.0261)
Completed years of education	−0.000	−0.006	0.004
	(0.0051)	(0.0078)	(0.0025)
HH averages years of education	−0.007**	−0.007	−0.008**
	(0.0032)	(0.0051)	(0.0042)
Married	−0.033**	−0.033	−0.009
	(0.0168)	(0.0250)	(0.0262)
Land owned	−0.000	0.000	−0.000**
	(0.0000)	(0.0000)	(0.0000)
Female HH head	−0.013	−0.002	
	(0.0217)	(0.0385)	
HH head primary education	0.000	0.012	
	(0.0235)	(0.0362)	
HH head secondary education	0.027	0.060	
	(0.0442)	(0.0686)	
HH head higher secondary education	0.072	0.206*	
	(0.0694)	(0.1175)	
HH head tertiary/above education	−0.018	0.067	
	(0.0795)	(0.1291)	
Has electricity	−0.023**	−0.027	−0.022*
	(0.0109)	(0.0201)	(0.0128)
Owns a phone	−0.023*	−0.028	−0.020
	(0.0124)	(0.0222)	(0.0154)
Receives remittance	0.009	−0.030	0.036*
	(0.0145)	(0.0217)	(0.0199)
Distance to nearest marketplace	−0.001	−0.004	0.000
	(0.0029)	(0.0045)	(0.0037)
Distance to nearest public transport	0.000	−0.000	0.001
	(0.0010)	(0.0015)	(0.0013)
Distance to nearest hospital	0.001	0.001	0.000
	(0.0011)	(0.0017)	(0.0014)
Observations	6130	2261	3869
Location fixed effects	*Yes*	*Yes*	*Yes*

Standard errors in parentheses clustered at village level
Sample: All members in col. 1, all but HH head in col. 2, and HH head in col. 3
Dependent variable: Dummy = 1 if occupational sector changed between 2011 and 2015, and 0 if occupational sector remained same in 2011 and 2015.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Relationship between heavier rainfall in period t and switching to the agricultural sector in period t+1

	(1)	(2)	(3)
Heavier monsoon rain in 2011	0.030*	−0.000	0.037**
	(0.0160)	(0.0291)	(0.0177)
Monsoon rainfall CV	0.009	0.009	0.008
	(0.0067)	(0.0109)	(0.0071)
Mean summer temperature in 2011	0.011*	0.011	0.010
	(0.0062)	(0.0094)	(0.0069)
Age	−0.005	−0.007	−0.001
	(0.0031)	(0.0058)	(0.0044)
Age squared	0.000**	0.000*	0.000
	(0.0000)	(0.0001)	(0.0001)
Female	0.140***	0.133***	0.022
	(0.0310)	(0.0373)	(0.0477)
Completed years of education	−0.004	0.011	−0.003
	(0.0064)	(0.0098)	(0.0035)
HH averages years of education	−0.003	−0.009	0.001
	(0.0049)	(0.0079)	(0.0063)
Married	0.026	0.034	0.005
	(0.0224)	(0.0308)	(0.0397)
Land owned	0.000**	0.000*	0.000
	(0.0001)	(0.0001)	(0.0001)
Female HH head	−0.067**	−0.043	
	(0.0296)	(0.0332)	
HH head primary education	0.013	−0.068	
	(0.0315)	(0.0497)	
HH head secondary education	0.028	−0.165**	
	(0.0554)	(0.0827)	
HH head higher secondary education	0.012	−0.164	
	(0.0844)	(0.1487)	
HH head tertiary/above education	−0.068	−0.325*	
	(0.0955)	(0.1705)	
Has electricity	−0.000	0.011	−0.008
	(0.0162)	(0.0249)	(0.0188)
Owns a phone	−0.004	−0.006	−0.007
	(0.0168)	(0.0317)	(0.0187)
Receives remittance	0.079***	0.044	0.106***
	(0.0238)	(0.0352)	(0.0314)
Distance to nearest marketplace	0.007*	−0.001	0.010**
	(0.0041)	(0.0055)	(0.0052)
Distance to nearest public transport	0.000	0.001	−0.000
	(0.0012)	(0.0023)	(0.0013)
Distance to nearest hospital	0.002	0.003	0.001
	(0.0014)	(0.0027)	(0.0014)
Observations	2928	886	2042
Location fixed effects	*Yes*	*Yes*	*Yes*

Standard errors in parentheses clustered at village level
Sample: All members in col. 1, all but HH head in col. 2, and HH head in col. 3
Dependent variable: Dummy = 1 if switched to agricultural sector in 2015, and 0 if stayed in non-agricultural sector in 2011 and 2015.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Relationship between heavier rainfall in period t and switching to the non-agricultural sector in period t+1

	(1)	(2)	(3)
Heavier monsoon rain in 2011	−0.023	−0.060*	−0.000
	(0.0225)	(0.0339)	(0.0273)
Monsoon rainfall CV	−0.011	0.002	−0.016**
	(0.0066)	(0.0108)	(0.0083)
Mean summer temperature in 2011	−0.002	−0.001	−0.004
	(0.0060)	(0.0079)	(0.0076)
Age	−0.005*	−0.004	0.001
	(0.0028)	(0.0051)	(0.0048)
Age squared	0.000	0.000	−0.000
	(0.0000)	(0.0001)	(0.0000)
Female	−0.156***	−0.136***	−0.150***
	(0.0168)	(0.0458)	(0.0363)
Completed years of education	0.004	−0.011	0.010***
	(0.0071)	(0.0098)	(0.0032)
HH averages years of education	−0.009**	−0.001	−0.018***
	(0.0043)	(0.0063)	(0.0057)
Married	−0.114***	−0.168***	0.003
	(0.0337)	(0.0498)	(0.0436)
Land owned	−0.000***	−0.000***	−0.000***
	(0.0000)	(0.0001)	(0.0001)
Female HH head	0.021	0.134*	
	(0.0303)	(0.0780)	
HH head primary education	−0.024	0.020	
	(0.0330)	(0.0468)	
HH head secondary education	0.007	0.129	
	(0.0625)	(0.0884)	
HH head higher secondary education	0.109	0.388**	
	(0.1054)	(0.1622)	
HH head tertiary/above education	0.086	0.197	
	(0.1209)	(0.1579)	
Has electricity	−0.024	−0.028	−0.019
	(0.0163)	(0.0239)	(0.0211)
Owns a phone	−0.036**	−0.051*	−0.026
	(0.0178)	(0.0281)	(0.0239)
Receives remittance	−0.035*	−0.062**	−0.022
	(0.0179)	(0.0275)	(0.0250)
Distance to nearest marketplace	−0.009**	−0.003	−0.013**
	(0.0039)	(0.0052)	(0.0055)
Distance to nearest public transport	0.000	−0.001	0.001
	(0.0013)	(0.0020)	(0.0020)
Distance to nearest hospital	−0.000	−0.001	−0.000
	(0.0015)	(0.0021)	(0.0020)
Observations	3202	1375	1827
Location fixed effects	*Yes*	*Yes*	*Yes*

Standard errors in parentheses clustered at village level
Sample: All members in col. 1, all but HH head in col. 2, and HH head in col. 3
Dependent variable: Dummy = 1 if switched to non-agricultural sector in 2015, and 0 if stayed in agricultural sector in 2011 and 2015.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Welfare Effects

To identify the welfare effects of occupational diversification, we estimate Equation 2 through the two-stage least squares method, where the occurrence of excessive monsoon rainfall in 2011 are used as an instrumental variable. The estimates indicate the average change in household welfare in response to the shift in occupations for households induced by exogenous variation in rainfall. As an IV, rainfall is often criticized for violating the exclusion restriction as it might affect the outcome through other unobserved means. In our case, excessive and uncertain rainfall can form a certain pattern of expenditure and dietary intake. To control for the potential heterogeneity due to past experience of rainfall, we include the 30-year monsoon rainfall coefficient of variation as an explanatory variable and exclude it as a candidate for IV. Thus, the dummy representing excessive monsoon rainfall in 2011 will show the immediate effect on household welfare channeled through transitions in occupational sectors.[6]

As shown in Table 10, a statistically significant and positive effect is observed on household per capita food expenditure; households food expenditure is likely to increase by 12% if the household heads shift to the agriculture sector in response to excessive rainfall and fluctuations. Although the impact on non-food expenditure and household dietary diversity is insignificant, the positive effect on the total per capita household expenditure suggests that households prioritize food consumption when they resort to occupational change due to climate variability. In contrast, households where the heads switch to the non-agriculture sector are 13% more likely to experience a decrease in food expenditure. Total expenditure is also 10% likely to decrease, while non-food and dietary diversity remains unaffected.

Our findings, therefore, suggest that occupational change induced by rainfall variation affects household welfare mostly through food consumption where the switch towards agriculture sector has turned out to have a favorable effect on welfare while the effect simply reverses when the switch is towards the non-agriculture sector. This contrasting result indicates the possibility of not having better options in the non-agriculture sector. The policy focus thus needs to be shifted towards creating a wider range of non-agriculture sector jobs in climate-vulnerable areas.

[6] To control for other adaptation mechanisms, the models include variables representing whether a household receives remittances and the value of assets held. Households facing climate shocks may influence their members to migrate and/or may need to deplete their assets.

Table 10: Welfare effects of switching to agricultural sector

	(1) Total	(2) Food	(3) Non- Food	(4) DDS
Switched to agricultural sector	0.078*	0.127**	−0.023	−0.030
	(0.0450)	(0.0526)	(0.0363)	(0.1046)
Monsoon rainfall CV	−0.005	−0.009	0.005	−0.047
	(0.0089)	(0.0113)	(0.0121)	(0.0351)
HH head age	0.002*	0.003*	0.001	0.005
	(0.0012)	(0.0014)	(0.0011)	(0.0035)
HH head age (mean-centred squared)	−0.000***	−0.000	−0.000***	−0.000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Female HH head	−0.144**	−0.192***	−0.141***	−0.589***
	(0.0569)	(0.0700)	(0.0466)	(0.1490)
HH head primary education	0.079***	0.046*	0.124***	0.288***
	(0.0225)	(0.0266)	(0.0254)	(0.0733)
HH head secondary education	0.223***	0.044	0.445***	0.433***
	(0.0526)	(0.0567)	(0.0662)	(0.1640)
HH size	−0.128***	−0.120***	−0.143***	0.024
	(0.0087)	(0.0105)	(0.0084)	(0.0240)
HH size (mean-centred squared)	0.011***	0.009***	0.014***	−0.004
	(0.0024)	(0.0025)	(0.0027)	(0.0067)
Land owned (decimals)	0.001***	0.001***	0.000*	0.000
	(0.0001)	(0.0002)	(0.0002)	(0.0004)
Land owned (mean-centred squared)	−0.000***	−0.000***	−0.000**	−0.000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Dependency ratio	−0.040	−0.012	−0.130*	−0.336
	(0.0735)	(0.0888)	(0.0716)	(0.2067)
Receives remittance	−0.002	−0.054	0.072*	0.061
	(0.0327)	(0.0363)	(0.0370)	(0.0931)
House in good condition	0.178***	0.078*	0.311***	0.056
	(0.0393)	(0.0467)	(0.0428)	(0.1047)
Experienced adverse event	0.021	−0.042	0.125***	−0.029
	(0.0229)	(0.0273)	(0.0252)	(0.0735)
Covered by SSN	−0.023	−0.034	0.034	−0.002
	(0.0242)	(0.0301)	(0.0245)	(0.0815)
Has electricity	0.094***	0.084**	0.111***	0.107
	(0.0304)	(0.0370)	(0.0288)	(0.0893)
Has separate toilet	0.050**	0.037	0.052**	−0.047
	(0.0253)	(0.0275)	(0.0264)	(0.0759)
Owns a phone	0.041	0.026	0.123***	0.116
	(0.0353)	(0.0438)	(0.0320)	(0.1163)
Owns a TV	0.099***	0.076*	0.126***	0.138
	(0.0343)	(0.0391)	(0.0335)	(0.0973)
Value of assets	0.188***	0.145***	0.257***	0.341***
	(0.0129)	(0.0150)	(0.0141)	(0.0394)
Constant	6.554***	6.676***	4.333***	6.885***
	(0.2507)	(0.3120)	(0.3319)	(0.9481)
Observations	2134	2134	2134	2134
Location fixed effects	*Yes*	*Yes*	*Yes*	*Yes*

Standard errors in parentheses clustered at village level
Note: Per capita total/food/non-food expenditures and dietary diversity score used as dependent variables. Switch to agricultural sector is instrumented by a dummy representing excess monsoon rainfall in 2011.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Welfare effects of switching to non-agricultural sector

	(1) Total	(2) Food	(3) Non- Food	(4) DDS
Switched to non-agricultural sector	−0.095***	−0.137***	0.005	−0.063
	(0.0283)	(0.0341)	(0.0321)	(0.0892)
Monsoon rainfall CV	−0.016**	−0.024**	0.009	−0.071**
	(0.0080)	(0.0097)	(0.0091)	(0.0303)
HH head age	0.001	0.002	0.001	0.001
	(0.0012)	(0.0014)	(0.0011)	(0.0041)
HH head age (mean-centred squared)	−0.000*	−0.000	−0.000***	−0.000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Female HH head	−0.084	−0.099	−0.069	−0.313**
	(0.0539)	(0.0616)	(0.0479)	(0.1508)
HH head primary education	0.010	0.004	0.034	0.099
	(0.0242)	(0.0276)	(0.0253)	(0.0814)
HH head secondary education	0.125**	0.054	0.237***	0.249
	(0.0594)	(0.0676)	(0.0823)	(0.2069)
HH size	−0.103***	−0.088***	−0.136***	0.054**
	(0.0076)	(0.0091)	(0.0089)	(0.0233)
HH size (mean-centred squared)	0.009***	0.009***	0.011***	−0.006
	(0.0015)	(0.0018)	(0.0017)	(0.0051)
Land owned (decimals)	0.000***	0.001***	0.000*	0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0003)
Land owned (mean-centred squared)	−0.000**	−0.000***	−0.000	−0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Dependency ratio	0.175**	0.287***	−0.107	0.401*
	(0.0771)	(0.0897)	(0.0703)	(0.2417)
Receives remittance	0.029	−0.040	0.140***	0.188**
	(0.0304)	(0.0348)	(0.0326)	(0.0823)
House in good condition	0.186***	0.072*	0.332***	0.078
	(0.0356)	(0.0386)	(0.0454)	(0.1054)
Experienced adverse event	−0.006	−0.080***	0.137***	−0.136*
	(0.0209)	(0.0246)	(0.0257)	(0.0725)
Covered by SSN	−0.007	−0.014	0.020	0.020
	(0.0250)	(0.0282)	(0.0277)	(0.0772)
Has electricity	0.090***	0.060*	0.134***	0.312***
	(0.0299)	(0.0338)	(0.0293)	(0.1022)
Has separate toilet	0.003	−0.019	0.043	0.015
	(0.0324)	(0.0374)	(0.0322)	(0.0984)
Owns a phone	0.138***	0.130***	0.134***	0.410***
	(0.0338)	(0.0416)	(0.0368)	(0.1253)
Owns a TV	0.069**	0.054*	0.085***	0.248**
	(0.0270)	(0.0302)	(0.0331)	(0.0983)
Value of assets	0.185***	0.142***	0.262***	0.316***
	(0.0174)	(0.0204)	(0.0183)	(0.0512)
Constant	6.814***	7.013***	4.145***	6.951***
	(0.2710)	(0.3181)	(0.3069)	(0.8788)
Observations	1831	1831	1832	1832
Location fixed effects	*Yes*	*Yes*	*Yes*	*Yes*

Standard errors in parentheses clustered at village level
Note: Per capita total/food/non-food expenditures and dietary diversity score used as dependent variables. Switch to non-agricultural sector is instrumented by a dummy representing excess monsoon rainfall in 2011.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Conclusion

Despite contributing less than one percent of the global emissions, Bangladesh has emerged as one of the most climate-vulnerable countries.[7] Its geographical location and topography have made it particularly susceptible to erratic weather patterns, including a sustained rise in temperature and precipitation[8]. Over the past five decades, the country has experienced a significant increase in temperature, with summers getting hotter and longer, winters warmer, and monsoon seasons becoming erratic in nature.[9] Bangladesh no longer enjoys its distinct six seasons like before; rather, there exists an overlap between summer, monsoon and winter seasons at various times of the year. Furthermore, the country frequently experiences heavy precipitation and tropical cyclones due to its humid and warm climate influenced by pre-monsoon, monsoon, and post-monsoon circulations, facing about 2,200 milimeters of rainfall on average per year.[10] These changes in climate patterns are likely to bring about uncertainties to lives and livelihoods of its people, especially to those living in rural areas and working on agriculture-based occupations.

In Bangladesh, the agriculture sector largely consists of subsistence farming, with rice being the primary crop. Variations in monsoon rainfall can have significant implications for agricultural productivity. For instance, changes in temperature and rainfall patterns can significantly affect rice yield (Alam, Hridoy, Tusher, Islam, & Islam, 2023). Moreover, excessive rainfall during the monsoon can lead to flooding of agricultural lands, resulting in crop loss. On the other hand, insufficient rainfall can lead to droughts, affecting the irrigation of crops.

In this study, we examine how household members diversify their occupations as a coping strategy in response to exogenous variations in monsoon rainfall. We utilize panel data on household characteristics and the actual rainfall experienced by the households during the survey years, along with historical rainfall data collected from the Bangladesh Meteorological Department. These datasets allow us to monitor the overtime change in occupations and exploit the exogeneity of rainfall variability to draw a causal link. We find that excessive monsoon rainfall can induce unemployed household members to take up work in the next period, mostly in the agriculture sector. In terms of switching sectors, we find a stronger preference for the agriculture sector and a lower preference for non-agriculture. This could be due to the possibility that, despite climatic uncertainties, the preference for agriculture stems from familiarity and convenience of household members seeking jobs. In addition, households may also perceive excessive rainfall as a factor contributing to better harvests; natural rainfall reduces the costs of fuel and electricity associated

[7]See https://www.climaterealityproject.org/blog/how-climate-crisis-impacting-bangladesh
[8]See https://www.worldbank.org/en/news/video/2021/10/07/climate-afflictions-in-bangladesh
[9]See https://reliefweb.int/report/bangladesh/bangladesh-climate-afflictions
[10]See https://climateknowledgeportal.worldbank.org/country/bangladesh/climate-data-historical

with artificial irrigation. On the other hand, a lack of skills, opportunities, essential infrastructure and market linkage required to earn a decent living in the non-agriculture sector may also act as push factors for choosing agricultural employment.

This study also reveals that cccupational diversification induced by rainfall variability has a positive effect on food expenditure but no significant effect on non-food expenditure. Households having to cope with climate uncertainties by changing occupations might be too vulnerable to only be concerned about food expenditure and not to consider altering their non food requirements. They do not have the ability to attain higher dietary diversity that can lead to better health, nutrition and well-being. Regardless of higher food expenditures, higher levels of welfare may not be reflected due to a low proportion of non-food consumption in the total household expenditure (Zimmerman, 1932) and no observable change in the quality of food intake. This leaves significant room for targeted policy to support those affected by variable rainfall and thus struggle to maintain a certain level of welfare.

From a policy perspective, firstly, there is a need for greater emphasis on providing informational, input, credit, and relevant marketing support to households in climate-vulnerable regions to facilitate their transition towards more viable non-agricultural sectors, given the tendency to focus on the agriculture sector. Secondly, as households struggle to adjust their food consumption patterns in the face of climate variability, the government needs to expand its safety net programs in these vulnerable regions through targeted initiatives, particularly aimed at mothers and children, to meet their long-term nutritional needs. Thirdly, recognizing the challenges faced by households in diversifying their non-food consumption, it is crucial to improve access to healthcare and educational facilities in climate-vulnerable regions. Lastly, to aid vulnerable communities in climate-sensitive areas, it is imperative to ensure effective utilization of relevant climate change funds, while also directing government poverty reduction policies towards these regions.

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A Appendix

A.1 Heterogeneity by Sex

Table A.1: Relationship between excessive rainfall in period t and taking up work in period t+1 (heterogeneity by sex)

	(1)	(2)	(3)
Excessive monsoon rain in 2011	0.007	0.005	−0.049
	(0.0096)	(0.0094)	(0.0892)
Female	−0.012	−0.016	-0.280^{***}
	(0.0104)	(0.0103)	(0.0899)
Excessive monsoon rain in 2011 × Female	0.017	0.013	0.186^{*}
	(0.0124)	(0.0123)	(0.0981)
Monsoon rainfall CV	-0.003^{*}	-0.004^{**}	0.005
	(0.0017)	(0.0017)	(0.0108)
Observations	12171	11561	610
Location fixed effects	*Yes*	*Yes*	*Yes*

Standard errors in parentheses clustered at village level. Control variables not shown for brevity.
Sample: All members in col. 1, all but HH head in col. 2, and HH head in col. 3
Dependent variable: Dummy = 1 if non-earning in 2011 and earning in 2015,
and 0 if non-earning in 2011 and 2015.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Relationship between excessive rainfall in period t and taking up work in the agricultural sector in period t+1 (heterogeneity by sex)

	(1)	(2)	(3)
Excessive monsoon rain in 2011	0.014**	0.010*	0.017
	(0.0060)	(0.0056)	(0.0873)
Female	0.036***	0.030***	−0.147
	(0.0078)	(0.0075)	(0.0907)
Excessive monsoon rain in 2011 × Female	0.018*	0.018*	0.117
	(0.0096)	(0.0094)	(0.0964)
Monsoon rainfall CV	−0.002	−0.002	−0.004
	(0.0015)	(0.0015)	(0.0102)
Observations	11670	11109	561
Location fixed effects	*Yes*	*Yes*	*Yes*

Standard errors in parentheses clustered at village level. Control variables not shown for brevity.
Sample: All members in col. 1, all but HH head in col. 2, and HH head in col. 3
Dependent variable: Dummy = 1 if non-earning in 2011 and earning in agricultural sector 2015, and 0 if non-earning in 2011 and 2015.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Relationship between excessive rainfall in period t and taking up work in the non-agricultural sector in period t+1 (heterogeneity by sex)

	(1)	(2)	(3)
Excessive monsoon rain in 2011	−0.007	−0.005	−0.086
	(0.0084)	(0.0082)	(0.0793)
Female	−0.050***	−0.047***	−0.244***
	(0.0082)	(0.0080)	(0.0807)
Excessive monsoon rain in 2011 × Female	0.000	−0.004	0.126
	(0.0094)	(0.0093)	(0.0817)
Monsoon rainfall CV	−0.001	−0.002**	0.013
	(0.0011)	(0.0011)	(0.0085)
Observations	11175	10699	476
Location fixed effects	*Yes*	*Yes*	*Yes*

Standard errors in parentheses clustered at village level. Control variables not shown for brevity.
Sample: All members in col. 1, all but HH head in col. 2, and HH head in col. 3
Dependent variable: Dummy = 1 if non-earning in 2011 and earning in non-agricultural sector 2015, and 0 if non-earning in 2011 and 2015.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Relationship between excessive rainfall in period t and switching occupational sectors in period t+1 (heterogeneity by sex)

	(1)	(2)	(3)
Excessive monsoon rain in 2011	0.026**	0.018	0.030**
	(0.0122)	(0.0269)	(0.0138)
Female	0.018	0.008	0.041
	(0.0215)	(0.0332)	(0.0528)
Excessive monsoon rain in 2011 × Female	−0.075***	−0.062*	−0.097*
	(0.0243)	(0.0362)	(0.0578)
Monsoon rainfall CV	−0.002	0.004	−0.005
	(0.0033)	(0.0057)	(0.0040)
Observations	6713	2467	4246
Location fixed effects	*Yes*	*Yes*	*Yes*

Standard errors in parentheses clustered at village level. Control variables not shown for brevity.
Sample: All members in col. 1, all but HH head in col. 2, and HH head in col. 3
Dependent variable: Dummy = 1 if occupational sector changed between 2011 and 2015, and 0 if occupational sector remained same in 2011 and 2015.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Relationship between excessive rainfall in period t and switching to the agricultural sector in period t+1 (heterogeneity by sex)

	(1)	(2)	(3)
Excessive monsoon rain in 2011	0.031**	0.004	0.040**
	(0.0138)	(0.0253)	(0.0165)
Female	0.132***	0.102*	0.117
	(0.0444)	(0.0571)	(0.0835)
Excessive monsoon rain in 2011 × Female	−0.039	0.021	−0.118
	(0.0520)	(0.0654)	(0.0924)
Monsoon rainfall CV	0.004	0.006	0.004
	(0.0045)	(0.0085)	(0.0054)
Observations	3215	961	2254
Location fixed effects	*Yes*	*Yes*	*Yes*

Standard errors in parentheses clustered at village level. Control variables not shown for brevity.
Sample: All members in col. 1, all but HH head in col. 2, and HH head in col. 3
Dependent variable: Dummy = 1 if switched to agricultural sector in 2015,
and 0 if stayed in non-agricultural sector in 2011 and 2015.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Relationship between excessive rainfall in period t and switching to the non-agricultural sector in period t+1 (heterogeneity by sex)

	(1)	(2)	(3)
Excessive monsoon rain in 2011	0.004	−0.042	0.015
	(0.0210)	(0.0621)	(0.0226)
Female	−0.120***	−0.220***	−0.080
	(0.0281)	(0.0595)	(0.0689)
Excessive monsoon rain in 2011 × Female	−0.053*	−0.019	−0.072
	(0.0307)	(0.0665)	(0.0751)
Monsoon rainfall CV	−0.009*	0.003	−0.017***
	(0.0046)	(0.0072)	(0.0058)
Observations	3498	1506	1992
Location fixed effects	*Yes*	*Yes*	*Yes*

Standard errors in parentheses clustered at village level. Control variables not shown for brevity.
Sample: All members in col. 1, all but HH head in col. 2, and HH head in col. 3
Dependent variable: Dummy = 1 if switched to non-agricultural sector in 2015,
and 0 if stayed in agricultural sector in 2011 and 2015.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$