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Climate variability, rainfall shocks, and farmers' income diversification in India ☆

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HIGHLIGHTS

- Rainfall shocks adversely affect Indian farmers' agricultural income.
- Farmers respond to rainfall shocks through diversifying their income with agricultural wage and non-farm wage jobs.
- Rainfall shocks affect farmers' agricultural income less in places with more historically variable weather.
- Farmers diversify more through wage income in places with less historically variable weather.

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ABSTRACT

Rainfall in India has become much more variable as a result of global climate change. Responses to rain shocks vary depending on the level of climate variation a community experiences historically. Using data spanning three decades in 230 villages in India, I find that farmers tend to diversify their income with non-farm wage jobs in response to rainfall shocks. This diversification strategy is employed less in places with more variable historical weather as people are more adapted. As climate change causes more variable weather in the coming years, my results suggest that places with historically less variable weather may become more vulnerable in this changing climate.

1. Introduction

Climate change poses significant impacts on developing countries due to changing weather patterns, as people in these countries depend heavily on agriculture for their livelihoods. Lacking formal resources to deal with shocks, people in developing countries often cope through informal means, such as self-insurance (Deaton, 1991), income diversification activities (Dercon, 2002), and risk-sharing through migration–marriage (Rosenzweig and Stark, 1989). In the worst scenario, households withdraw children from schools to respond to unexpected shocks (Jacoby and Skoufias, 1997; Jensen, 2000). The existing literature on risk-coping strategies largely focuses on idiosyncratic shocks—ones that impact individuals—as opposed to aggregate shocks that affect the whole community (Dercon, 2008).

This paper asks two questions: (1) How do rainfall shocks affect sources of income in households? (2) Do farmers' income diversification strategies vary across regions with different historical weather patterns? When it comes to aggregate shocks, many economists examine income diversification through labor choice responses, specifically, wage jobs (Dimova et al., 2014; Gao and Mills, 2018; Ito and Kurosaki, 2006; Kijima et al., 2006; Kochar, 1999; Mathenge and Tschirley, 2015; Rose, 2001) and internal migration (Gröger and Zylberberg, 2016; Jessoe et al., 2018; Minale, 2018) as key coping strategies. I make two contributions in this article. First, I explore the regional heterogeneity in income diversification, specifically, how historical weather patterns affect

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Table 1
Summary statistics.

Variable	Mean	Std Dev	Obs	Source	Available year
Weather					
Monsoon total rainfall (mm)	822.79	419.79	5943	University of Delaware	1900–2008
June temperature	30.60	3.07	5943	University of Delaware	1900–2008
20-year average monsoon rainfall	776.25	381.84	5943	University of Delaware	1900–2008
20-year monsoon rainfall SD	199.87	78.82	5943		
20-year average June temperature	30.46	2.95	5943	University of Delaware	1900–2008
Household demographics					
Age	49.92	13.45	5942	ARIS	1970, 1981, 1998
Education (year)	2.18	1.80	5943	ARIS	1970, 1981, 1998
household size	6.37	2.62	5943	ARIS	1970, 1981, 1998
Land area (acres)	3.35	5.29	5943	ARIS	1970, 1981, 1998
Same caste as the village majority	0.68	0.47	1981	ARIS	1982
Village information					
Total # of jobs among household head	2.52	1.57	689	ARIS	1982
Distance to a city	74.05	44.76	689	Calculated through ArcGIS	
Population	2,214.93	4,213.91	689	ARIS	1970, 1981, 1998
Income per capita					
Total income	7,345.37	9,766.46	5943	ARIS	1970, 1981, 1998
Agricultural income	5,058.12	8,850.90	5943	ARIS	1970, 1981, 1998
Agricultural wage income	298.24	766.93	5943	ARIS	1970, 1981, 1998
Non-farm wage income	1,124.55	3,401.55	5943	ARIS	1970, 1981, 1998
Business income	552.33	2,229.43	5943	ARIS	1970, 1981, 1998
Livestock income	312.14	1,125.71	5943	ARIS	1970, 1981, 1998

farmers' *ex ante* adaptation. Second, my data contains richer spatial and temporal variations compared to most existing studies. To answer these questions empirically, I merge historical weather data with household survey data in the year 1970, 1981, and 1998. The final dataset allows me to examine farmers' income diversification over a long period of time. The identification comes from the fact that rainfall deviation from the mean is random across space, after I control for important household and village level characteristics, historical weather patterns, and state fixed effects.

Results indicate that rainfall shocks negatively affect farmers' agricultural income. In response to shocks, farmers diversify their incomes through other wage jobs. Such diversification has a spatial pattern: households in places with greater historical weather variation are less responsive to contemporaneous rainfall shocks, compared to those in places with smaller historical weather variation. In other words, farmers can be already adapted to a certain extent through income diversification in places that historically have more fluctuating weather. My results suggest the necessity of incorporating agents' *ex ante* response into economic models when studying climate change (Kala (2017) and Dimova et al. (2014) are good examples), and distinguishing short-run vs. long-run adaptation (Burke and Emerick, 2016). The result also indicates that policymakers should be more attentive to places that are historically less prepared for climate change.

2. Data and variables

Household data: The main dataset is a household panel conducted in 230 Indian villages in 1970, 1981, and 1998. This dataset covers 16 major provinces of India and is representative in rural areas of India in the initial year of the survey (Foster and Rosenzweig, 2004). The data is collected by the National Council of Applied Economics Research (NCAER) in India, which combines information from three sources: (i) the 1970–1971 NCAER Additional Rural Income Survey (ARIS), (ii) the 1981–1982 NCAER Rural Economic Development Survey (REDS), and (iii) the 1999 NCAER Village REDS. This dataset includes detailed information at the household level, such as demographic background, income by different sources, and information at the village level, such as population, distance to city, etc. An overview of the variables is presented in Table 1.

I consolidate households' income sources into agricultural, agricultural wage, and non-farm labor. Agricultural wage and non-farm labor jobs are both wage jobs and are the main target outcomes in this paper as literature suggested that households may diversify their income through wage jobs. Non-farm wage jobs are defined as wage/salary earners mainly working for others in sectors such as production, transportation, service, sports, and recreational. I exclude business income and livestock income since they only account for a small fraction of the total income, 8 percent and 5 percent respectively, in the baseline year. For the share of different income sources, I only include those who have at least one positive value in that source over the survey period.[1]

Weather data: The weather data from the Center for Climate Research at the University of Delaware includes monthly precipitation and temperature from 1900 to 2008 on a 0.5 degree latitude by 0.5 degree longitude global grid. The final measurement used in this paper is interpolated at the village level and weighted by the inverse-square of the distance between each nearby gridded observation (distance within 1.5 decimal degree) and the center point of the district. Mean temperature in June is included to control for germination condition.[2] Because monsoon rainfall is a critical determinant of agricultural productivity in India, and frequently used by scientists to understand the threat of climate change on agricultural returns, I use total monsoon rainfall from June to September as the benchmark to determine a rainfall shock similar to the literature (Giné et al., 2007; Jacoby and Skoufias, 1998; Kala, 2017; Rosenzweig and Binswanger, 1992; Taraz, 2017).

1 Sectoral hedging is also an important mean to cope with shocks (Shenoy, 2018). However, I have not seen evidence in the data either because that this kind of adaptation does not happen before the 90s, or the data is too sparse to begin with. I present the adaptation result through livestock and business income in the Supplementary Material Table A1. As the last two columns indicate, the effect of rainfall shock on livestock and business income is similar to its impact on agricultural income.

2 I also include an alternative specification using mean temperature from June to September as the robustness check (See Supplementary Material).

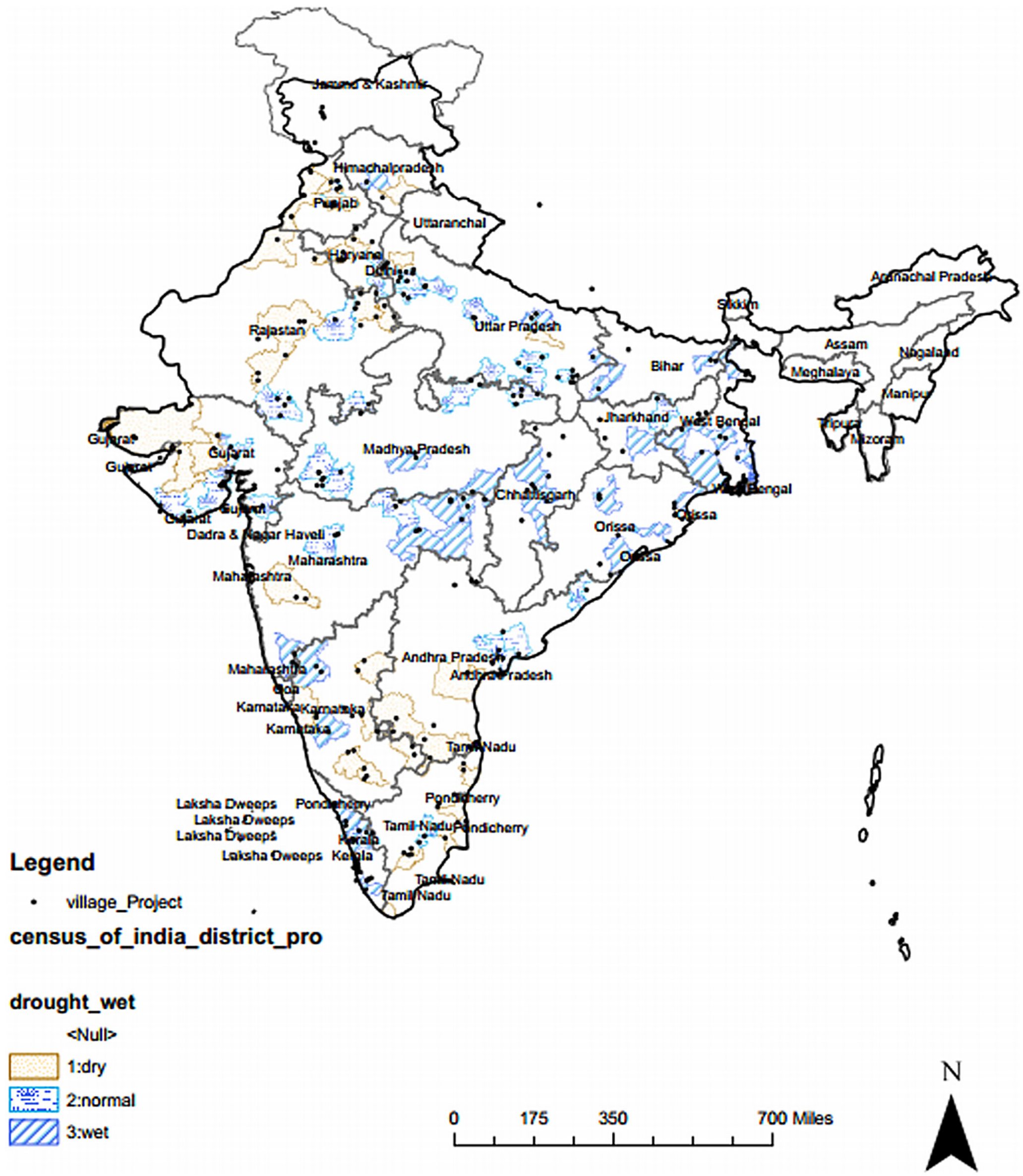

Fig. 1. A Map of India with Historical Weather Distribution.

For comparison, I generate a 20-year average (before the contemporaneous year) for the precipitation and temperature variables. I then create a shock variable "$RainShock_{jt}$" using contemporaneous rainfall minus village j's past 20-year average rainfall at time t. The bigger this number, the larger the contemporaneous rainfall relative to the historical average.

The following map in Fig. 1 illustrates the distribution of historical monsoon rainfall patterns in the survey regions.

3. Empirical strategy

Reduced form analysis is used to empirically determine how rainfall shocks affect different sources of income. I test two hypotheses:

Hypothesis 1. Households engage less in agricultural activities and more on other wage activities in response to negative rainfall shocks.

Because a rainfall shock decreases the value of the marginal productivity of labor in agricultural production, households will more likely shift their on-farm labors to non-farm jobs (e.g. construction, service, transportation, etc.) in response to rainfall shocks. Note that there are two types of wage jobs in my data: agricultural wage and non-farm wage. Households may also increase their labor supply in the agricultural wage jobs.

Hypothesis 2. Households in places with greater historical rainfall variation shift fewer labor resources to wage activities in response to rainfall shocks.

Next, I look at the shock effect by comparing riskier places, i.e. places with larger historical rainfall variation, to less risky places. In riskier places, households may have already diversified labor due to the historical weather information (*ex-ante* labor choice), thus shift less labor to wage activities in the contemporaneous period (*ex-post* labor input decision).

I estimate the following model:

$$\begin{aligned} Y_{ijt} = {} & \gamma_1 20yearRainSD_{jt} + \gamma_2 RainShock_{jt} + \gamma_3 temp_{jt} \\ & + \gamma_4 20yearRainSD_{jt} RainShock_{jt} \\ & + \gamma_5 20yearRainSD_{jt} RainShock_{jt} Year81 \end{aligned}$$

$$+ \gamma_6 20yearRainSD_{jt} RainShock_{jt} Year99$$
$$+ \gamma_7 20yearRain_{jt} + \gamma_8 20yearTemp_{jt} + \gamma_9 X_{ijt} + State_s + v_t + \varepsilon_{ijt}$$

where one set of the outcome variables (Y_{ijt}) is different sources of income, such as total income, agricultural income, agricultural wage income, and non-farm wages for household i in village j at time t; the other set of outcome variables is the share of those different income sources. The income of household i in village j at time t (i.e. year 1970, 1981, 1998) is assumed to be a function of the rainfall shock, the household's characteristics, and village characteristics.

Variable $20yearRainSD_{jt}$ represents the riskiness of the region, measured by the 20-year standard deviation of monsoon rainfall; $RainShock_{jt}$ captures the contemporaneous rainfall shock, calculated as logarithm monsoon rainfall – logarithm 20-year monsoon rainfall; $temp_{jt}$ is June temperature in village j at time t. A positive (negative) value of $RainShock_{jt}$ indicates a positive (negative) rainfall shock. This measure captures the contemporaneous rainfall deviation from the historical weather. I use this rainfall shock definition in order to (1) take care of the outlier issue and (2) easily interpret the result as percentage deviation referencing from the historical information.[3] Variable $20yearTemp_{jt}$ is the 20-year average June temperature at village j; $20yearRain_{jt}$ is the 20-year average monsoon rainfall. I use the historical weather information to account for the climate normals of the region, measured by the 20-year information before the survey period. For example, I take averages for each temperature and monsoon rainfall variable over 1950–1969 for the year 1970, 1961–1980 for the year 1981, 1978–1997 for the year 1998. Vector X_{ij} is a set of household characteristics. I control for household size, land size, and village population, as well as the household head's age and education as proxies for experiences and skills in farming. The distance to a city is also included to control for accessibility to non-farm jobs and price endogeneity in different sectors. I also include state fixed effects ($State_s$) to control for many time-invariant characteristics, such as cropping patterns, soil types, and socio-economic status. In addition, time dummies (v_t) are controlled. To understand how these relationships may have changed over time, I add year by year interaction to see the evolvement of γ_4. Finally, ε_{ijt} is the error term.

My identification strategy assumes that rainfall shocks do not affect households' risk preferences and the shape of the production function. Moreover, as historical weather patterns may confound with access to non-farm wage income (manufacturing jobs may cluster at places where agriculture is more sensitive to rainfall shocks), my inclusion of village characteristics, distances to a city, and state fixed effects helps mitigate this problem.

To test farmers' diversification in response to rainfall shock (Hypothesis 1), I expect that negative contemporaneous shocks have a negative impact on agricultural income, causing $\gamma_2 > 0$. Households shift their labor from agricultural activities to other wage activities, leading $\gamma_2 < 0$ in the specification where non-farm wage income is the outcome variable. That said, negative rainfall shocks correlate with increased non-farm wage income.

Also, agricultural wage jobs can be another coping strategy if households seek jobs from other landowners, leading $\gamma_2 < 0$. However, agricultural wage may be pushed down by landowners as a coping mechanism to smooth the loss in agricultural productivity, leading $\gamma_2 > 0$ (Jayachandran, 2006). In the regression with agricultural wage income as the outcome variable, the sign of γ_2 depends on the magnitude of the labor participation adaptation effect and the wage adjustment effect.

To test the heterogeneous responses to rainfall shocks (Hypothesis 2), I expect that adaptation through diversification of income will be less in riskier places because households have diversified their resources away from agricultural activities *ex ante*, and thus, γ_4 will exhibit an opposite sign from γ_2.

4. Results

Rainfall shocks have a negative impact on households' total income (see column 1 row 1 in Table 2). A 10 percent decrease from the historical rainfall average leads to an approximately 8 percent reduction in total income. The effect is more pronounced on agricultural income. Column 2 shows a 10 percent decrease from the historical rainfall average lowers agricultural income by around 15 percent.

The results confirm Hypothesis 1. The negative coefficients in column 3 and 4 suggest that households engage in more wage-earning activities, both agricultural and non-farm work, to mitigate negative rainfall shocks. The increase in agricultural wage income may seem counterintuitive. Technically, this means that the labor participation adaptation is larger than the wage adjustment effect.[4] Some may question whether households find enough hours of agricultural work to supply their labor in the event of rainfall shocks. This is only possible if the aggregate shock does not affect households uniformly. I provide some evidence in Table 3 that farmers with larger land see no significant decrease in agricultural income, while those with smaller land are hit harder by the shock (see the coefficients in row 1). Gaurav (2015) provides similar evidence in India that smaller landholders are at more risk of smoothing their consumption in the event of shocks, in contrast to larger farmers.

For Hypothesis 2, I find all the coefficients in row 2 to have the opposite signs to those in row 1 in Table 2. This means that the negative impacts of rainfall shocks on total income and agricultural income are both diminished in riskier places. On the other hand, the positive sign of the interaction term between historical rainfall SD and shock in columns 3 and 4 means that the marginal increases in agricultural wage and non-farm wage income due to negative rainfall shocks are less salient in high rainfall SD places. In other words, households in riskier places are less responsive in diversifying income sources when facing shocks. This heterogeneous responses to shocks may be because that households have already diversified labors in riskier places.[5]

All the results stated are consistent when using the share of different income sources (see Table 4).[6] I further use two alternative specifications for the rainfall shock variable, and overall results are on par with the main result.[7] I also use monsoon temperature

[3] Since there is no consensus regarding what the correct specification should be, I also use two other specifications to capture rainfall shock as the robustness check. One is to use monsoon rainfall minus 20-year monsoon rainfall. The other is to estimate the coefficient on rainfall shock controlling for village fixed effects to difference out the 20-year historical average.

[4] Unfortunately, agricultural wage income may reflect both the wage adjustment and the labor supply effect in response to rainfall shock. Even though the wage data is not available, we can treat this estimation as the lower bound. This means that the labor participation effect will be even stronger in the absence of the wage effect.

[5] I further test the relationship between 20-year rainfall SD and the share of wage income (including both agricultural wage and non-farm wage). Results are in the Supplementary Material Table A2. Controlling for the similar covariates as in Table 2 and village fixed effects to utilize the panel feature of the data, I find that places with higher historical monsoon rainfall SD are positively correlated with higher share of wage income.

[6] The results in row one and two are quite consistent with the results in Table 2. Although the coefficients are not statistically significant for agricultural wage income, the signs and the magnitude of the first and second rows show a consistent tendency to support Hypotheses 1 and 2. This may be because that the role of non-farm wage is more important to mitigate shocks as this source of income is less weather dependent.

[7] First, I use village fixed effects to account for the historical weather instead of using 20-year mean. Second, I define shock variable without the logarithm function. Overall results are on par with that in the main result. However, the coefficients on the first row are no longer statistically significant using the second specification; Yet the signs and the coefficients on the interaction terms are consistent with our main result (See Tables A3 and A4 in the Supplementary Material).

Table 2
Long-run effects of weather on different sources of income.

Dependent variable: Log income measured in rupees				
	Total income (1)	Agricultural income (2)	Agricultural wage (3)	Non-farm wage (4)
Rainfall shock	0.790***	1.455***	−0.680*	−1.113**
	(0.197)	(0.441)	(0.372)	(0.460)
Historical monsoon rainfall SD*Shock	−0.00449***	−0.00845***	0.00549***	0.00456*
	(0.00101)	(0.00226)	(0.00191)	(0.00236)
Historical monsoon rainfall SD (20-year average)	0.000696*	0.000585	−0.00221***	−0.000808
	(0.000404)	(0.000905)	(0.000763)	(0.000944)
Historical monsoon rainfall SD*Shock*1981	0.00105	0.000792	−0.00116	0.00412**
	(0.000842)	(0.00189)	(0.00159)	(0.00196)
Historical monsoon rainfall SD*Shock*1999	0.00110	0.00214	−0.00499***	0.00187
	(0.00100)	(0.00224)	(0.00189)	(0.00234)
Historical monsoon rainfall (20-year average)	9.47e−05	0.000484**	0.000233	0.000291
	(9.98e−05)	(0.000223)	(0.000188)	(0.000233)
Year = 1981	0.154***	−0.120	−0.0773	−0.481***
	(0.0551)	(0.123)	(0.104)	(0.129)
Year = 1999	0.0323	−0.959***	0.494***	0.411**
	(0.0692)	(0.155)	(0.131)	(0.162)
Observations	5,942	5,942	5,942	5,942
R-squared	0.168	0.230	0.206	0.097
State fixed effects	Yes	Yes	Yes	Yes

***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.
Note: All monetary units are in 1982 rupees. Coefficients are estimated using seemingly unrelated regressions as dependent variables are correlated. Rainfall shock = log (contemporaneous total monsoon rainfall)−log(20-year average total monsoon rainfall). Control variables include June temperature, historical June temperature, household size, household head's years of education and age, land size, village population, and distance to a city. Historical weather variables are defined as 20-year average before the contemporaneous year. All coefficients are based on weighted analysis using the original sampling weight.

Table 3
Heterogeneous adaptation by farmers' type.

Dependent variable: Log income measured in rupees			
Sample	Ag income Landless farmers (1)	Ag income Small farmers (2)	Ag income Medium & large farmers (3)
Rainfall shock	1.386	1.785***	0.277
	(1.026)	(0.524)	(0.291)
Historical monsoon rainfall SD*Shock	−0.0116**	−0.0151***	−0.00338**
	(0.00527)	(0.00285)	(0.00152)
Historical monsoon rainfall SD (20-year average)	−0.00516**	0.00161	0.00125*
	(0.00203)	(0.000995)	(0.000645)
Historical monsoon rainfall SD*Shock*1981	0.00736*	0.00589***	0.00325**
	(0.00445)	(0.00228)	(0.00131)
Historical monsoon rainfall SD*Shock*1999	−0.00934**	0.00974***	0.00349**
	(0.00448)	(0.00277)	(0.00158)
Historical monsoon rainfall (20-year average)	0.00175***	−0.000122	−0.000185
	(0.000502)	(0.000246)	(0.000154)
Year = 1981	−1.460***	−0.372***	−0.0958
	(0.238)	(0.135)	(0.0901)
Year = 1999	−0.892***	−0.632***	−0.469***
	(0.317)	(0.199)	(0.102)
Observations	1,263	1,584	3,095
R-squared	0.232	0.123	0.134
State fixed effects	Yes	Yes	Yes

***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.
Note: All monetary units are in 1982 rupees. Coefficients are estimated using seemingly unrelated regressions as dependent variables are correlated as in Table 2 (the results using agricultural wage and non-far wage income as the dependent variables are not reported). Rainfall shock = log (contemporaneous total monsoon rainfall)−log(20-year average total monsoon rainfall). Control variables include June temperature, historical June temperature, household size, household head's years of education and age, land size, village population, and distance to a city. Small farmers are those whose landholding are less than the 33rd percentile, while big farmers are those whose landholding are larger and equal to the 33rd percentile. Farmers' type is time-variant. Historical weather variables are defined as 20-year average before the contemporaneous year. All coefficients are based on weighted analysis using the original sampling weight.

Table 4
Long-run effects of weather on share of different sources of income.

Dependent variable: Percentage of different income sources among total income			
	Agricultural income (1)	Agricultural wage (2)	Non-farm wage (3)
Rainfall shock	0.145** (0.0566)	−0.0600 (0.0423)	−0.0935** (0.0457)
Historical monsoon rainfall SD*Shock	−0.000611** (0.000290)	0.000336 (0.000217)	0.000522** (0.000235)
Historical monsoon rainfall SD (20-year average)	0.000182 (0.000116)	−3.76e−05 (8.68e−05)	0.000101 (9.38e−05)
Historical monsoon rainfall SD*Shock*1981	−0.000505** (0.000242)	−2.67e−05 (0.000181)	0.000361* (0.000195)
Historical monsoon rainfall SD*Shock*1999	0.000207 (0.000288)	−3.76e−06 (0.000215)	−9.61e−05 (0.000233)
Historical monsoon rainfall (20-year average)	3.48e−05 (2.87e−05)	−2.46e−05 (2.14e−05)	−2.26e−05 (2.32e−05)
Year = 1981	−0.0385** (0.0158)	−0.000288 (0.0118)	−0.0548*** (0.0128)
Year = 1999	−0.159*** (0.0199)	0.110*** (0.0149)	0.0759*** (0.0161)
Observations	5,942	5,942	5,942
R-squared	0.217	0.183	0.114
State fixed effects	Yes	Yes	Yes

***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.
Note: All monetary units are in 1982 rupees. Coefficients are estimated using seemingly unrelated regressions as dependent variables are correlated. Rainfall shock = log (contemporaneous total monsoon rainfall)−log(20-year average total monsoon rainfall). Control variables include June temperature, historical June temperature, household size, household head's years of education and age, land size, village population, and distance to a city. Historical weather variables are defined as 20-year average before the contemporaneous year. All coefficients are based on weighted analysis using the original sampling weight.

instead of only June temperature for another robustness check and the result is nearly identical to Table 2 (See Table A5 in the Supplementary Material).

5. Conclusion

Similar to previous studies, this paper confirms that rainfall shocks significantly affect farmers' agricultural income and farmers adapt through income diversification in response to these shocks. Using long-term historical rainfall variations, I show that farmers in places with greater historical rainfall variations may have already adapted over time, and thus respond less to negative rainfall shocks through income diversification. I recognize that this study has limitations. The paper is constrained by the inaccessibility of more detailed information on wage and prices. It is also beyond the scope to model the general equilibrium effect of the shocks. Nevertheless, my results provide important evidence to consider interactions between farmers' *ex ante* and *ex post* adaptation strategies to weather shocks in policy decisions. The conventional wisdom is to focus on places with larger historical rainfall variation, but my study suggests the opposite. Places with smaller historical rainfall variation may be more vulnerable as people there are less prepared for shocks. Policymakers and researchers will need to consider farmers' interaction with local historical weather conditions in future climate adaptation efforts.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2018.10.015.

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