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Income Diversification and Income Inequality: Household Responses to the 2013 Floods in Pakistan

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Abstract: In this paper we investigate the economic response of rural households to the 2013 floods in Pakistan. The case study illustrates the important roles of labor supply adjustments and income diversification in coping with climate-related risks. Using detailed household panel data that were collected before and after the 2013 floods, we find that the exposure to flood results in lower participation in farm activities. The overall effects are decreased diversification in the sources of income and ambiguous reduction in inequality which is associated with overall declines in incomes. These changes could be locked in if affected households do not have sufficient assets to resume farming. The results suggest intervention points for public policy, related to labor mobility and access to capital.

Keywords: employment; floods; income diversification; income inequality; Pakistan

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1. Introduction

Climatic factors such as rainfall patterns, temperature variations and natural disasters are known to affect economic outcomes (e.g., [1–4]). In developing countries where agriculture is the primary source of livelihoods and where welfare levels are already close to the poverty line [5], disasters such as floods are particularly harmful to the lives and livelihoods of rural households.

Affected households have developed a range of coping mechanisms to reduce the impact of climate extremes, often compensating for insufficient national disaster risk management programs and Government support schemes. Frequent options include temporary migration [6,7], extended family support [8], the sale of livestock or other productive assets [9,10], and adjustments to farm sizes through land rental or sale [11].

Our interest is in labor adjustments—that is, the reallocation of labor to different income generating activities—and our case study is the 2013 floods in Pakistan. Existing literature on adjustments in income generation activities as a risk mitigation strategy mostly focused on labor market dynamics such as the impact on wages (e.g., [12–14]), while we are interested in income preservation strategies. Specifically, we focus on participation in and returns from farm and non-farm employments.

Rural Pakistan is a good case study to analyze climate-imposed changes in income generation strategies. Pakistan is one of the 10 most affected countries by extreme flooding, according to the long-term climate risk index [15]. Between 1999 and 2018 the country experienced 152 extreme climate events, resulting in around USD 3.8 billion in losses [16]. The 2010 "super flood" affected most of the country, with the most severe impacts in the provinces of Punjab, Sindh, Balochistan and Khyber Pakhtunkhwa (KPK). Subsequently, a series of locally more concentrated floods during 2011–2013 hit some of the same regions, affecting their recovery from the 2010 flood. Our interest is in the 2013 floods, which have been studied less than the 2010 super flood.

Analytically, we took advantage of a very detailed and wide-ranging household dataset, the Pakistan Rural Household Panel Survey (PRHPS), which was collected both before and after the 2013 floods. Two of the three survey waves (PRHPS I and II) took place before 2013, with a third round (PRHPS III) carried out after the 2013 floods (Figure 1). The dataset and timing of events allowed us to consider mouza-level heterogeneity in flood exposure (i.e., affected and unaffected mouzas; a mouza is composed of several contiguous villages) and, therefore, to identify the adverse effects of the 2013 floods using a difference-in-difference setup. The overall context is one of recurring climate shocks: all PRHPS regions were affected by the 2010 super flood and in 2013 many households were still recovering from earlier flood events.

Figure 1. Timeline of 2010–2014 events.

We find that, compared to unaffected households, flood-affected households have increased participation in farm activities which, however, has not been translated to increased farm incomes. Consequently, flood affected regions experienced lower diversification in the sources of income. Although regional inequalities have decreased, they were associated with lower overall incomes in the affected regions.

Our findings contribute to a growing literature on the adaptation response of households to climate shock, which includes empirical work on Pakistan (e.g., [17,18]). Deen (2015) and Kirsch et al. (2012) investigated the aftermath of the 2010 flood, documenting widespread economic [19,20], social and health impacts. Kurosaki (2017) investigated the speed of recovery from the 2010 floods using a panel survey conducted in KPK, where virtually all households were affected [21]. In earlier work, Kurosaki (2015) used a two-period panel dataset, which predates the recent floods, to investigate consumption smoothing and risk sharing by flood-exposed households [5]. Mueller et al. (2014) studied the impact of floods on long-term migration [7].

2. Recent Flooding and Adaptation Responses in Pakistan

With its diverse terrain, ranging from mountains in the north to floodplains and deserts in the south, Pakistan is one of the world's most vulnerable countries to climate risks and related hazards. The floodplains of the Indus River, in the southeast of the country, experience recurrent flooding, usually caused by excessive monsoon rainfall and glacial melt.

The 2013 floods occurred in a particularly calamitous period. Between 2001 and 2015, Pakistan experienced 45 major flood events [16], including a series of severe floods during 2010–2013 (Table 1). The 2010 flood was one of the biggest ever to hit the country, impacting the Indus River basin across the provinces of KPK, Sindh, Punjab and Balochistan. Beginning in late July 2010, the flood affected more than 20 million people across a fifth of Pakistan's land area (Annual Flood Report 2010). In addition to almost 2000 deaths [16], the 2010 flood damaged or destroyed more than 1.6 million houses and destroyed unharvested crops covering 2.4 million hectares of farmlands [22,23].

The 2010 flood was followed by back-to-back floods during 2011–2013 in some parts of the country, again affecting agricultural production and setting back recovery from the harms of the 2010 flood. The August-September torrential monsoon rains of 2011 especially hit the southeastern parts of Sindh province and some parts of Punjab. Consequent floods affected about 9.3 million people from an area of about 26.3 thousand square kilometers, claiming about 516 lives, and damaging about 1.4 million houses and 1.9 million acres of cropped lands [23].

Table 1. The 2010–2013 floods in Pakistan.

Event	Direct Losses (USD Million)	No. of Deaths	No. of Affected Villages	Flooded Area (Sq. km)
2010 Flood	10,000	1985	17,553	160,000
2011 Flood	3730	516	38,700	27,581
2012 Flood	2640	571	14,159	4746
2013 Flood	2000	333	8297	4483

Data sources [16,24,25].

Next, heavy rainfall in late August and early September in 2012 led to flash floods in hilly areas and ultimately caused flooding in several districts of KPK, Upper Sindh, Southern Punjab and Northeastern Balochistan. The 2012 floods affected 4.85 million people in over 14,000 villages, claiming 571 lives, damaging over 640,000 houses, and inundating 1.2 million acres of cropped land [23].

Finally, the 2013 floods were triggered by heavy rainfall events in July and August, which caused inundations in the catchment areas of rivers Kabul, Chenab, Indus, Jhelum and Ravi. The 2013 flood primarily affected several districts from Punjab and Sindh provinces (Table 2). The 2013 flood affected about 1.5 million people and over 1.1 million acres of cropped land in 8297 villages, claiming 333 lives and damaging or destroying about 80,000 houses.

Table 2. Flood affected mouzas.

Province	District	Affected Mouzas	Unaffected Mouzas
Punjab	Multan	• Umrana Shumali	• Chak 007/2 Thal Janubi • Chak Sarkar Bahi Wal • Wijhi
Punjab	Bhakkar	• Baryana	• Bunga Sighwal • Chak 118 SB • Saleem Abad
Sindh	Hyderabad	• Charbatti • Shaikh Haji Turabi • Talli • Uheb	
Sindh	Sanghar	• Shori Jagir	• Andheji Kasi • Gharo • Khuda Abad Jagir
Sindh	Jaccobabad	• Kacho Khanoth	• Charo • Narki • Saeed Pur
No. of households		205	291

Data sources [16,24,25].

The Government response to the 2010–2013 flood events was led by the National Disaster Management Authority (NDMA), which is responsible for mobilizing emergency funds, coordinating between relevant departments (including the Federal Flood Commission, the Emergency Relief Cell and the Pakistan Meteorological Department as well as the army, civils society organizations and several international NGOs. At a more local scale, irrigation departments, district disaster management authorities, agriculture department and district coordination offices played key roles in flood warning and evacuation services), issuing flood warnings and planning for disaster risk management. Affected provinces received funding under the Public Sector Development Program (PSDP). However, the allocated funds were only about a quarter of what had been demanded [24], restricting the implementation of recovery programs. The long-term recovery from the harms of floods remains a neglected phase of disaster risk management [26], forcing affected households to rely on their own individual coping strategies.

The adaptation challenges faced by Pakistani households are shared by rural households across the developing world. Poor households in rural areas are vulnerable to natural disasters for several interrelated reasons [27,28]. The agricultural systems, on which their livelihood heavily depend, are inherently vulnerable to disasters. Floods directly affect agricultural systems through contaminating waterbodies, destroying irrigation systems and other infrastructure, causing loss of harvest or livestock and increasing susceptibility to human and livestock diseases, ultimately resulting in losses in farm yield and affecting local and national food security [29].

Although there are well-established, often indigenous coping strategies, low-income farmers are often lack adaptive capacity [29], resulting in a slower recovery from any weather risks they get exposed to. Their recovery is further affected by constraints to important markets and support systems, such as credit markets, insurance schemes [30], extension services and social safety nets [9].

Households faced by weather shocks try to sustain agricultural income in a first instance by implementing on-farm mitigation measures such as crop switching, levies to prevent flooding and supplementary irrigation to offset lack of rainfall [30]. Eskander and Barbier (2016) found that disaster-affected rural households intensify agricultural activities by increasing their operational farm size through increased transactions in the land rental market [11]. The sale of livestock and other farm assets may help to smooth income, making livestock an important indicator of household wealth [31,32]. However, a successful return to farming will require farmers to maintain sufficient means of production, including livestock and seed.

Income diversification and increased labor supply, the subject of interest in this paper, are part of a suite of off-farm coping strategies, which also includes migration and informal support from family networks. When disaster-affected people decide to migrate to less disaster-prone regions (e.g., [33,34]), such migration is often temporary and conditional on a household's ability to find alternative employment [35,36]. Bohra-Mishra et al. (2014) analyzed province-to-province movement of more than 7000 households in Indonesia over 15 years to find that while there can be a nonlinear permanent migration response to climatic variations, the evidence of permanent migration is minimal among disaster-affected households [37]. In Bangladesh, Penning-Rowsell et al. (2013) found that rural people are less likely to migrate permanently [38], even in the face of extreme disasters, although they may temporarily move to safer places.

3. Materials and Methods

3.1. Flood Regions

In PRHPS III, a total of 113 households reported that their villages were affected by floods in last one year (i.e., in 2013). We generalized this information to define mouza-level exposure to the 2013 floods: we define an indicator variable as 1 if the mouza was flood affected (i.e., when at least one household from a mouza reported that their village was affected), and 0 if the mouza was not flood affected (i.e., no households from a mouza reported to be flood affected). Since mouzas within the same district share similar geographic and socioeconomic attributes, we restricted our analysis to the districts where at least one mouza was categorized as flood affected.

There are 8 mouzas from 5 districts from Punjab and Sindh provinces from where at least one household (out of 113) reported to be affected by the 2013 floods. The 205 households that belong to these affected mouzas are treated as affected households. On the other hand, households from the remaining 12 unaffected mouzas are treated as unaffected households. Altogether, we have 205 affected and 291 unaffected households over two survey rounds (i.e., PRHPS II and III) that form our estimating sample (Table 2).

3.2. Empirical Specifications

We first investigated household's decision to participate in different economic activities. A household i from mouza m participates in an economic activity in time t according to the following linear probability model (LPM) with two-way fixed effects:

$$I_{itm} = \beta_0 + \beta_1 flood_m + \beta_2 post_t + \beta_3 (flood_m \times post_t) + X_{it}\beta_4 + \Delta_i + \rho_t + \epsilon_{it} \quad (1)$$

where the binary outcome variable I_{itm} denotes households' willingness to participate in the generation of income y, and is defined as $I_{it} = 1$ if the household participates (i.e., $y > 0$) and 0 if not (i.e., $y = 0$). We considered four economic activities: farm self-employment (FSE), non-farm self-employment (NFSE), farm wage-employment (FWE) and non-farm wage-employment (NFWE).

The dummy variable $flood_m$ denotes flood exposure: 1 if mouza m is affected by the 2013 flood and 0 if not. Similarly, $post_t$ denotes post-flood year: 1 if post-flood year (i.e., 2014) and 0 if pre-flood year (i.e., 2013). X_{it} are the vector of control variables. Δ_i and ρ_t are the household and year fixed effects to control for any potential omitted variable bias.

Despite the binary nature of dependent variables, LPMs provide good estimates of the partial effects for average values of the explanatory variables and the coefficients allow for a straightforward interpretation of the effects [39]. In addition, LPMs suffer less from measurement errors than discrete choice models such as logit and probit models. We report robust standard errors since the residuals ϵ_{it} are heteroskedastic.

Next, a household i from mouza m generates income or wage y in time t according to the following panel regression model with two-way fixed effects:

$$y_{itm} = \beta_0 + \beta_1 flood_m + \beta_2 post_t + \beta_3 (flood_m \times post_t) + X_{it}\beta_4 + \Delta_i + \rho_t + \xi_{it} \quad (2)$$

where $\xi_{it} \sim \left(0, \sigma^2\right)$. All the explanatory variables follow the definition in Equation (1).

We define the outcome variables, y_{itd}, as the income or wage from economic activities by household i in time t. In particular, self-employed *farm income* from household-operated agricultural activities includes the cash and imputed values of all harvested crops at the local market price. *Non-farm income* from self-employment in non-agricultural activities includes all the entrepreneurial profits by any member of the household from their ownerships and operations of businesses, rental incomes, remittances receipts and any other incomes and receipts.

Wage earnings that come from paid employment are split into farm and non-farm wages as follows. *Farm wages* include cash and (imputed) kind receipts of all the household members from their paid employments in farming activities that are not owned or operated by the household itself. Consistent with the norm in literature, we do not include self-employment in agricultural activities in farm wage calculation, which are rather incorporated in their farm income. Similarly, *non-farm wages* include cash and (imputed) kind receipts of all the household members from their non-farm paid employments, which do not include labor time allocated to household-owned businesses.

In both Equations (1) and (2), β_3, the coefficient of the interaction term $(flood_m \times post_t)$ is the coefficient of interest that shows the differential effects of the 2013 flood on respective outcome variables. That is, it identifies the change in the dependent variable attributable to the 2013 flood in comparison to the no floods situation. We set our null and alternative hypotheses as: $H_0: \ \beta_3 = 0$ and $H_A: \ \beta_3 \neq 0$.

X_{it} is the vector of controls that includes several household, farm and community-level attributes. Household characteristics include household size and access to electricity (1 if the household has electricity connection, 0 if not). Farm-level characteristics include ownership of important assets such as tractors, plow–yokes, irrigation pump and other agricultural assets (1 if a household owns at least one of these assets, 0 if not), as well as operational farm size (hectares).

Although assumed exogenous, components of X_{it} are often endogenous since households may determine their optimal levels through different means. However, such adjustments can take a longer planning horizon whereas PRHPS second and third rounds were conducted in a years' time. Moreover, while this will remain a limitation, since appropriate instruments for these potentially endogenous variables are either unavailable or difficult to conceive, we follow the tradition of Skoufias (1995) and treat them to be determined outside of the model [40].

Finally, $flood_m$ and $post_t$ drop out from our regression as they are perfectly collinear with fixed effects Δ_i and ρ_t. Therefore, our regression results based on Equations (1) and (2) do not include the respective coefficients.

3.3. PRHPS Data

The USAID-funded Pakistan Rural Household Panel Survey (PRHPS) covers a representative sample of the rural areas of Punjab, Sindh and Khyber Pakhtunkhwa (KPK). The first round of the survey, PRHPS I, was completed in April 2012, covering 2090 households in 76 primary sampling units in the rural areas of these three provinces. PRHPS II (conducted in April–May 2013) and PRHPS III (May–June 2014) re-interviewed 2002 and 1876 households, respectively. Each round of the survey covers data from the previous production year (i.e., 2011, 2012 and 2013, respectively) on, among others, sources of income and household- and farm-level attributes.

Table 3 summarizes variables used in our empirical analysis. Income variables are expressed in USD at the rates of 93.4 Pakistani Rupees per USD 1 as in 2012. In both survey rounds, households have highest participation in farm self-employment, followed by non-farm wage-employment. Consistently, farm income accounts for the majority of total income, followed by non-farm wages, whereas farm wages and non-farm income have relatively smaller contributions. Moreover, while they have similar participations in all other activities, participation in farm self-employment has increased considerably between rounds. Other attributes, e.g., household size, asset ownership, electricity and cultivated land, remain at similar levels.

Table 3. Variable description and summary statistics.

Variables	Description	PRHPS II	PRHPS III
Pr(FSE)	Farm self-employment: 1 if the household earns farm incomes, 0 if not	0.38 (0.49)	0.51 (0.50)
Pr(NFSE)	Non-farm self-employment: 1 if the household earns non-farm incomes, 0 if not	0.14 (0.35)	0.18 (0.38)
Pr(FWE)	Farm wage-employment: 1 if the household earns farm wages, 0 if not	0.25 (0.43)	0.24 (0.43)
Pr(NFWE)	Non-farm wage-employment: 1 if the household earns non-farm wages, 0 if not	0.37 (0.48)	0.37 (0.48)
Farm income	Annual household income from farm activities, last 12 months (USD)	777.82 (4340.75)	782.42 (1954.70)
Non-farm income	Annual household income from non-farm activities, last 12 months (USD)	125.51 (697.41)	352.97 (2239.80)
Farm wages	Wages earned from paid farm employment, last 12 months (USD)	76.97 (208.38)	58.21 (159.07)
Non-farm wages	Wages earned from paid non-farm employment, last 12 months (USD)	312.02 (684.19)	410.82 (823.99)
Household size	Total number of members in the household	6.47 (2.81)	6.87 (2.89)
Asset ownership	1 if the household owns one of these assets: tractor, plough-yoke, irrigation pump, and other farming equipment; 0 if not	0.84 (0.36)	0.93 (0.25)
Electricity	1 if the household has electricity connection; 0 if not	0.70 (0.46)	0.69 (0.46)
Cultivated land	Total cultivated land (hectares)	1.45 (2.64)	1.42 (2.38)
No. of households	Number of households in each PRHPS round	496	496

Notes: We report mean values of each variable, with standard deviations in parentheses. Summary statistics are restricted to the estimating sample of 496 households from PRHPS rounds II and III. All monetary values are expressed in USD. All land measures are expressed in hectares.

4. Results and Discussion

4.1. Base Year Profiles

Table 4 reports the base year characteristics of affected and unaffected households. Although affected households have significantly higher participation in farm self-employments, lower participation in non-farm wage employments, and lower non-farm wages than unaffected households, they mostly have similar characteristics at the base year. Therefore, the affected and unaffected households are broadly comparable.

Table 4. Base year characteristics.

Variables	Unaffected Mouzas	Affected Mouzas	Difference
Pr(FSE)	0.33 (0.47)	0.66 (0.47)	−0.33 *** (0.04)
Pr(NFSE)	0.17 (0.37)	0.15 (0.35)	0.22 (0.03)
Pr(FWE)	0.24 (0.43)	0.24 (0.43)	0.00 (0.04)
Pr(NFWE)	0.65 (0.48)	0.39 (0.49)	0.26 *** (0.04)
Farm income	1247.50 (5845.17)	860.28 (2018.59)	387.22 (425.15)
Non-farm income	230.37 (1306.58)	121.90 (413.76)	108.47 (94.45)
Farm wages	83.66 (249.17)	58.61 (137.37)	25.05 (19.18)
Non-farm wages	575.56 (691.81)	286.36 (583.24)	289.20 *** (59.19)
Age	46.06 (14.07)	41.37 (12.01)	4.69 *** (1.21)
Education	2.74 (3.80)	2.51 (3.29)	0.23 (0.33)
Gender	0.99 (0.10)	1.00 (0.07)	−0.01 (0.01)
Household size	6.47 (2.68)	5.61 (2.51)	0.86 *** (0.24)
Asset ownership	0.34 (0.47)	0.25 (0.44)	0.09 ** (0.04)
Electricity	0.84 (0.37)	0.47 (0.50)	0.37 *** (0.04)
Cultivated land	1.77 (5.45)	1.84 (2.97)	−0.07 (0.42)
No. of obs.	291	205	

Notes. We report mean values of each variable, with standard deviations in parentheses. ***, ** represent statistical significance at 1%, 5% levels, respectively. Summary statistics are restricted to 205 affected and 291 unaffected households from PRHPS round I. All monetary values are expressed in USD. All land measures are expressed in hectares. Differences are calculated as "Difference = mean (Unaffected)−mean (Affected)". The four economic activities are farm self-employment (FSE), non-farm self-employment (NFSE), farm wage-employment (FWE) and non-farm wage-employment (NFWE).

However, some attributes had significant variations. In particular, unaffected households have significantly higher household size, asset ownership and access to electricity in the base year. Therefore, we have controlled for them in our regression analyses.

4.2. Participation and Income

Table 5 reports LPM results on decisions to participate in economic activities. Results show that flood affected households increase farm activities but decrease their involvements in alternative economic activities. This is an indication of lack of non-farm economic opportunities in rural areas of Pakistan, which is a major impediment preventing fast economic recovery from natural disasters such as floods. However, negative effects on participation in alternative economic activities are statistically insignificant.

Table 5. Participation decisions.

Variables	Pr(FSE)	Pr(NFSE)	Pr(FWE)	Pr(NFWE)
Flood 2013 regions × Post-flood year	0.077 **	−0.003	−0.054	−0.062
	(0.038)	(0.033)	(0.043)	(0.047)
Household size	−0.009	0.017	−0.025	−0.023
	(0.035)	(0.017)	(0.022)	(0.030)
Asset ownership	0.004	0.033	0.092	−0.017
	(0.046)	(0.048)	(0.058)	(0.065)
Electricity	−0.088 *	0.054	0.163 **	0.022
	(0.053)	(0.034)	(0.071)	(0.080)
Cultivated land	0.066 ***	−0.013	−0.017 *	−0.007
	(0.012)	(0.010)	(0.010)	(0.009)
Constant	0.453 *	0.001	0.254	0.543 **
	(0.236)	(0.128)	(0.163)	(0.227)
No. of Obs.	992	992	992	992
R^2	0.840	0.752	0.728	0.702
Household FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: Robust standard errors are shown in parentheses. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively. LPM estimations follow Equation (1). The four economic activities are farm self-employment (FSE), non-farm self-employment (NFSE), farm wage-employment (FWE) and non-farm wage-employment (NFWE).

In comparison to unaffected households, affected households are 7.7% more likely to participate in farm self-employments, whereas they have lower likeliness to participate in other activities. Altogether, flood-affected households try to leverage their lost employments during floods through increasing their post-flood farming activities.

Table 6 reports regression results for effects of 2013 floods on the components of income. Although affected households experienced declines in their incomes, none of those negative effects are statistically significant. However, while the other components of income remain roughly at similar levels, affected households experience an insignificant yet large decline in their non-farm incomes.

Table 6. Effects on incomes.

Variables	Farm Incomes	Non-Farm Incomes	Farm Wages	Non-Farm Wages
Flood 2013 regions × Post-flood year	−8.460	−108.169	−9.431	−21.254
	(455.411)	(99.103)	(18.644)	(73.223)
Household size	83.695	−12.432	10.894	−48.698
	(150.104)	(105.670)	(14.024)	(40.475)
Asset ownership	7.811	123.269	52.402	−12.159
	(185.540)	(153.238)	(34.047)	(103.848)
Electricity	−88.686	58.879	27.843	139.797 *
	(133.025)	(131.695)	(29.944)	(81.918)
Cultivated land	556.554 ***	−656.237 *	−7.116	9.807
	(186.270)	(382.681)	(5.681)	(30.977)
Constant	−518.903	1134.219	−58.833	590.053 **
	(1099.993)	(737.077)	(91.788)	(278.452)
No. of Obs.	992	992	992	992
R^2	0.616	0.736	0.686	0.700
Household FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: Robust standard errors are shown in parentheses. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively. Estimations follow Equation (2).

4.3. Implications for Diversity and Inequality

Usually, farmers intensify their post-flood agricultural activities to make up for the lost income from farming activities (Table 5). However, due to relative scarcity of necessary resources that can enable their successful recovery, Pakistani farmers were not able to recover their lost farm incomes through increased participation in agriculture (Table 6). Together, these results suggest implications for post-flood income diversification and income inequality.

To measure income diversification, we calculated Herfindahl–Hirschman index (HHI) as the sum of squared share of each component of income. The HHI ranges between 0 and 1 where HHI = 0 denotes perfect diversification and HHI = 1 denotes no diversification.

We then calculated Theil-T index (TTI), a measure of regional inequality, according to $TTI = \frac{1}{N}\sum_{i=1}^{N}\frac{y_i}{\overline{y}}\ln\left(\frac{y_i}{\overline{y}}\right)$ where N is the number of regions, y_i is the income in region i and $\overline{y}$ is the average income across all regions. TTI ranges between 0 and ∞ where zero represents equal distribution and higher values represent higher levels of disproportion.

Table 7 reports income diversification and income inequality by flood exposure and survey years. While the unaffected regions experience a small decline in their HHI between survey rounds (from 0.79 to 0.78), affected regions experienced a relatively large increase in their HHI (from 0.74 to 0.79). That is, affected regions have decreased diversification in their post-flood income opportunities, whereas unaffected regions have greater diversification than before.

Table 7. Income inequality.

	Unaffected Mouzas		Affected Mouzas	
Variables	**2013**	**2014**	**2013**	**2014**
Herfindahl–Hirschman index	0.79	0.78	0.74	0.79
Theil-T index	0.95	0.70	1.63	0.91

Notes: All monetary values are expressed in USD. Herfindahl–Hirschman index (HHI) is calculated as the sum of squared share of each component of income. Theil-T index (TTI) is calculated as $TTI = \frac{1}{N}\sum_{i=1}^{N}\frac{y_i}{\overline{y}}\ln\left(\frac{y_i}{\overline{y}}\right)$ where N is the number of regions, y_i is the per-capita income in region i and $\overline{y}$ is the average per-capita income across all regions. We calculated HHI and TTI for flood regions over survey years.

On the other hand, both the affected and unaffected regions experience decreased inequality between survey rounds. Affected regions experienced a larger decrease in inequality (from 1.63 to 0.91) than the unaffected households (from 0.95 to 0.70). However, together with greater participation in farm activities but (insignificantly) lower farm incomes than unaffected regions, such a decline in inequality is also associated with an overall decrease in incomes.

5. Conclusions

Exposure to floods, and the coping strategies they trigger, influence the livelihood decisions of affected households. This paper explores to what extent rural households in Pakistan have adjusted their income portfolios in response to the 2013 floods. We found that flood exposure resulted in an increased participation in farm activities by affected households, but they were not able to increase their participation in alternative economic activities. Moreover, although statistically insignificant, flood exposure resulted in income adversities. Consequently, despite some questionable reductions in regional inequality, we identify decreased income diversification due to the 2013 floods.

Our results imply that the success of these coping strategies is uneven, resulting in lower income diversification especially in flooded regions. This has important poverty implications. Agricultural yields per hectare in Pakistan are among the lowest in the world and food insecurity is rampant. According to the World Food Program (2009), more than 48% of the population is food insecure, a situation that is made worse by the high incidence of flooding [41].

Our findings reinforce the case for proactive disaster risk management by government agencies, including the promotion and co-development of climate-resilient agriculture and non-farm employment opportunities [1,42]. These structural measures can complement more traditional (though equally lacking) measures to aid flood recovery and risk mitigation schemes, such as insurance programs, micro-lending schemes, safety nets programs such as cash-for-work schemes, the rebuilding of infrastructure and other measures to reassemble village economies. Without such government support, flood exposure will remain a constant risk to the wealth and welfare of rural communities in Pakistan.

Despite multiple contributions, this research has some limitations as well. First, we used a relatively small sample size. Future research can use a larger dataset, if available, to investigate similar issues for the case of Pakistan or a different country with similar context. Next, farmers generally tend to resume agricultural activities after floods. However, as floods become more frequent, many will not have the means to continue farming on silted land and reinvest in seeds, livestock and fertilizers [42]. Future research can potentially investigate the effects of disaster exposure on such essential agricultural reinvestments. Finally, future research may also extend the analysis at a more disaggregated level and can also distinguish between rural and urban variations in disaster risk management activities and their impacts.

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