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Climate Shocks, Household Food Security and Welfare in Afghanistan

by

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Abstract

The increasing impact of natural disasters (floods, earthquakes, landslides, and avalanches) in Afghanistan, notably flooding and similar climate shocks, poses a growing concern as vulnerability to climate change intensifies the potential severity of these impacts in future. This paper uses two household surveys (2011/12 and 2013/14) combined with other data to assess the effects of climate shocks (especially floods) on the welfare of agricultural households, allowing also for conflict and price shocks. We evaluate the impacts of shocks on several measures of food security, dietary diversity, household food consumption spending, farm revenue and income comparing affected to non-affected households. The analysis is based on endogenous switching regressions (ESR) and propensity score matching (PSM) allowing for selection bias and addressing endogeneity. Floods are the main shock and have significant adverse effects on food security and welfare indicators. For example, the estimated average treatment effect in 2013-14 implies a decrease of about a third in food consumption expenditures, with similar reductions in household income and farm revenue. The findings highlight the need for better disaster risk reduction and planing strategies to support affected populations to respond to and recover from climate shocks.

JEL Classification: Q12, Q54, O12, O13, D12

Keywords: Natural disasters, household food security, household welfare, econometric methods, disaster risk management, conflict, Afghanistan

Centre for Research in Economic Development and International Trade, University of Nottingham

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Outline

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1. Introduction

Poor and fragile countries like Afghanistan are hit hardest by natural disasters; the incidence of disasters, especially climate shocks such as floods, has increased and the population has low ability to cope with, respond to, and recover from such shocks. Literature on poverty and environment points to a vicious circle between poverty and disaster losses; poverty is a major driver of vulnerability to natural disasters, which in turn increase poverty as the poor tend to lose a larger fraction of their wealth when affected by natural disasters (Hallegatte *et al*., 2015, 2020; Jongman *et al*., 2015). Afghanistan has also faced conflict, increasing household fragility and limiting responses to natural disasters. Climate shocks and natural disasters exacerbate resource scarcity and social grievances that increase the risk of violent conflict (Nel and Righarts, 2008; Xu *et al*., 2016). Conflict and fragility are associated with weak state capacity so communities are less resilient and have limited coping capacities (Peters, 2021), whilst armed conflict increases vulnerability to disasters (Caso *et al*., 2023).

This paper fills a gap for Afghanistan by providing evidence on the short-term impacts of climate shocks and natural disasters on household welfare and food insecurity. We utilize nationally representative cross-section household surveys with large samples in 2011/12 and 2013/14 with econometric analysis based on endogenous switching regressions (ESR) and propensity score matching (PSM) allowing for selection bias and addressing endogeneity. The approach establishes counterfactuals against which affected populations are compared, estimating average treatment effects on the treated (the affected group) and the untreated (the non-affected group had they been exposed) to assess the impacts of shocks on food security, dietary diversity, household consumption and income. The evidence shows that floods are the main shocks associated with natural disaster risk and have significant adverse effects on food security and welfare indicators; estimated treatment effects are significant, indicating a notable increase in hunger and food insecurity with decreases (of about a third on average) in food consumption expenditure, income and farm revenue.

Afghan households have become increasingly vulnerable due to almost four decades of conflict and exposure to natural disasters, notably floods, earthquakes, avalanches, and landslides, due to its geography and years of environmental degradation (Hagen and Teufert, 2009). Natural and climate shocks affect almost 60 per cent of the population, with over 16,000 deaths from earthquakes and floods since 1990, whereas 19 per cent experienced shocks related to security (World Bank, 2018), with estimated annual damages of $54 million from flooding, $80 million from earthquakes, and $3 billion in agricultural loses from extreme droughts (Ranghieri *et al*., 2017). Avalanches and landslides cause the closure of some of the main roads every year, including the Salang Pass connecting Kabul to the northern areas. Strong earthquakes occur every few years across Afghanistan, with approximately 100 damaging earthquakes recorded since 1900 (Daniell *et al*., 2011), frequently causing high casualties (Essar *et al*., 2022). Prolonged droughts have a significant impact on agricultural output, the main livelihood source for Afghans, especially given the frequent lack of irrigation infrastructure. Severe floods displace populations (Blanchet and Shafique, 2023) and increase poverty; floods and drought are major drivers of food insecurity and malnutrition (Oskorouchi and Sousa-Poza, 2021; Kochhar and Knippenberg, 2023). This is exacerbated by conflict: households in provinces with higher levels of conflict experience greater declines in food security; a 1% increase in fatalities per 10,000 inhabitants can reduce consumption by 9.2% (D'Souza and Jolliffe, 2013).

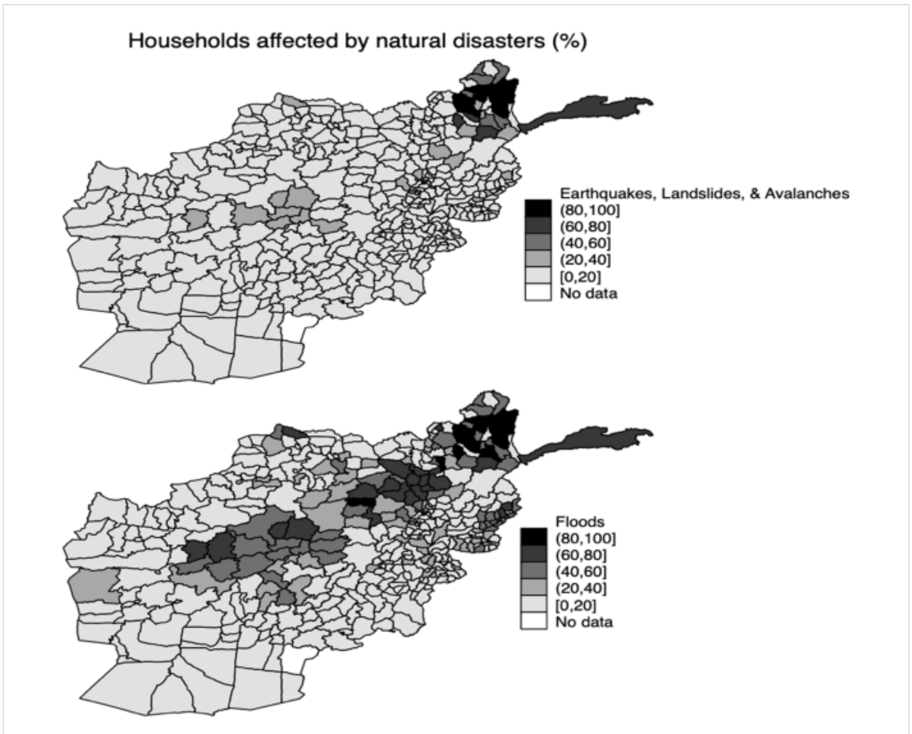
Effective disaster risk management is crucial to support Afghanistan's development and stability, but the lack of reliable data on exposure and risks, compounded by security concerns that prevent field observations and data collection, has hindered disaster risk management efforts (World Bank, 2018). There is a general lack of information on rainfall statistics, infrastructure vulnerability and the impacts of natural disasters on livelihoods. Consequently, the majority of disaster risk management initiatives focus on response and recovery (Shroder, 2014; Sadiqi *et al*., 2017) rather than mitigation.

This paper contributes by estimating the impact of natural disasters on household welfare; with the implications may not be implementable in Afghanistan under the current Taliban regime, it adds to broader literature on the adverse effects of climate change, especially from increased flooding. The rest of the paper is organized as follows: Section 2 outlines the context and provides an overview of related literature and Section 3 explains the conceptual framework and estimation techniques. Section 4 discusses the data and descriptive statistics while Section 5 presents and discusses empirical results. Section 6 draws conclusions and implications; while these may not be applicable in Afghanistan since the second Taliban takeover they nevertheless highlight the importance of addressing climate risk in fragile environments to mitigate adverse impacts on household welfare.

2. Natural Disasters in the Afghan Context

Afghanistan is one of the most vulnerable countries to natural disasters in the world, exacerbated by the combined effects of conflict, rugged mountainous landscape, and climate change (Hagen and Teufert, 2009; World Bank, 2018). The most common natural disasters are flooding, prolonged drought, earthquakes, landslides and avalanches, and extreme weather such as heavy snowfalls, hailstorms, and late damaging frosts (World Bank and ADB, 2021). The vulnerability of communities has been further aggregated in recent decades due to the conflict (Gupta, 2010).

Figure 1: District-level map of natural disasters (2011-2014)



Source: Authors, constructed from the NRVA and ALCS data.

The majority of districts and provinces are affected by at least one or several types of natural disasters (Figure 1); floods are the most common especially in central and north-eastern, eastern and southwestern regions, and about 70% of all natural disasters are attributable to floods (Oskorouchi and Sousa-Poza, 2021). Earthquakes and associated hazards such as landslides and avalanches are most common in the mountainous and seismically active central and north-eastern provinces.

2.1. Impact assessment of natural disasters

Afghanistan faces rates of warming higher than the global average and is one of the most vulnerable nations to climate change impacts in the world, ranked 176th out of 181 countries in the 2020 ND-GAIN Index (World Bank and ADB, 2021). Rising temperatures have led to more frequent and devastating floods, altering rainfall patterns, and exacerbating the severity of extreme weather events (Oskorouchi and Sousa-Poza, 2021). Analysis of historical data by Qutbudin *et al*. (2019) reveals increases in drought severity and frequency in Afghanistan over a period of 100 years. Consequently, the country is faced with increased risks from recurrent climate-related impacts, amplifying hazards, exposure, and vulnerability. Recent political instability has exacerbated the food insecurity of Afghan households, leading to a humanitarian crisis. According to the latest updates by IPC[1], approximately 17.2 million Afghans (40%) were experiencing high levels of acute food insecurity, classified as Crisis or Emergency (IPC Phase 3 or 4) in April 2023. This includes nearly 3.4 million people (around 8%) experiencing Emergency (IPC Phase 4) levels of food insecurity (IPC, 2023).

Oskorouchi and Sousa-Poza (2021) assess the impact of floods on household food security in Afghanistan using the 2011/12 household survey, showing that exposure to flooding significantly reduces daily calorie consumption and increases the probability of iron and vitamin deficiencies among affected households; floods are also linked to anaemia problems in women (Oskorouchi *et al*., 2018). The 2018 drought reduced monthly consumption expenditures and increased poverty for households under severe stress (Kochhar and Knippenberg, 2023).

3. Estimation Methods

A growing literature investigates the relationship between weather conditions and economic outcomes in the context of the potential economic impacts of climate change (Dell *et al*., 2014; Arouri *et al*., 2015). In estimating the impact of weather and climate shocks on household welfare, two empirical challenges dominate: selection bias and endogeneity. Individuals choose their place of residence according to the natural environment and/or the occurrence of historical natural disasters. This may introduce sample self-selection commonly addressed using propensity score matching (PSM) to alleviate bias. While many studies treat natural disasters as exogenous, there is potential endogeneity due to unobserved factors and omitted variable bias. The probability or impact of a natural disaster in a location

[1] The Integrated Food Security Phase Classification (IPC) is an innovative multi-partner system that categorizes food security outcomes into different phases. The IPC classifies food (in)security in five phases including phase 1 “minimal”, phase 2 “stressed”, phase 3 “crisis”, phase 3 “emergency”, and phase 5 “catastrophe/famine”. For details on the IPC and different phases, see the IPC technical manual at: https://www.ipcinfo.org/ipcinfo-website/resources/ipc-manual/en/

may be correlated with unobserved variables (both commune and household level), such as local culture and practices (Baker and Bloom, 2013; Arouri *et al.*, 2015). Thomas *et al.* (2010) argued that experience may affect the level of consumption: households in regions where natural disasters occur frequently are likely to adapt to these unfavourable conditions to reduce *ex ante* exposure or even *ex post* capacity to cope. This implies endogeneity of natural disasters.

If households are not randomly assigned or exposed to natural disasters, the possibility that a household experiences a natural disaster shock could be considered endogenous. Natural disasters do not occur randomly across geographical areas; floods are more likely in river deltas, and landslides in mountainous areas (Nguyen and Minh Pham, 2018). Although reverse causation is unlikely to be a major concern as weather conditions are exogenously determined (Dell *et al.*, 2014), omitted variable bias caused by the correlation of weather variables with local characteristics (long-term climate, geographical, agro-ecological conditions) may be correlated with living standards (Botzen *et al.*, 2019; Wu *et al.*, 2022).

Human and economic losses from disasters are likely to depend on the level of development of the affected area so the direct damage from natural disasters is likely to be endogenously determined (Becchetti *et al.*, 2017; Kirchberger, 2017; Oliveira, 2019). Moreover, the adoption mechanisms that households choose to respond and recover from natural disasters could also be potentially endogenous. To deal with endogeneity, studies employ fixed effect (Keerthiratne and Tol, 2018; Henry *et al.*, 2020), commune fixed effect regressions (Arouri *et al.*, 2015; Nguyen *et al.*, 2020) or instrumental variables (Oskorouchi and Sousa-Poza, 2021). The choice of method is often guided by the type of data available and all have limitations (Shiferaw *et al.*, 2014). A commonly used method that addresses many endogeneity concerns to provide causal inference is the endogenous switching regression (ESR) that estimates simultaneously the equation for the likelihood of a natural disaster and the outcome equation with endogenous switching using full information maximum likelihood (Di Falco *et al.*, 2011). We adopt a parametric binary ESR and non-parametric PSM techniques to mitigate the endogeneity bias and capture both the observed and unobserved heterogeneity influencing the outcome variable and the likelihood of a natural disaster.

3.1.Empirical Strategy

The relationship between natural disaster and household food security or welfare outcomes can be represented by following equation:

$$Y_i = \beta Z_i + \phi X_i + \varepsilon_i \qquad (1)$$

where Y_i denotes household welfare outcomes, Z_i is a binary measure of natural disasters and X is a vector of observed household demographic and socioeconomic characteristics, climate and shocks (rainfall, temperature, weather and price shocks, and conflict), proximity to services (access to roads and local markets), landscape and locational characteristics. The household characteristics include household demographics and composition such as household size, age of head, education and literacy of head, dependency ratio, head employment status, and land ownership. Our baseline identification strategy relies on the estimation of OLS and 2SLS models using instrumental variables.

The empirical challenge in estimating the impact of natural disasters in (1) using observational data is establishing a suitable counterfactual against which the impact can be measured. This challenge arises due to the self-selection and endogeneity problems. To accurately measure the impact of natural disasters on welfare, the exposure to a shock should ideally be randomly assigned so that the effect of observable and unobservable characteristics between the affected (treatment) and unaffected (comparison) groups is the same, and the effect is attributable entirely to the treatment (Shiferaw *et al*., 2014). However, when the treatment groups are not randomly assigned, the likelihood of a household to experience a shock are likely to be influenced both by unobservable (e.g., managerial skills, culture and practice of local people, location) and observable heterogeneity that may be correlated to the outcome of interest.

Endogenous Switching Regression (ESR)

The ESR framework follows two stages. In the first stage, the factors associated with natural disasters are estimated using a binary probit model for selection as in (1), while in the second stage linear regression is employed to assess the association between the outcome variable and occurrence of natural disasters (Di Falco *et al*., 2011). The likelihood of a household to be exposed to a natural disaster shock can be modelled in a random utility framework. Let Z^* denote the difference between the utility achieved by the households that are affected by a shock (U_{is}) and the utility realized by households that did not experience any shocks (U_{in}), such that a household will derive higher utilities if unexposed ($Z^* = U_{in} - U_{is} > 0$). The two utilities are unobservable but can be expressed as a function of observable components in a latent variable model:

$$Z_i^* = \alpha + \gamma Q_i + \varepsilon_i \quad with\, Z_i = \begin{cases} 1 \text{ if } Z_i^* > 0 \\ 0 \text{ otherwise} \end{cases} \tag{2}$$

where Z_i^* is a binary variable that takes the value 1 if the household has experienced a natural disaster shock and 0 otherwise; Q_i is a vector of exogenous variables influencing the likelihood of a household to experience a climate shock/natural disaster, including household and location characteristics; γ represents a vector of coefficients to be estimated; α is the intercept and ε_i a random error term with zero mean and a constant variance. Assuming that the outcome variable (household welfare, food security or dietary diversity) is a linear function of Z_i conditional on a vector collecting other covariates (X), the ESR model is defined in (3a) and (3b) for the outcome variables under different switching regimes:

$$Regime\ 1: \ Y_{1i} = \alpha + X_{1i}\beta_1 + \theta_{1i}Z_1 + \eta_{1i}$$

$$if\ Z_i = 1 \quad \text{for affected households} \quad (3a)$$

$$Regime\ 2: \ Y_{2i} = \alpha + X_{2i}\beta_2 + \theta_{2i}Z_2 + \eta_{2i}$$

$$if\ Z_i = 0 \quad \text{for unaffected households} \quad (3b)$$

where Y_i represents the outcome variable (household welfare) of household i for each regime (1 = affected and 2 = unaffected); X_i and Z_i are as already defined; η_{1i} and η_{2i} are independently and identically distributed error terms of the outcome variable equations; and β, θ, and ρ are parameters to be estimated. The variables in vectors X_i may overlap with Q in (1), but the ESR approach requires that at least one variable in Q does not appear in X. The Inverse Mills Ratio (IMR) $\lambda_{1i} = \frac{\phi Z_i(\alpha)}{\Phi Z_i(\alpha)}$ and $\lambda_{2i} = \frac{\phi Z_i(\alpha)}{1-\Phi Z_i(\alpha)}$ of likelihood of shocks experienced are computed from (1) and included in (3a) and (3b) to correct for potential endogeneity bias in the two-step estimation procedure. The error terms in (1) and (2) are assumed to have a trivariate normal distribution with mean zero and covariance matrix specified as:

$$\Omega = cov(\varepsilon;\ \eta_1;\ \eta_2) = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon 1} & \sigma_{\varepsilon 2} \\ \sigma_{\varepsilon 1} & \sigma_1^2 & . \\ \sigma_{2\varepsilon} & . & \sigma_2^2 \end{bmatrix}$$

where $\sigma_\varepsilon^2 = var(\varepsilon)$, $\sigma_1^2 = var(\eta_1)$, $\sigma_2^2 = var(\eta_2)$, $\sigma_{\varepsilon 1} = cov(\varepsilon, \eta_1)$, and $\sigma_{21} = cov(\varepsilon, \eta_2)$, It can be assumed that σ_ε^2 equal to 1, (α is estimable only up to a scalar factor). Since Y_1 and Y_2 are never observed simultaneously, the covariance between η_{1i} and η_{2i} is not defined. An important implication of the error structure is that because the error term of (1) ε_1 is correlated with the error terms in (3a and 3b) (η_{1i} and η_{2i}), the expected values of η_{1i} and η_{2i} conditional on the sample selection are non-zero.

The ESR is estimated using full information maximum likelihood (FIML), ensuring consistent standard errors while simultaneously fitting binary and continuous parts, and used to estimate the average treatment effect on the treated (ATT) and the untreated (ATU) by comparing the expected values of the outcomes of affected and unaffected in actual and counterfactual scenarios. The ATT computes the average difference in outcomes of affected with and without a shock, whereas the ATU computes the average difference in outcomes of the unaffected had they experienced and not experienced a shock. Following Di Falco *et al*. (2011), and Khonje *et al*. (2015), we calculate the ATT and ATU as follows:

Affected with natural disaster shocks experienced (observed in the sample):

$$E(Y_{1i}|Z = 1; X) = X_{1i}\beta_1 + \sigma_{1\varepsilon}\lambda_{1i} \qquad (4a)$$

Non-affected without natural disaster shocks experienced (observed in the sample):

$$E(Y_{2i}|Z = 0; X) = X_{2i}\beta_2 + \sigma_{2\varepsilon}\lambda_{2i} \qquad (4b)$$

Non-affected had they been affected by the natural disaster shocks (counterfactual):

$$E(Y_{1i}|Z = 0; X) = X_{2i}\beta_1 + \sigma_{1\varepsilon}\lambda_{2i} \qquad (4c)$$

Affected had they not experienced any natural disaster shocks (counterfactual):

$$E(Y_{2i}|Z = 1; X) = X_{1i}\beta_2 + \sigma_{2\varepsilon}\lambda_{1i} \qquad (4d)$$

Equations (4a) and (4b) represent the actual expectations observed from the sample, while (4c) and (4d) are the counterfactual expected outcomes. Using these conditional expectations, the following mean welfare outcome difference can be computed. The expected change in welfare outcomes of the affected by the natural disaster shocks, the effect of treatment on the treated (ATT) is computed as the difference between (4a) and (4d):

$$\begin{aligned} ATT &= E(Y_{1i}|Z = 1; X) - E(Y_{2i}|Z = 1; X) \\ &= X_{1i}(\beta_1 - \beta_2) + \lambda_{1i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \qquad (5) \end{aligned}$$

Similarly, the expected change in welfare outcomes of the non-affected by any natural disaster shocks, the effect of the treatment on the untreated (ATU) is given as the difference between (4c) and (4b):

$$ATU = E(Y_{1i}Z = 0; X) - E(Y_{2i}|Z = 0; X) \\ = X_{2i}(\beta_1 - \beta_2) + \lambda_{2i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \quad (6)$$

Propensity Score Matching (PSM)

Although the ESR model has the capability to correct for selectivity and endogeneity bias, it may be sensitive to the underlying exclusion restriction. We use propensity score matching (PSM) as a robustness check for treatment effect results from ESR. The PSM estimates the effect of a treatment by accounting for the covariates that predict receiving the treatment using observable characteristics of households in the sample to generate a control group that is comparable to the treated group conditional on identified exogenous or observable factors. By creating comparable counterfactual households for treated households, PSM reduces the bias due to observables and resembles randomised assignment to treatment, and has been used to estimate the impacts of natural disasters (Hudson *et al*., 2014; Wu *et al*., 2022).

If the individual households in a match are similar, a substantial amount of selection bias can be removed and the average difference in outcomes between the matches is a reliable estimate of the ATT (Rosenbaum and Rubin, 1983; Caliendo and Kopeinig, 2008; Wooldridge, 2010). After matching (if the matching quality is satisfied), the ATT can be estimated as the mean difference of expected welfare of the flood affected household matched with non-affected who are balanced on the propensity scores and fall within the region of common support. We examine the impact of natural disaster shocks on household wealth using three different matching algorithms, K-nearest neighbour matching (with K=1 and K=5), Kernel matching, and multivariate distance matching.

3.2.Identification

To ensure (2) is identified, the X variables in the first stage probit (1) must contain at least one selection instrument in addition to those automatically generated by the nonlinearity of the selection model of adoption (Di Falco *et al*., 2011; Khonje *et al*., 2018). Instrumental variables should be included in (1) but excluded from the outcome equation (2). Previous studies used the disaster incidence in other regions in the same province as the instrumental variable (Dell *et al*., 2014; Lu *et al*., 2022).

Following Oskorouchi and Sousa-Poza (2021), we use two sets of instrumental variables, a standard leave-out mean instrument (Townsend, 1994) and heteroscedasticity-based instruments (Lewbel, 2012), to identify the selection equation. The leave-out mean instrument is defined as the share of households in a district affected by natural disasters excluding household *i*. Households that operate in the same geographical conditions, and face similar demographic, economic, and institutional characteristics, are likely to experience similar shocks. The leave-out mean instrument takes a different value for each district and is assumed to be uncorrelated with the household (*i*) unobserved heterogeneity and welfare outcomes.

The heteroscedasticity-based identification of Lewbel (2012) increases efficiency by providing overidentifying information (the leave-out means instrument alone is exactly identified) and is especially useful when other sources of identification are not available, for instance when only one or no external instrumental variable is available or when the external instruments are weak (Iosifidi, 2016; Lu *et al*., 2022). The Lewbel instruments can be constructed in two steps (Baum and Lewbel, 2019). In the first step the endogenous variable is regressed on the instrument and a set of control variables, and the predicted residuals are obtained. In the second step, the instruments are generated by multiplying the exogenous variables that have been centred at their respective means with the predicted residuals from the first step $(Q_i - \bar{Q}_i)\hat{\varepsilon}_i$, where $\bar{Q}_i$ is the sample mean of Q. This process can be implemented using the *ivreg2h* command in Stata.

The Lewbel (2012) approach requires the presence of heteroscedasticity of the residuals in the first-stage regression (using the Breusch-Pagan test for heteroscedasticity of Q variables) so the Q variables are picked based on the highest Chi-Square values when we regressed the endogenous variable (Z) on each of the Q variables individually. Lewbel (2018) confirms that heteroscedasticity-based instruments are also valid for discrete endogenous variables such as the dummy indicator variable of natural disasters in our case. Instrument validity is tested through under-identification (Kleibergen-Paap rk LM statistic), weak identification (Cragg-Donald Wald F statistic) and overidentification (Hansen J statistic) tests in the baseline estimation using 2SLS with the *ivereg2* command in Stata.

4. Data and Definition of Variables

The analysis is based on two waves of a nationally representative household survey that gives repeated cross-section data for 2011/12 and 2013/14 (the 2016/17 survey did not collect information on flooding, the most important disaster in Afghanistan). The Afghanistan Living Condition Survey (ALCS, formerly the National Risk and Vulnerability Assessment) is conducted by the Afghanistan National Statistics and Information Authority (NISA, formerly the Central Statistics Organization (CSO) of Afghanistan). The ALCS provides data on welfare and living standards, the change over time, and the distribution among households with the goal of tracking Afghanistan's progress. A sample of roughly 21,000 households in 398 districts and 35 strata (34 for the provinces and one for the nomadic population) are included in each round. The sample, which was produced using a stratified sampling approach with a two-stage cluster design for each stratum, is representative for both urban and rural households at the national, seasonal, and first administrative levels (34 provinces). The collection of data was evenly spread out throughout a year in order to guarantee that it is seasonally representative (Central Statistics Organization, 2014, 2016).

Combining the two ALCS surveys gives a total sample of about 41,667 households. The *Kuchi* population, nomadic landless livestock pastoralists accounting for about 2.7 per cent of the total households, is excluded. Omitting households with missing values for key variables results in a final analytical sample just ove 40,500 households.

4.1. Measuring Household Food (In)security

Food security is achieved if households have access to sufficient nutritious food to meet dietary needs for a healthy life (Carletto *et al*., 2013; Deléglise *et al*., 2023). There are four key dimensions: the availability of appropriate quantities of high-quality food, universal access to resources enabling food procurement, the stability of food access over time despite natural or economic challenges, and the proper utilization of food, including considerations like hygiene, storage, and cooking. Food security metrics may focus on food availability, access, utilization, the stability of food security over time, or some combination of these domains (Jones *et al*., 2013). Given the complexity of food security, many food (in)security measures and indicators exist, capturing different dimensions of food security (Maxwell *et al*., 2014), and it is useful to use several indicators (Deléglise *et al*., 2023).

The analysis includes several measures: the Household Food Consumption Score (HFCS), Household Hunger Scale (HHS), Reduced Coping Strategy Index (rCSI), household food consumption expenditures, and the share of household food consumption expenditure in total consumption (Appendix A1(ii), A1(iii), and A1(iv) provide details on the construction). These indicators capture the frequency, accessibility, quantity and quality of food consumption.

Each measure captures different dimensions of food security so can produce very divergent estimates of the prevalence of food insecurity. The HFCS is a composite score that includes information on household dietary diversity (food groups consumed in the past 7 days), frequency of food group consumption (number of days in the past week), and nutritional value using weights (Leroy *et al*., 2015) and ranges between 1 and 112, with higher values indicating higher food security (dietary diversity). While HFCS measures food varieties and consumption frequencies, capturing food insecurity by low-quality diets, HHS and rCSI assess access and consumption behaviour linked to coping strategies during food shortages. The rCSI assesses the frequency of severe coping strategies (survival mechanisms when faced with unexpected livelihood failures) when households face challenges accessing sufficient food (Maxwell *et al*., 2014; Leroy *et al*., 2015). The rCSI gauges the frequency and severity of changes in consumption patterns to identify vulnerable households (Jones *et al*., 2013). The maximum score for the rCSI is 56 corresponding to severe food insecurity while scores of 19 or above are categorized as crisis food-based coping status. The HHS, derived from the Household Food Insecurity Access Scale (HFIAS), focuses on the quantity dimension of food access with a culturally invariant subset of questions on the occurrence of severe experiences of food shortage and restricted access to food (Maxwell *et al*., 2014). The HHS is good at flagging highly food-insecure households in Phase 4 Emergency and Phase 5 Famine stages of the IPC (Maxwell *et al*., 2023). The HHS ranges from 0 to maximum 6, with 6 showing the highest degree of hunger.

4.2.Measuring household welfare

Household economic welfare is captured by household food consumption expenditures, income, and farm revenues. Household food consumption reflects ability to acquire a sufficient and diverse range of food, going beyond calorific intake or nutritional diversity; food expenditure (total spending on food items reported during the previous month) is a reliable proxy for meeting basic household needs (Antonelli *et al*., 2022). Although self-reported income may be unreliable and sensitive to seasonal variations in earnings, we employ household income as a broad measure of economic resources available to a household. Given that agriculture is the primary activity in the rural setting and constitutes a significant portion of household income, we also utilize farm revenues as an indicator of welfare. Aggregate crop revenues at the household level serve as a measure of farm performance and earnings, highlighting the impact of natural hazards on the primary livelihoods of households. Farm revenue represents the aggregate physical output of crops, weighted by the prices of the respective crops. All measures are standardized per adult equivalent and expressed in Afghani in constant base prices using the OECD modified equivalence scale, assigning a value of 1 to the household head, 0.5 to each additional adult member, and 0.3 to each child (Appendix A1(i), Table A1).

4.3.Measuring natural disasters, conflict, and other shocks

The NRVA and ALCS surveys uses a 13-section structured questionnaire to gather information on a range of topics. The shock module covers several shocks experienced by households including the most common natural disasters – flooding, landslides and avalanches, earthquakes, and hailstorms. The majority (about 85%) of the households covered by the ALCS survey are located in rural areas. We rely on self-reported primary data from households, encompassing natural disasters and various other shocks, such as weather-related incidents (e.g., frosts, extreme weather conditions), price shocks, and instances of violence and insecurity. Our key measure for natural disaster shocks is a binary variable, assigning a value of one if a household reported flooding, earthquakes, landslides, or avalanches.

In the context of Afghanistan, the incidence of conflict is likely to affect household consumption; when violence intensifies households may concentrate on subsistence activities (Arias *et al.*, 2019). Conflict could affect the way natural resources are manged (Peters, 2021) while natural disasters may elevate the likelihood and risk of violent civil conflicts (Nel and Righarts, 2008). Two measures of conflict shocks are included. First, the number of incidents with fatalities in the district from the Upsala Conflict Data Program (UCDP), a pooled measure of conflict for 2011 to the end of 2014.[2] Second, a household self-reported measure, a binary variable equal to 1 if the household experienced any conflict and insecurity in the past 12 months..

Exposure to price shocks is a binary variable from the survey question if households experienced any price shocks in the previous 12 months. Several characteristics are included, such as household head age, literacy rate, education, dependency ratio, household size and composition (dependency ratio). Dummy variables capture landscape characteristics and residence (urban or rural).

4.4 Descriptive Statistics

Table 1: Distribution of experiencing natural disasters

	2011/12	2013/14	Pooled sample
Unaffected	15353	15577	30930
	76.02	*82.04*	*78.93*
Affected	4844	3411	8255
	23.98	*17.96*	*21.07*
Total	20197	18988	39185

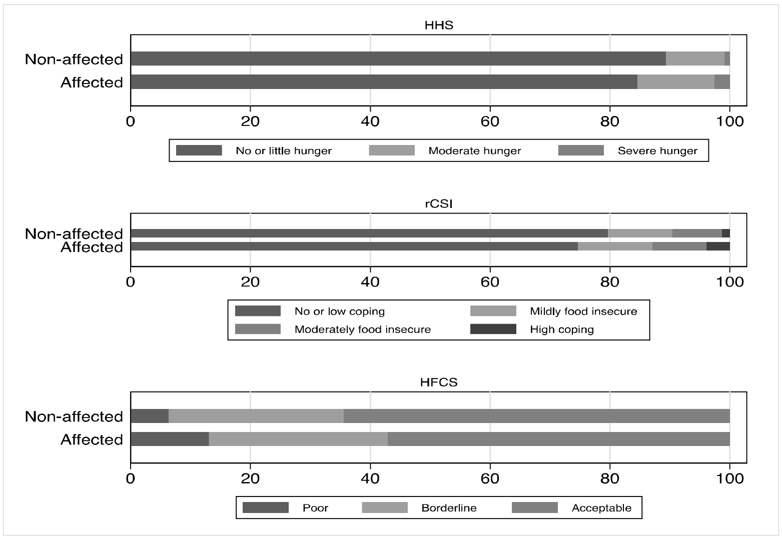
Note: First row under each category has *frequencies* and the second row has *column percentages*.

Table 1 provides a breakdown of the sample distribution based on natural disaster shocks for the years 2011/12 and 2013/14, and the pooled sample; fewer households reported incidents in 2013-14 (see Table 1 and Map B1 in the appendix). Overall, one-fifth of surveyed households in the pooled data reported being affected; floods are the most prevalent natural

[2] Data are pooled over the first years as many districts have zero values in each year. The Global Dataset of Events, Language and Tone (GDELT) database is not used as it only provides detailed information on the Afghan conflict from the start of 2017.

disaster affecting around 20% of households with about 5% experiencing earthquakes, landslides or avalanches (most also reported being affected by flooding).

Figure 2: Distribution of Household Welfare Indicators



Notes: Shows distribution of HHS, rCSi and HFCS for affected and non-affected households based on the respective cut-offs in Appendix Tables A3, A5 and A7.

Table 2: Descriptive statistics of the key variables

	Means by natural disasters			Pooled sample	
	Affected	Non-affected			
Variables	mean	mean	difference	mean	sd
Outcome variables					
Household food consumption (HFCS)	40.36	43.08	-2.73***	42.50	15.84
Household hunger scale (HHS)	0.663	0.457	0.207***	0.494	0.881
Reduced coping strategy index (RCSI)	2.934	2.137	0.797***	2.28	4.776
Real food expenditures (AFN)	1298.215	1358.303	-60.10***	1345.63	809.85
Share of food expenditures (%)	77.425	75.85	1.576***	76.18	16.98
Real income (AFN)	32336.15	38706.71	-6370.57***	37363.32	31370.97
Real farm revenue (AFN)	9146.26	14021.09	-4874.83***	12641.44	19828.36
Shocks					
Natural disasters (0/1, 1= yes)				0.211	0.408
Insecurity and violence (0/1, 1= yes)	0.215	0.173	0.043***	0.181	0.385
Price shock (0/1, 1= yes)	0.647	0.502	0.145***	0.533	0.499
Weather shocks (0/1, 1= yes)	0.570	0.163	0.408***	0.248	0.432
Observations	8,255	30,930		39,185	

Notes: Income, expenditures and farm revenue measured per adult equivalent; share of food expenditures is relative to total consumption expenditures. Difference is affected minus non-affected means; *, **, and *** denote significance at 10%, 5% and 1%, respectively.

Table 2 compares key variables between households affected and unaffected by natural disasters in the pooled sample. Affected households exhibit lower household food consumption scores, elevated hunger levels, and increased reliance on coping strategies. The HFCS scores indicates a higher proportion of affected households falling into the poor and borderline categories compared to the unaffected households (Figure 2 and Table A3), while HHS and rCSi show a higher percentage of affected households experience moderate and severe hunger and adopt more intensive coping strategies (Figure 2 and Tables A5 and A7). Affected households have lower consumption expenditures (especially in 2013-14 – see Table A10), lower income and farm revenue, highlighting their increased vulnerability. The t-test of mean difference confirms the statistical significance of these disparities. The table also highlights the coincidence of shocks, with affected households more likely to report violence and insecurity, price fluctuations, and weather-related shocks.

5. Empirical Results and Discussion

Tables 3 and 4 present the estimated impact of natural disasters on household food security and welfare outcomes. The baseline employs Ordinary Least Squares (OLS) for Table 3 and Two-Stage Least Squares (2SLS) for Table 4. The 2SLS estimates are greater than the OLS estimates, suggesting a downward bias in the OLS estimation attributable to endogeneity (as confirmed in Notes to Table 4 the tests for instrument validity are met).

Table 3: Baseline OLS for Welfare Indicators

Variables	(1) HFCS	(2) HHS	(3) rCSI	(4) Food expenditure	(5) Share food	(6) Income	(7) Farm revenue
Panel A: 2011-12							
Disaster	-1.620***	-	-	0.113***	0.009***	-0.072***	-0.103***
	(.276)			(.012)	(.003)	(.014)	(.021)
Panel B: 2013-14							
Disaster	-2.579***	0.044**	0.355***	-0.008	0.010***	-0.119***	-0.025
	(.305)	(.018)	(.098)	(.011)	(.003)	(.014)	(.024)
Panel C: Pooled sample							
Disaster	-2.094***	0.044**	0.355***	0.051***	0.009***	-0.081***	-0.057***
	(.206)	(.018)	(.098)	(.008)	(.002)	(.010)	(.016)
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
N	39147	18974	18981	38994	39156	38876	19813
R-squared	.139	.062	.024	.136	.112	.156	.390

Notes: Income, food (consumption) expenditures and farm revenue measured as log of real per adult equivalent; share of food expenditures is relative to total consumption expenditures. Disaster a binary variable equal to 1 if household experienced a natural disaster. Results for HHS and rCSI for 2013-14 only (data unavailable for the 2011-12 survey). Full results reported in Table A11 in the appendix. Robust standard errors are in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

In both tables, Columns 1-3 present the estimated impacts of natural disasters on indicators of household food (in)security and Columns 4-7 show effects on welfare measures. The estimated coefficients consistently indicate that exposure to natural disasters is significantly associated with reduced food security and dietary diversity, and adverse welfare. Although coefficients on food expenditures and share of food expenditures are sometimes positive, this is in a context of lower income so other spending has to be reduced to try and maintain food consumption.

Table 4: Baseline results from the 2SLS estimation

Variables	(1) HFCS	(2) HHS	(3) RCSI	(4) Food spending	(5) Share food	(6) Income	(7) Farm revenue
Panel A: 2011-12							
Natural dis	-8.776***	-	-	0.144***	0.075***	-0.548***	-0.457***
	(.678)			(.026)	(.008)	(.036)	(.056)
Panel B: 2013-14							
Natural dis	-34.759***	0.375***	3.111***	-0.56***	-0.027**	-1.861***	0.105
	(2.18)	(.104)	(.606)	(.057)	(.013)	(.113)	(.087)
Panel C: Pooled sample							
Natural dis	-6.757***	0.375***	3.111***	0.393***	0.078***	-0.514***	-0.435***
	(.647)	(.104)	(.606)	(.025)	(.007)	(.034)	(.051)
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
N	39147	18974	18981	38873	39156	38876	19813
R-squared	0.128	0.045	0.017	0.089	0.090	0.113	0.373
idstat test	2336.29	329.84	329.76	2363.66	2376.09	2323.91	1432.08
Overidentification	0.30	0.84	0.406	0.817	0.287	0.194	0.075
Weak IV test	1723.75	200.07	200.12	1760.89	1770.83	1719.16	1005.72

Notes: As for Table 3. Full results are reported in Table A12. The under-identification idstat test (Kleibergen-Paap rk LM statistic) rejects the null hypothesis that the models are weakly identified in the pooled sample (unreported p-values <0.005). The over-identfication (Hensen *J)* test (p-values) shows that over-identification restriction is satisfied (cannot be rejected at 5% level). The Weak IV test is the Kleibergen-Paap Wald rk F statistic (appropriate with robust standard errors) and confirms that instruments are not weak in the pooled sample.

While OLS and 2SLS offer a good starting point as a baseline specification, results should be interpreted with caution as potential selectivity and endogeneity may lead to biased estimates. Notably, the OLS model is particularly susceptible to endogeneity bias, leading to potentially skewed estimates of the impact of natural disasters on food security and welfare. To address these concerns, we give preference to the results obtained from the preferred ESR model estimated by FIML in the next section.

5.1.Results from the endogenous switching regression (ESR)

The results from the ESR first stage and second stage are discussed briefly in the appendix (Tables A14 and A15) to focus here on the estimated treatment effects. Table 5 presents the treatment effects for affected and unaffected households and the difference for the pooled sample (but only the difference for individual survey years). Descriptive statistics (Table A6) show that, on average, 5% fewer households experienced natural disasters in 2013-14. The magnitude and severity of shocks and impacts varies between the surveys although qualitative inferences are similar. The treatment effects for each survey year qualitatively align with the results observed in the pooled sample: natural disasters lead to lower household welfare and food security outcomes, although the magnitude of these effects varies. The impact appears almost doubled in 2013-14 (Table 5), suggesting the occurrence of more severe disasters.

The results from the pooled sample exhibit both qualitative and quantitative consistency with the findings from the 2SLS model, but differ quantitatively from the baseline OLS. Both the 2SLS and ESR estimates consistently demonstrate larger quantitative effects compared to the OLS estimates, suggesting a potential downward bias in the outcome equations due to endogeneity issues. For comparability with the 2SLS results, ATE is preferred to ATT.

Table 5: Treatment effects from the ESR model

Outcome variable	effect	2011/12	2013/14	Pooled sample Mean treatment effect on outcome		
				Affected	Unaffected	Difference
HFCS	ATE	-8.205***	-19.342***	34.662	43.547	-8.885***
	ATT	-5.098***	-11.449***	40.331	45.391	-5.06***
	ATU	-9.186***	-21.071***	33.148	43.055	-9.906***
rCSI	ATE	-	2.703***	5.002	2.299	2.703***
	ATT	-	7.330***	2.949	-4.382	7.330***
	ATU	-	1.689***	5.451	3.762	1.689***
HHS	ATE	-	0.377***	0.595	0.217	0.377***
	ATT	-	1.343***	0.662	-0.680	1.343***
	ATU	-	0.165***	0.580	0.414	0.165***
Log Real HH food consumption expenditure (AFN)	ATE	0.178***	-0.427***	7.171	7.002	0.169***
	ATT	0.216***	-0.770***	7.032	6.846	0.186***
	ATU	0.166***	-0.352***	7.208	7.043	0.164***
Share of food cons. expenditures in total cons. exp. (%)	ATE	0.071***	-0.059***	0.994	0.755	0.238***
	ATT	0.052***	-0.256***	0.779	0.728	0.051***
	ATU	0.077***	-0.015***	1.051	0.763	0.289***
Log Real HH income (AFN)	ATE	-0.518***	-0.831***	9.795	10.326	-0.531***
	ATT	-0.386***	-0.634***	10.077	10.412	-0.334***
	ATU	-0.559***	-0.875***	9.72	10.303	-0.583***
Log Real farm revenue (AFN)	ATE	-0.446***	-0.071***	8.628	9.044	-0.416***
	ATT	-0.880***	-0.139***	8.527	9.440	-0.912***
	ATU	-0.241***	-0.049***	8.668	8.885	-0.217***

Note: Variables and significance as for Table 3. Estimated by FIML using the *movestay* command in Stata. For the pooled sample column 5 reports the mean of the estimated treatment effect (ATE) for the affected, column 6 the mean for the unaffected and the final column is the difference in means (significance based on a *t* test). Columns 3 and 4 for individual years (2011/12 and 2013/14) only report the differences in means of the estimated treatement effects for affected and unaffected households.

Households affected by natural disasters consume a more limited variety of foods with a score approximately 9 points lower on the HFCS scale. Considering the mean HFCS score of 43 (Table 2), this translates to consuming 3 fewer main staples and 1 less fruit and/or vegetable item per week (Table A2). The estimated treatment effect for Household Hunger Scale (HHS) and Reduced Coping Strategies Index (rCSI) are both positive and significant. This suggests that exposure to natural disaster shocks forces households to adopt consumption coping strategies due to food shortages. The estimated treatment effect of rCSI at 2.7 suggests significant changes in household coping strategies given the rCSI scale

(Table A4 in appendix). Considering the mean score of rCSI in the pooled sample (2.28) and the distribution of rCSI score based on pre-established cut-offs (Table A5), this impact is likely to push significant number of households in the No or Low coping (rCSI=0-3) category to higher levels of food insecurity. Approximately 13% of households initially categorized as Mildly Food Insecure (rCSI=4-6) could shift to Moderately Food Insecure (rCSI=9-18), or about 10 % of households in the Moderately Food Insecure (rCSI=9-18) category could move to High Coping (rCSI >18).

The estimated average treatment effect for the HHS is 0.377; given the mean HHS score of 0.494 and the distribution based on pre-established cut-offs (Tables A6 and A7), the analysis suggests that approximately 67% of households initially classified as experiencing Little or No hunger (0-1) could potentially transition to the Moderate hunger (3-4) category. Alternatively, around 8% of households initially categorized as Moderate hunger (3-4) could shift to the more severe Severe hunger (4-6) category.

The impact on food consumption expenditure is negative and significant in 2013-14 but positive and significant in 2011-12 (and for the difference in mean outcomes for the pooled sample). This may suggest an anomaly in the data, but could arise if price changes are very different in the two periods (expenditure could fall if it is possible to substitute cheaper foods and would rise if all prices increased). The estimated ATE of -0.427 in 2013-14 indicates an average decrease of approximately 35%[3] in food consumption expenditures, consistent with worsening dietary diversity and food insecurity. Several factors may be responsible for an increase in spending (even if insufficient to maintain dietary diversity), including increased demand and scarcity of food items due to supply chain disruptions, displacement and loss of resources prompting purchases of more expensive alternatives, emergency buying in the aftermath of disasters, inflation affecting overall food prices, and relocation-related costs incurred by households.

The estimated ATE for the impact and intensity of natural disasters on household income and farm revenue are negative and significant in both years (greater in 2011-12); on average, there is a reduction of about 40% in household real adult equivalent income and a third in real adult equivalent farm revenues. This is consistent with expectations as flooding — the most common disaster in the country — significantly affects agricultural production, farm revenues and, consequently, household income.

5.2.Results from propensity score matching (PSM)

As the results of the ESR model may be sensitive to underlying assumptions of the exclusion restriction, PSM estimates of ATT and ATE are used to check the robustness. Several matching methods were used, including single nearest neighbour matching (NNM, k=1), kernel-based matching (KBM), five nearest neighbour matches (k=5), and radius matching. The results for NNM and KBM are presented in Table 6 (details for k=5 and radius matching in Table A16). The results are generally consistent across matching algorithms.

The PSM ATE are qualitatively similar to estimates obtained from the ESR and 2SLS models although quantitatively smaller (closer to OLS). This difference arises because PSM

[3] The estimated treatment effect is usually interpreted as percentage difference. However, when the outcome variable is log-transformed, multiplying the ATE by 100 is an approximation, and it's near enough only for differences <0.05 (5%). The exact percent difference is given by $100(e^{ATE} - 1)$ where e is exponential e and ATE is the average treatment effect provided by the analysis of the log-transformed variable (Asfaw *et al.*, 2012).

corrects for selection bias but not endogeneity bias (which introduces a downward bias in the estimates of natural disasters, as discussed earlier).

Table 6: Treatment effects from the PSM model

Outcome variable	effect	Mean of outcome variables based on matched observations					
		Nearest neighbour matching (NNM)			Kernel based matching (KBM)		
		Affected	Unaffected	Difference	Affected	Unaffected	Difference
HFCS	ATE	41.479	43.033	-1.554***	42.971	41.490	-1.481***
	ATT	40.324	42.951	-2.627***	40.440	42.865	-2.424***
	ATU	41.787	43.055	-1.268***	41.766	42.999	-1.232***
HHS	ATE	0.539	0.482	0.057**	0.522	0.481	0.041*
	ATT	0.663	0.595	0.067**	0.633	0.582	0.052**
	ATU	0.511	0.457	0.055*	0.498	0.459	0.039
rCSI	ATE	2.324	2.209	0.116*	2.336	2.203	0.134*
	ATT	2.934	2.535	0.400***	2.721	2.563	0.158*
	ATU	2.191	2.137	0.054	2.254	2.125	0.128
Food expenditure	ATE	7.096	7.030	0.066***	7.089	7.014	0.064***
	ATT	7.033	6.981	0.052***	7.027	6.979	0.048***
	ATU	7.113	7.043	0.070***	7.088	7.036	0.068***
Share food	ATE	0.770	0.759	0.011**	0.769	0.761	0.009***
	ATT	0.774	0.763	0.011**	0.774	0.764	0.010***
	ATU	0.769	0.759	0.011***	0.768	0.760	0.008***
Income	ATE	10.175	10.269	-0.09***	10.170	10.266	-0.096***
	ATT	10.077	10.139	-0.06***	10.073	10.160	-0.087***
	ATU	10.201	10.303	-0.10***	10.196	10.294	-0.099***
Farm revenues	ATE	8.744	8.802	-0.058**	8.724	8.794	-0.070***
	ATT	8.527	8.587	-0.06***	8.550	8.622	-0.072***
	ATU	88.830	8.888	-0.06***	8.792	8.862	-0.070***

Notes: Variables and significance as for Table 3.

Although PSM is commonly used to reduce selection bias due to observed characteristics, validity depends on three assumptions: (1) sufficient overlap of propensity scores between affected and non-affected households before matching, (2) balancing in the covariates between affected and non-affected households after matching, and (3) conditional independence or unconfoundedness, stating that observable characteristics must be independent of potential outcomes, which implies that in the selection function there is unobserved or omitted variable that is correlated with both the propensity to be affected by flooding choice and welfare outcomes. Tests of assumptions (1) and (2) are reported in Figures A1 and A2 in the appendix and both are satisfied. Assumption (3) cannot be tested empirically so the ESR estimates are preferred.

5.3.Heterogeneity in the impact of natural disasters: Exposure to additional shocks

The impact of natural disasters on household food security may vary depending on exposure to additional shocks. Descriptive statistics in Table 2 show that households affected by natural disasters also reported higher exposure to other shocks, including conflict and price fluctuations and severe weather events. The impact may differ based on household location as rural areas are more susceptible. We created a dummy indicator =1 if the household reported experiencing any other shocks to assess potential heterogeneity in the overall sample and rural sample. Table 7 shows that differences are greater, comparing households exposed to disasters and other shocks (Shock=1) to those exposed to only disasters (Shock=0), for the HHS, rCSi and farm revenue indicators, particularly in rural areas. Specifically, households tend to adopt significantly higher coping strategies when exposed to other shocks. Exposure to multiple shocks may increase the perceived risk by households, prompting them to proactively adopt more coping strategies to safeguard their well-being. Previous exposure to shocks could lead households to adapt and learn from their experiences. They may develop a proactive approach, implementing coping strategies learned from past incidents to reduce vulnerability.

Table 7: Exposure to other shocks and impacts of natural disasters

Outcome	ATE (all sample)		ATE (rural sample)	
	Shock=0	Shock=1	Shock=0	Shock=1
HFCS	-8.826***	-8.798***	-8.265***	-8.260***
HHS	0.341***	0.399***	0.385***	0.461***
rCSI	1.615***	3.343***	1.783***	3.897***
Food expenditure	0.154***	0.177***	0.171***	0.196***
Income	-0.627***	-0.482***	-0.595***	-0.445***
Farm revenue	-0.355***	-0.443***	-0.368***	-0.451***

Notes: As for Table 6. Shock=0 for disasters only.

The impacts are higher on farm revenues when households are exposed to additional shocks. Extreme weather events, such as frosts or storms, can lead to crop failure or damage. This directly impacts farm productivity and results in lower yields and revenues. Similarly, exposure to violence and conflict often leads to the displacement of communities, forcing households to abandon their land and crops. Price shocks in the market can significantly affect the selling prices of agricultural products.

5.4.Robustness Checks

We conducted additional robustness tests to validate our main results derived from the ESR model. Initially, we re-estimated the ESR model using only the leave-out mean instruments. The resulting treatment effects (Table A13 in Appendix A2), both quantitatively and qualitatively, align closely with those presented in Table 4. This outcome is expected, as the primary advantage of incorporating Lewbel (2012) instruments lies in enhancing the efficiency of external instruments rather than significantly altering the treatment effect estimates.

In addition, we employed community-fixed effect regressions to assess the impact of disasters at the community level, utilizing data collected from over 2,000 communities (2,032 in 2011-12 and 2,021 in 2013-14) – summary statistics in Appendix Table B1 and B2. Commune fixed-effect regressions help mitigate the influence of unobserved time-invariant commune-level variables (Arouri *et al*., 2015). Natural disasters often exhibit significant direct and indirect effects, regardless of whether a household in a specific community is directly affected. Community fixed effects aid in analysing impacts at the community level. The type, magnitude, and subsequent impact of natural disasters can vary based on specific locations. Results from community-fixed effect regressions, reported in Table B3, demonstrate consistency and similarity with our primary household-level results from the OLS and ESR models, as presented in Table 5. We also separately included dummies for flooding and other natural disasters, such as earthquakes, landslides, and avalanches, to examine their impacts individually (Table B3, panel C), and our main results remain unchanged.

Following Pleninger (2022), we also conducted a difference-in-differences (DiD) analysis using community-level data. The DiD approach compares changes in outcomes over time between a treatment group (those exposed to natural disasters) and a control group (those not exposed to natural disasters). This method helps identify the causal impact of the treatment by controlling for time-invariant unobserved heterogeneity. The results presented in Table B4 are consistent with our main findings from the ESR and community-fixed effect regression. However, we acknowledge that these results may not meet the parallel trends assumption, that the trends in the outcome variable for the treatment and control groups would have been the same in the absence of the treatment, as we don't have prior data to test for parallel trends.

6. Conclusion and Implications

Afghanistan is highly exposed and vulnerable to natural disasters, with effects amplified by poverty, food insecurity, inequality and conflict. Recurrent natural disasters lead to the loss of lives and livelihoods, significantly affecting development. This paper provides evidence of the impact of natural disasters on household food security and welfare indicators, drawing on data from two national household surveys. Our analysis confirms that natural disasters have severe consequences across all indicators of household welfare. Higher precipitation raises the probability of households being affected, likely due to rainfall-induced flash flooding, landslides, and avalanches. Similarly, increased district-level temperatures elevate the likelihood of facing drought and other shocks as climate change leads to more frequent and intense precipitation. Exposure to shocks, including weather, price, and violence, emerges as a key factor influencing disaster risk. Rural, especially mountanous, areas are more susceptible.

We employ a variety of techniques and specifications that control for a wide range of household, climatic, and community characteristics and consider the potential endogeneity of natural shock events. In general, the estimated results are robust across all estimation strategies, indicating that natural disasters have significant effects on household food security and welfare. Compared to OLS and PSM, the 2SLS and ESR models generally showed greater effects of natural disasters on household food security and welfare outcomes. This underlines the need to use diverse empirical approaches to address selection and endogeneity bias due to unobserved confounders. Despite the different magnitude of the effects from various models, the general pattern derived from the results was consistent across methods.

Households affected by natural disasters experience a decrease in food security and resort to more desperate coping strategies. The estimated treatment effects on the Household Hunger Scale (HHS) and Reduced Coping Strategies Index (rCSI) are both positive and significant, indicating a notable increase in hunger levels and coping stress; two-thirds of households initially classified as experiencing little or no hunger could transition to the moderate hunger category. Furthermore, the estimated treatment effect of the rCSI at 2.7

suggests significant changes in household coping strategies, pushing many households from no or low coping stress to higher levels of food insecurity. The estimated treatment effect for the Household Food Consumption Score (HFCS) indicates a decrease of approximately 9 points on the HFCS scale, equivalent to consuming 3 fewer main staples and 1 less fruit or vegetable item per week compared to unaffected households. This decrease in food consumption is reflected in the estimated Average Treatment Effect (ATE) of -0.427 in 2013-14, signifying an average decrease of approximately 35% in food consumption expenditures, with lower dietary diversity and increased food insecurity. The negative and significant impact on household income and farm revenue, with reductions of about 40% and a third respectively, underscores the economic ramifications of climate shocks on agricultural production and household incomes.

The impacts of disasters are greater for households that experienced conflict and other shocks, especially in rural areas, forcing households to adopt extreme coping mechanisms due to food shortages and lack of access to food. This correlation suggests a potential link between conflicts, other shocks, and natural disasters, amplifying the impact of disasters and posing challenges to post-disaster recovery efforts.

In light of Afghanistan's vulnerability to the climate crisis and heightened concerns about food security, particularly following recent political changes, this study contributes to our understanding of the impact of natural disasters on various household indicators. The empirical evidence can enhance disaster risk reduction by informing the planning and development of post-disaster strategies for affected populations. This understanding of post-disaster impacts and losses is crucial for assessing risk perception and coping capacities, aiding both populations and policymakers to mitigate the potential for humanitarian crises.

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Appendix A Data and Additional Results

Appendix A1 Data Construction and Statistics

A1(i) Adult Equivalent Scale

The composition of households varies by the number and gender of adults and children who have different nutritional needs to account for in a consumption-based measure of welfare. Adjusting total household expenditure by adult equivalent scales (AES) is the standard practice and we apply the Organization for Economic Cooperation and Development (OECD) modified equivalence scale, initially proposed by Hagenaars *et al*. (1994), to apply different weights to adults and children (not differentiated by gender). The OECD modified AES assigns a value of 1 to the household head, of 0.5 to each additional adult member (allowing for economies of scale) and of 0.3 to each child. Alternative measures such as per capita consumption, square root scale, and the original OECD scale involve alternative assumptions for the weights assigned to the needs of different individuals (Regier *et al*., 2019). Table A1 illustrates these scales for given household sizes.

Table A1: Adult Equivalence Scales (AES), examples for different household sizes

Household size	Equivalence scale			
	Original OECD	OECD modified	Per capita consumption	unadjusted HH expenditures
1 adult	1	1	1	1
2 adults	1.7	1.5	2	1
2 adults, 1 child	2.2	1.8	3	1
2 adults, 2 children	2.7	2.1	4	1
2 adults, 3 children	3.2	2.4	5	1
Elasticity	0.73	0.53	1	0

Notes: Using household size as the determinant, equivalence scales can be expressed through an 'equivalence elasticity', i.e., the power by which economic needs change with household size. This Elasticity can range from 0 (when unadjusted household expenditures is taken as the consumption measure) to 1 (when per capita household consumption is used). The smaller the value for this elasticity, the higher the economies of scale in consumption.

A1 (ii) Constructing the Household Food Consumption Score (HFCS)

The HFCS is a composite score based on dietary diversity, food frequency, and relative nutritional importance of different food groups (World Food Program, 2007). As it includes a quantitative dimension of food access (number of foods) as well as diversity, the FCS is often used as a food security indicator (Wiesmann *et al*., 2009), although we prefer to incorporate food expenditure as an element of security as FCS does not capture the amount consumed. The score is calculated using the frequency of consumption of any item in each of eight different food groups (listed in Table A2, items in the ninth group are not counted) over the past week. If one or more items in a food group is consumed on one day in the last week the group is scored as 1 for that day, this is summed over each of the seven days an item is consumed and then the group weight is applied (to allow for differences in nutritional value). All groups are summed to get FCS as specified in equation A1. An important limitation is that the measure only considers the count of different food groups consumed per day but not the quantity consumed.

$$HFCS = \sum_{i=1}^{9} x_i p_i \tag{A1}$$

where x_i represents the frequency of consumption for each food group i and p_i is the weight of food group i.

Table A2: Food groups and food group weights

	Food group	Food items	Weight
1	Main staples	Maize, maize porridge, rice, sorghum, millet pasta, bread, other cereals	2
		Cassava, potatoes and sweet potatoes, other tubers, plantains	
2	Pulses	Beans. Peas, groundnuts, and cashew nuts	3
3	Vegetables	Vegetables, leaves	1
4	Fruits	Fruit	1
5	Meat and fish	Beef, goat, poultry, pork, eggs and fish	4
6	Milk	Milk yogurt and other diary	4
7	Sugar	Sugar and sugar products, honey	0.5
8	Oil	Oils, fats and butter	0.5
9	Condiments	spices, tea, coffee, salt, fish power, small amounts of milk for tea	0

Source: World Food Program (2007).

Table A3: HFCS thresholds and score distribution among households

HFCS cut-offs	By wave		By natural disaster		Pooled sample
	2011/12	2013/14	Non-affected	affected	
Poor (0-21)	903	2146	1970	1079	3049
	4.47	*11.30*	*6.37*	*13.07*	*7.78*
Borderline (21-35)	5072	6436	9040	2468	11508
	25.11	*33.90*	*29.23*	*29.90*	*29.37*
Acceptable (>35)	14222	10406	19920	4708	24628
	70.42	*54.80*	*64.40*	*57.03*	*62.85*
Total	20197	18988	30930	8255	39185

Note: First row under each category (poor, borderline and acceptable*)* has frequencies and the second row has *column (survey year) percentages*.

The maximum score for each food group before weighting is 7 (if item(s) are consumed each day during the week) and once the weights are applied the possible maximum is 112. The total score for the week is compared with pre-established thresholds to classify the food diversity status of the household: (1) poor food consumption, 0 to 21; (2) borderline food consumption, 21.5 to 35; and (3) acceptable food consumption >35. The distribution of households in our sample based on these thresholds is summarized in Table A3 and shows the significant deterioration in food diversity – almost three-quarters of households had acceptable diversity in 2011/12 declining to under 60% in 2013/14, while the percentage with poor diversity more than doubled to almost 12% by 2016/14. As shown below (Table A7), this is consistent with the marked increase in poverty after 2013.

A1 (iii) Reduced Coping Strategy Index (rCSI)

When livelihoods are negatively affected by a shock/crisis, households may adopt various mechanisms (strategies) to cope with reduced or declining access to food. The Coping Strategy Index (CSI) is commonly used as a proxy indicator of household food insecurity (Jones *et al*., 2013). The rCSI is based on a list of behaviours (pre-selected coping strategies) combining the frequency of each strategy (how many times adopted and the severity (how critical) for households reporting food consumption problems, with higher values indicating worse food security. There are two types: Full CSI (context-specific constructed using location-specific behaviours and/or if location or group-specific severity scores) and Reduced CSI, to compare food security across different contexts – a sub-set of the full CSI calculated using a specific set of behaviours with fixed severity weightings for each behaviour. Thhe rCSI uses a standard set of five individual coping behaviours that can be employed by any household, anywhere.

The rCSI is an estimate of the cumulative frequency of five potential food reduction strategies used over 7 days within each household surveyed. The frequency of each behaviour is weighted by its severity, where x_i is the frequency of behavior for the i^{th} household, and p_i is is the respective weight of the behavior as shown in Table A4:

$$rCSI = \sum_{i=1}^{5} x_i p_i \tag{A2}$$

Table A4: Coping strategies and weighted scores for rCSI

Coping Strategies During the **last 7 days**, on how many days, if any, did your household have to employ one of the following strategies (to cope with a lack of food or money to buy it)?)	[1] Frequency (days)	[2] Weight	Weighted Score ([1]x[2])
Rely on less preferred and less expensive foods	1-7	1	
Borrow food or rely on help from friends or relatives	1-7	2	
Limit portion size at mealtime	1-7	1	
Restrict consumption by adults in order for small children to eat	1-7	3	
Reduce number of meals eaten in a day	1-7	1	
Total household score			Max score=56

The total rCSI score is the basis to determine and classify the level of coping into four categories: No or low coping (rCSI= 0-3), Mildly food insecure (4-8), Moderately food insecure (rCSI = 9-18, high coping (rCSI >18). A high score is indicative of extensive use of negative coping strategies and hence increased food insecurity. The maximum score for the rCSI is 56 corresponding to server food insecurity, which would happen if a household used all five strategies every day for the last 7 days).

Table A5: Distribution of rCSI scores in the sample

Classification	Natural disaster		
	Non-affected	Affected	All
No or low coping (rCSI=0-3)	12408	2547	14955
	79.69	*74.67*	*78.79*
Mildly food insecure (rCSI=4-8)	1669	425	2094
	10.72	*12.46*	*11.03*
Moderately food insecure (rCSI=8-18)	1290	307	1597
	8.29	*9.00*	*8.41*
High coping (rCSI= >18	203	132	335
	1.30	*3.87*	*1.76*
Total	15,570	3,411	18,981

Note: The rCSI is based the survey round 2013/14 (data not collected in 2011/12). First row has *frequencies,* and second row has *column percentages.*

A1 (iv) Household Hunger Scale (HHS)

The Household Hunger Scale (HHS) is a proxy for food access. a household food deprivation scale based on the idea that the experience of food deprivation causes predictable reactions that can be captured by a survey and summarized in a scale. It focuses on the food quantity dimension of food access and does not measure dietary quality. HHS is often used only in areas with very high levels of food insecurity.

The HHS was derived from the Household Food Insecurity Access (HFIAS) as a culturally invariant subset of questions. It includes three specific questions that tend to represent the most severe manifestations of restricted access to food and is included in the acute food insecurity reference table for household group classification of the Integrated Food Security Phase Classification (IPC), a tool that aggregates various kinds of data into a single food insecurity classification ''phase'' covering various degrees of severity, and used to compare the severity of food insecurity across dissimilar contexts (Maxwell *et al*., 2014). The HHS is shown to have the highest potential to be internally, externally and cross-culturally valid among the various scales tested, including the full 9-item HFIAS and variations of it (Jones *et al*., 2013). The HHS is built around 3 questions about perceptions of a household on varying degrees of hunger by the number of times a household has experienced hunger within the past 30 days prior to the survey (Table A6).

Table A6: HHS questionnaire and frequency scores

Question	Frequency-of-occurrence	Frequency score
In the past 4 weeks, how often was there no food to eat of any kind in your household because of lack of resources to get food?	1 = Rarely (1-2 times) 2 = Sometimes (3-10 times) 3 = Often (more than 10 times)	0, 1, or 2
In the past 4 weeks, how often did you or any household member go to sleep at night hungry because there was not enough food?		0, 1, or 2
In the past 4 weeks, how often did you or any household member go a whole day and night without eating anything at all because there was not enough food?		0, 1, or 2
	Total score	Min=0, max=6

Notes: the frequency score 0 indicates that the response to all three question is "No" meaning that there was never a situation of no food of any kind in the house to eat because of lack of resources. Frequency scores 1 and 2 indicate that the household chose to respond, "rarely or sometime" and "often", respectively.

Table A7: Distribution of the HHS score in the sample

	Natural Disaster		
HHS hunger category	Non-affected	Affected	All
Little or no hunger (0-1)	13906	2885	16791
	89.35	*84.58*	*88.49*
Moderate hunger (3-4)	1517	438	1955
	9.75	*12.84*	*10.30*
Severe hunger (4-6)	140	88	228
	0.90	*2.58*	*1.20*
Total	15563	3411	18974

Note: As for Table A5.

The HHS is constructed directly from the household responses to each individual question. The original responses to each frequency-of-occurrence question are recoded from three frequency categories (rarely, sometimes, often) into two frequency categories (rarely or sometimes and often). For each of the new variables created a frequency response of rarely (originally coded as 1) is coded as 1; a frequency response of sometimes (originally coded as 2) is coded as 1; and a frequency response of often (originally coded as 3) is coded as 2. A code of 0 is for households that replied No to each question. The revised values for each question are then summed for each household to calculate the HHS score. The total HHS ranges from 0 to 6, with 6 showing the highest degree of hunger. To classify the level of hunger, the HHS score is classified to categorize households into three hunger groups – little or no hunger (1), Moderate hunger (2-3), and severe hunger (4-6). The HHS shows the lowest prevalence of food insecurity compared to the FCS and rCSI as it captures the most extreme consequences of food insecurity.

A1(v) Measuring Poverty in Afghanistan

In Afghanistan the welfare measure used for poverty is based on a household consumption aggregate using detailed food and non-food consumption data from household surveys, estimating the poverty line and applying the poverty line to the consumption aggregate value to identify the poor as those below the poverty line. The poverty line is estimated following the Cost of Basic Needs (CBN) approach (ALCS Survey Report, 2013-14).[4]

Table A8: Poverty Headcount and Poverty Lines – 2011/12 to 2016

Year	Headcount Poverty (%)	Poverty lines		
		Food	Non-food	Overall
2011-12	36.5	724	1,034	1,758
2013-14	39.1	724	1,034	1,758
2016-17	54.5	868	1,188	2,056

Notes: Poverty lines are in Afghani per person per month. The Poverty line was not changed between 2011-12 and 2013-14. There were no food consumption and price modules in the survey questionnaire for 2013-14 so the poverty head count ratio is based on imputed per capita consumption for each household relative to the poverty line of the base year 2011-12.

Source: NRVA/ALCS Survey Reports (2011-12, 2013-14, and 2016-17) and World Bank (https://documents1.worldbank.org/curated/en/451111535402851523/pdf/AUS0000426-REVISED-ALCS-Poverty-Chapter-upload-v2.pdf)

Table A8 shows that the poverty headcount increased by half between 2011 and 2017 to almost 55%. The deterioration is even worse taking 2007/08 as the starting year when national headcount poverty was 34%; rural (urban) poverty increased from 36% (26%) in 2007/08 to 59% (42%) in 2016/17.[5] Although poverty is not calculated in our analysis, it is clear that the deterioration in food diversity between 2011 and 2014 is consistent with increasing poverty. Similarly, it is likely that food security measured by rCSI and HHS in 2013/14 had deteriorated compared to earlier years (not calculated in 2011/12 due to lack of data). Available data suggests that poverty, hunger and food insecurity have all increased significantly since the Taliban takeover in 2021 but not survey are available permitting similar analysis for the most recent years.

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[4] Detail on the methodology can be found in https://documents.worldbank.org/en/publication/documents-reports/documentdetail/665241533556485812/poverty-measurement-methodology-using-alcs-2016-17 .

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A1(iv) Summary Statistics

Table A9: Descriptive Statistics by Natural Disasters

	Affected	Non-affected		Pooled sample	
Variables	mean	mean	difference	Mean	sd
Outcome variables					
Food consumption score (HFCS)	40.36	43.08	-2.73***	42.50	15.84
Real cons. expenditures (AFN)	1722.39	1838.81	116.42***	1814.21	1151.15
Real food cons. expenditures (AFN)	1298.22	1358.30	-60.09***	1345.63	809.85
Real income (AFN)	32336.15	38706.71	-6370.57***	37363.32	31370.97
Real farm revenue (AFN)	9146.26	14021.09	-4874.83***	12641.44	19828.36
HH hunger scale (HHS)	.663	.457	.207***	.494	.881
Reduced coping strategy index (RCSI)	2.93	2.14	.797***	2.28	4.78
Share food cons. expenditures (%)	77.43	75.85	1.576***	76.182	16.98
Explanatory variables					
Natural disaster (0/1, 1=yes)				.211	.408
Violence (0/1, 1=yes)	.215	.173	.043***	.184	.387
Opium cultivation (*Jeribs*)	39.935	42.538	-2.603	42.439	145.493
HH size (N)	7.717	7.579	.139***	7.613	3.368
Head age (years)	43.278	41.536	1.743***	41.89	13.705
Head employment (0/1, 1=yes)	.779	.812	-.033***	.805	.397
Head literacy (0/1, 1=read & write)	.336	.366	-.030***	.353	.478
Head education (years)	2.392	3.023	-.631***	2.841	4.828
Dependency ratio	1.297	1.262	-.036**	1.273	.896
Number of livestock (N)	9.235	7.795	1.44***	8.099	20.192
Distance to road (km)	2.27	2.606	-.336***	2.571	7.544
Weather shock (0/1, 1=yes)	.57	.162	.408***	.248	.432
Price shock (0/1, 1=yes)	.647	.502	.145***	.538	.499
Conflict incident (N)	26.286	48.799	-22.51***	43.748	59.465
Precipitation pooled	559.292	472.409	86.883***	-.551	23.656
Temperature pooled	8.641	11.688	-3.047***	-.763	1.477
Landscape (0/1, 1=hills)	.057	.02	.036***	.032	.175
Landscape (0/1, 1=valleys & hills)	.465	.232	.234***	.281	.449
Landscape (0/1, 1=valleys)	.186	.17	.015**	.174	.379
Landscape (0/1, 1=plain)	.292	.577	.286***	.514	.5
Resident code (0/1, 1=urban)	.057	.178	-.121**	.83	.375
Resident code (0/1, 1=rural)	.943	.822	.121***	.02	.139
Wave	1.413	1.504	-.090***	1.48	.5
Instrumental variable					
IV leave-out mean	.136	.019	.117***	.044	.119
Observations	8255	31930		39,534	

Notes: Household expenditures and revenues in constant Afghani per month applying AES. Difference is between means for affected and unaffected households, *, **, and *** denote significance level at 10%, 5% and 1%, respectively.

Table A10: Descriptive Statistics by Survey Year

	2011-12	2013-14	Pooled sample	
Variables	mean	mean	Mean	sd
Outcome variables				
HH food consumption score (HFCS)	45.58	39.232	42.507	15.846
Real AE cons. expenditures (AFN)	1794.403	1835.269	1814.207	1151.145
Real AE food cons. expenditures (AFN)	1264.891	1431.56	1345.628	809.854
Real AE income (AFN)	39286.378	35324.062	37363.316	31370.971
Real AE farm revenue (AFN)	11832.403	13640.134	12641.438	19828.359
HH hunger scale (HHS)	.	.494	.494	.88
Reduced coping strategy index (RCSI)	.	2.28	2.28	4.776
Share food cons. expenditures (%)	72.33	80.284	76.182	16.978
Explanatory variables				
Natural disaster (0/1, 1=yes)	.240	.18	.211	.408
Violence (0/1, 1=yes)	.205	.157	.181	.385
Opium cultivation (*Jeribs*)	42.08	41.893	41.99	144.151
HH size (n)	7.655	7.558	7.608	3.363
Head age (years)	41.359	42.481	41.903	13.7
Head employment (0/1, 1=yes)	.833	.775	.805	.396
Head literacy (0/1, 1=can read & write)	.348	.372	.36	.48
Head education (years)	2.917	2.861	2.89	4.855
Dependency ratio	1.285	1.252	1.269	.896
No of livestock (N)	9.202	6.925	8.099	20.192
Distance to road (km)	2.918	2.127	2.535	7.407
Weather shock (0/1, 1=yes)	.281	.213	.248	.432
Price shock (0/1, 1=yes)	.568	.496	.533	.499
Conflict incident (N)	40.958	47.353	44.057	60.052
Precipitation pooled (annual sum in mm)	494.384	486.807	490.713	275.501
Temperature pooled (mean in celcius)	10.906	11.195	11.046	6.708
Landscape (0/1, 1=hills)	.027	.03	.028	.166
Landscape (0/1, 1=valleys & hills)	.302	.259	.281	.45
Landscape (0/1, 1=valleys)	.18	.166	.174	.379
Landscape (0/1, 1=plain)	.491	.545	.517	.5
Resident code (0/1, 1=urban)	.139	.167	.153	.36
Resident code (0/1, 1=rural)	.861	.833	.847	.36
Instrumental variable				
IV leave-out mean	.058	.029	.044	.120
Observations	8340	39.15	39,534	

Notes: Household expenditures in constant Afghani per month applying AES.

Table A11: OLS estimates

Variables	(1) HFCS	(2) HHS	(3) RCSI	(5) Food expenditure	(6) Share food	(7) Income	(8) Farm revenue
Natural dis.	-2.092***	.044**	.355***	.051***	.009***	-.081***	-.057***
(0/1, 1=yes)	(.206)	(.018)	(.098)	(.008)	(.002)	(.010)	(.016)
Violence	1.446***	.037**	.373***	-.037***	-.029***	-.062***	.056***
(0/1, 1=yes)	(.199)	(.018)	(.099)	(.008)	(.002)	(.01)	(.017)
Opium cult	-.001**	.001***	.001***	.001***	.001***	.001***	0.001
(jeribs)	(.001)	(.000)	(.000)	(.000)	(.000)	(.000)	(.01)
HH size (n)	.576***	-.01***	.04***	-.017***	-.003***	-.022***	-.073***
	(.026)	(.002)	(.011)	(.001)	(.000)	(.001)	(.002)
Head age	.039***	-.001***	-.007**	.001***	.001***	.001***	-.003***
(yrs)	(.006)	(.001)	(.003)	(.000)	(.000)	(.000)	(.001)
Head emp	2.002***	-.128***	-.425***	.10***	-.002	.142***	.053***
(0/1, 1=yes)	(.204)	(.016)	(.088)	(.007)	(.002)	(.009)	(.017)
Head literacy	2.151***	-.138***	-.38***	.077***	-.018***	.032***	-.054***
(0/1, 1=yes)	(.251)	(.019)	(.107)	(.009)	(.003)	(.011)	(.021)
Head edu	.19***	-.003	-.021*	.013***	-.001***	.025***	-.003
(yrs)	(.026)	(.002)	(.011)	(.001)	(.000)	(.001)	(.002)
Dep ratio	-.97***	.036***	.231***	-.022***	.012***	-.106***	.002
	(.085)	(.007)	(.04)	(.003)	(.001)	(.004)	(.008)
Dist. to road	.057***	.001	-.005	-.001***	-.001***	.001***	.004***
(km)	(.011)	(.001)	(.004)	(.000)	(.000)	(.000)	(.001)
Landscape	1.202**	.040	-.664***	-.014	.013**	-.233***	-.012
(1=hills)	(.491)	(.038)	(.213)	(.017)	(.005)	(.022)	(.049)
Landscape	2.038***	-.198***	-1.01***	-.137***	-.010*	-.273***	.015
(1=valleys)	(.503)	(.04)	(.22)	(.018)	(.005)	(.023)	(.05)
Landscape	4.633***	-.083**	-1.22***	.081***	-.002	-.08***	.222***
(1=plain)	(.487)	(.039)	(.213)	(.017)	(.005)	(.022)	(.05)
Price shock	-1.703***	.09***	.236***	-.03***	.017***	-.064***	-.098***
(1=yes)	(.156)	(.013)	(.071)	(.006)	(.002)	(.007)	(.014)
Weath. shock	-.065	.249***	.339***	-.014**	-.021***	-.112***	.017
(0/1, 1=yes)	(.185)	(.017)	(.092)	(.007)	(.002)	(.009)	(.015)
Prcp pooled	.010***	.001***	.001***	.001***	.001***	.001***	.001***
	(.000)	(.001)	(.000)	(.001)	(.001)	(.001)	(.000)
Temp pooled	.198***	.008***	.011	-.004***	-.001***	-.008***	.007***
	(.015)	(.001)	(.007)	(.001)	(0)	(.001)	(.001)
Incidents (n)	-.001	.001**	-.002***	.001***	.001***	.001***	.002***
	(.001)	(.000)	(.001)	(.000)	(.001)	(.000)	(.000)
Livestock (n)	.089***	-.002***	-.012***	.002***	.001	.004***	.003***
	(.006)	(.000)	(.002)	(.000)	(.000)	(.000)	(.000)
Rural	-1.855***	.040**	-.444***	-.265***	.016***	-.22***	.279***
(0/1, 1=yes)	(.253)	(.020)	(.111)	(.009)	(.003)	(.011)	(.042)
Wave	-6.378***	-	-	.042***	.082***	-.118***	-.032**
(2013-14)	(.153)			(.006)	(.002)	(.007)	(.013)
Input exp	-	-	-	-	-	-	.001***
							(.000)
Total land	-	-	-	-	-	-	.005***
(jeribs)							(.000)
No. crops (n)	-	-	-	-	-	-	.464***
							(.009)
_cons	29.793***	.452***	3.228***	7.451***	.72***	10.951***	8.111***
	(.699)	(.055)	(.302)	(.025)	(.007)	(.032)	(.074)
Observations	39173	18974	18981	38994	39156	38876	19813
R-squared	.139	.062	.024	.136	.112	.156	.39

Notes: As for Table 3.

Table A12: 2SLS estimates

Variables	(1) HFCS	(2) HHS	(3) RCSI	(5) Food expenditure	(6) Share food	(7) Income	(8) Farm revenue
Natural disaster	-6.821***	.375***	3.111***	.393***	.078***	-.514***	-.435***
(0/1, 1=yes)	(.635)	(.104)	(.606)	(.025)	(.007)	(.034)	(.051)
Violence	1.395***	.037**	.367***	-.073***	-.028***	-.066***	.048***
(0/1, 1=yes)	(.200)	(.018)	(.11)	(.009)	(.002)	(.01)	(.016)
Opium cult	-.001***	.001***	.001***	.001***	.001**	.001***	001
(*jeribs*)	(.001)	(.000)	(.000)	(.000)	(.005)	(.001)	(.050)
HH size (n)	.58***	-.011***	.038***	-.022***	-.003***	-.022***	-.072***
	(.027)	(.002)	(.012)	(.001)	(0)	(.001)	(.002)
Head age (yrs)	.046***	-.002***	-.011***	.001***	.001***	.002***	-.002***
	(.006)	(.001)	(.003)	(.000)	(.003)	(.000)	(.001)
Head employed	2.021***	-.131***	-.457***	.088***	-.002	.143***	.052***
(0/1, 1=yes)	(.205)	(.018)	(.097)	(.008)	(.002)	(.010)	(.017)
Head literacy	2.247***	-.131***	-.325***	.038***	-.02***	.040***	-.037*
(0/1, 1=yes)	(.251)	(.018)	(.099)	(.01)	(.003)	(.012)	(.021)
Head edu (yrs)	.181***	-.003*	-.024***	.012***	-.001***	.024***	-.004*
	(.026)	(.002)	(.009)	(.001)	(.000)	(.001)	(.002)
Dependency ratio	-.958***	.033***	.212***	-.009**	.011***	-.105***	.005
	(.086)	(.008)	(.045)	(.004)	(.001)	(.004)	(.008)
Dist. to road (km)	.047***	.001	-.004	-.002***	-.001***	.001	.003***
	(.011)	(.001)	(.004)	(.000)	(.000)	(.030)	(.001)
Landscape	.94*	.063	-.475	.02	.017***	-.256***	-.07
(1=hills & valleys)	(.493)	(.045)	(.29)	(.019)	(.005)	(.022)	(.044)
Landscape	1.324***	-.146***	-.581*	-.094***	.001	-.338***	-.084*
(0/1, 1=valleys)	(.512)	(.047)	(.302)	(.021)	(.005)	(.024)	(.047)
Landscape	3.778***	-.017	-.667**	.137***	.01*	-.158***	.116**
(0/1, 1=plain)	(.499)	(.048)	(.304)	(.02)	(.005)	(.023)	(.048)
Price shock	-1.463***	.074***	.099	-.017***	.014***	-.042***	-.068***
(0/1, 1=yes)	(.16)	(.014)	(.074)	(.006)	(.002)	(.007)	(.015)
Weather shock	1.417***	.16***	-.402**	-.153***	-.042***	.024*	.139***
(0/1, 1=yes)	(.271)	(.033)	(.185)	(.011)	(.003)	(.014)	(.022)
Precipitation	.01***	.001***	.001	.001***	.001***	.001***	.001***
	(.000)	((.000)	(.006)	(.000)	(.000)	(.000)	(.000)
Temperature	.179***	.008***	.005	-.002***	-.001***	-.01***	.005***
	(.016)	(.001)	(.008)	(.001)	(0)	(.001)	(.001)
Incidents (n)	-.003**	001	001	.001***	.001***	.001***	.001***
	(.001)	(.004)	(.001)	(.000)	(.000)	(.000)	(.000)
Livestock (n)	.086***	-.002***	-.011***	.002***	0**	.003***	.003***
	(.005)	(.000)	(.003)	(.000)	(.000)	(.000)	(.000)
Rural	-1.544***	.031	-.515***	-.263***	.011***	-.191***	.292***
(0/1, 1=yes)	(.257)	(.021)	(.115)	(.01)	(.003)	(.011)	(.053)
Wave	-6.514***			.168***	.084***	-.13***	-.051***
(2013-14)	(.155)			(.006)	(.002)	(.007)	(.014)
_cons	30.59***	.427***	3.016***	7.028***	.709***	11.023***	8.246***
	(.713)	(.059)	(.374)	(.028)	(.008)	(.033)	(.082)
Observations	39173	18974	18981	38873	39156	38876	19813
R-squared	.128	.045	-.017	.089	.090	.113	.373
idstat	2336.29	329.84	329.76	2363.66	2376.09	2323.91	1432.08
J (p-values)	.30	.84	.406	.817	.287	.194	.075
Weak IV test	1723.75	200.07	200.12	1760.89	1770.83	1719.16	1005.72

Notes: Estimated using the *ivreg2* command in Stata. Input expenditure, number of crops and land area all positive and highly significant for Farm revenue (omitted from tables). The under-identification idstat test (Kleibergen-Paap rk LM statistic) rejects the null hypothesis that the models are weakly identified in the pooled sample (unreported p-values <0.005). The over-identfication (Hensen *J*) test (p-values) shows that over-identification restriction is satisfied (cannot be rejected at 5% level). The Kleibergen-Paap Wald rk F statistic for the Weak IV test confirms that instruments are not weak in pooled sample.

Table A13 ESR results (LoM only estimation)

Outcome variable	Treatment effect	Mean outcomes		
		Affected	Non-affected	Difference
HFCS	ATT	40.331	45.653	-5.321***
	ATU	32.486	43.053	-10.567***
	ATE	34.141	43.602	-9.46***
Food consumption expenditure (AFN)	ATT	7.033	6.859	.175***
	ATU	7.188	7.043	.145***
	ATE	7.155	7.004	.15***
Share of food (%)	ATT	.778	0.725	.053***
	ATU	1.097	0.759	.339***
	ATE	1.03	0.752	.279***
Income (AFN)	ATT	10.077	10.428	-.351***
	ATU	9.679	10.304	-.625***
	ATE	9.763	10.329	-.567***
Farm revenue (AFN)	ATT	8.528	9.437	-.908***
	ATU	8.671	8.891	-.220***
	ATE	8.626	9.043	-.417***

Notes: Variables and significance as for Table 5 except leave-out mean (LoM) the only instrument. Estimated by full information maximum likelihood (FIML) using the *movestay* command in Stata, ensuring consistent standard errors while simultaneously fitting binary and continuous parts.

Table A14 ESR results for HFCS, food expenditures, income, and farm revenues

	(1)	(2)		(3)		(4)		(5)	
	Selection	HFCS		food expenditure		income		farm revenue	
Variables	Natural disaster	Affected	Non-affected	Affected	Non-affected	Affected	Non-affected	Affected	Non-affected
Violence	0.051**	1.389***	0.799*	-0.069***	-0.078***	-0.095***	0.033	0.036*	0.080***
(0/1, 1=yes)	(0.02)	(0.22)	(0.43)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)
Opium clt.	-0.001***	-0.001*	-0.004***	-0.001***	0.001***	-0.001***	0.001***	-0.001	-0.001
(Jerib)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HH size (n)	0.003	0.613***	0.427***	-0.020***	-0.025***	-0.021***	-0.023***	-0.074***	-0.069***
	(0.00)	(0.03)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Head age (yrs)	0.005***	0.043***	0.067***	0.001***	0.001***	0.001***	0.003***	-0.003***	0.001
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Head emp.	0.092***	2.402***	0.764*	0.095***	0.062***	0.127***	0.176***	0.019	0.118***
(0/1, 1=yes)	(0.02)	(0.23)	(0.41)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)
Head literacy	0.023	2.911***	-0.238	0.032***	0.052***	0.047***	-0.007	-0.014	-0.055
(0/1, 1=yes)	(0.03)	(0.29)	(0.50)	(0.01)	(0.02)	(0.01)	(0.03)	(0.03)	(0.03)
Head edu. (yrs)	0.001	0.127***	0.367***	0.012***	0.010***	0.022***	0.031***	-0.008***	0.007**
	(0.00)	(0.03)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Dep. ratio	0.014	-1.024***	-0.715***	-0.005	-0.013*	-0.104***	-0.100***	0.011	-0.002
	(0.01)	(0.10)	(0.18)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Dist. to road	-0.004***	0.060***	-0.053*	-0.002***	-0.005***	0.001**	-0.003**	0.003***	0.005**
(km)	(0.00)	(0.01)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Landscape	-0.339***	-0.159	1.756**	0.000	0.001	-0.186***	-0.333***	-0.314***	0.127**
(0/1, 1=valleys & hills)	(0.05)	(0.61)	(0.81)	(0.03)	(0.03)	(0.03)	(0.03)	(0.07)	(0.05)
Landscape	-0.570***	0.010	2.662***	-0.154***	-0.063*	-0.221***	-0.463***	-0.327***	0.022
(0/1, 1= valleys)	(0.05)	(0.62)	(0.88)	(0.03)	(0.03)	(0.03)	(0.04)	(0.08)	(0.06)
Landscape	-0.707***	2.965***	3.234***	0.095***	0.065**	-0.039	-0.318***	-0.140*	0.241***
(0/1, 1=plain)	(0.05)	(0.60)	(0.90)	(0.02)	(0.03)	(0.03)	(0.04)	(0.08)	(0.06)
Price shock	0.152***	-1.093***	-2.566***	-0.019***	0.031**	-0.082***	0.059***	-0.050***	-0.061**
(0/1, 1=yes)	(0.02)	(0.17)	(0.37)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
Weather shock	0.773***	1.238***	1.879***	-0.069***	-0.143***	-0.007	-0.048*	0.268***	0.056*
(0/1, 1=yes)	(0.02)	(0.28)	(0.50)	(0.01)	(0.02)	(0.01)	(0.03)	(0.03)	(0.03)
Prcp. pooled	0.001***	0.007***	0.018***	0.001***	0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Temp. pooled	0.005***	0.080***	0.352***	-0.002***	-0.002	-0.009***	-0.011***	0.006***	-0.001

	(0.00)	(0.02)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Incidents (n)	-0.003***	-0.005***	0.019***	0.001***	0.001	0.001***	-0.001***	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Livestock (n)	-0.002***	0.086***	0.088***	0.002***	0.003***	0.003***	0.004***	0.002***	0.004***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Resident code	0.408***	-2.104***	2.623***	-0.257***	-0.188***	-0.203***	-0.142***	0.372***	0.034
(0/1, 1=Rural)	(0.03)	(0.27)	(0.79)	(0.01)	(0.03)	(0.01)	(0.04)	(0.06)	(0.10)
Wave 2	0.496***	-5.884***	-10.297***	0.191***	0.048***	-0.115***	-0.206***	-0.063***	0.007
	(0.02)	(0.17)	(0.38)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
Input exp. (AFN)	-							0.001***	0.001***
								(0.00)	(0.00)
Total land (*Jeribs*)	-							0.006***	0.002
								(0.00)	(0.00)
No. of crops n)	-							0.469***	0.412***
								(0.01)	(0.02)
IV (LoM)	2.671***	X		X		X		X	
	(0.05)								
Lewbel IV1	0.013**	-		-		X		-	
	(0.01)								
Lewbel IV2	0.010***	X		X		-		-	
	(0.00)								
Lowbel IV3	-0.017***	-		-		-		X	
	(0.00)								
_cons	-2.055***	33.452***	14.973***	7.038***	7.291***	10.953***	10.460***	8.542***	7.852***
	(0.07)	(0.84)	(1.55)	(0.03)	(0.06)	(0.04)	(0.08)	(0.11)	(0.14)
Diagnostic parameters									
Sigma		14.466***	15.05***	0.584***	0.533***	0.68***	.763***	.978***	.853***
		(0.004)	(0.010)	(0.004)	(0.007)	(.033)	(0.009)	(0.016)	(0.011)
Rho		0.116***	0.314***	-0.127***	-0.128***	.252***	.244***	.578***	0.123***
		(0.034)	(0.031)	(0.019)	(0.034)	(0.026)	(0.038)	(0.051)	(0.040)
LR test		99.82***		31.39****		154.94***		70.11***	
Log-likelihood	-14623.58	-175299.31		-47962.12		-54906.68		-34827.865	
Wald		4342.32***		5554.48***		4749.41***		5387.03***	
observations	39,185	8,255	30,754	8,222	30,651	8.198	30,678	5,679	14,134

Notes: As for Table A13 except with all instruments. LoM is the leave-out means instrument. Lewbel IV1, Lewbel IV2, and Lewbel IV3 are selected based on the highest F statistic obtained from the Breusch-Pagan test for heteroscedasticity in the first stage. These variables correspond to HH size, age, and distance to road, respectively. The symbol of X indicates which instrumental variables are included in their respective models.

Table A15 ESR Results for HHS and rCSI (only wave 2013-14)

Variables	Select	HHS1	HHS2	RCSI1	RCSI2
Violence (0/1, 1=yes)	0.036**	-0.012	0.182***	2.430***	-0.212**
	(0.03)	(0.02)	(0.05)	(0.254)	(0.101)
Opium clt *(Jerib)*	-0.001*	0.001***	0.001***	0.006***	0.001***
	(0.00)	(0.00)	(0.00)	(0.001)	(0.000)
HH size (N)	0.010***	-0.010***	-0.000	0.091***	0.013
	(0.00)	(0.00)	(0.01)	(0.030)	(0.011)
Head age (yrs)	0.005***	-0.002***	-0.001	-0.005	-0.009***
	(0.00)	(0.00)	(0.01)	(0.007)	(0.003)
Head emp. (0/1, 1=yes)	0.111***	-0.137***	0.001	0.180	-0.512***
	(0.03)	(0.02)	(0.05)	(0.232)	(0.088)
Head literacy. (0/1, 1=yes)	-0.091**	-0.138***	-0.182***	-0.027	-0.219**
	(0.04)	(0.02)	(0.05)	(0.315)	(0.108)
Head edu (yrs)	0.012***	0.000	-0.000	-0.045	-0.028**
	(0.00)	(0.00)	(0.01)	(0.034)	(0.011)
Dependency ratio	0.028**	0.044***	0.025	0.147	0.166***
	(0.01)	(0.01)	(0.02)	(0.107)	(0.040)
Dist. to road (km)	0.002	-0.003***	0.015***	-0.016	-0.000
	(0.00)	(0.00)	(0.00)	(0.015)	(0.004)
Landscape (0/1, 1=valleys & hills)	-0.235***	0.205***	-0.097	-1.066***	2.047***
	(0.06)	(0.05)	(0.10)	(0.388)	(0.224)
Landscape (0/1, 1= valleys)	-0.437***	0.013	-0.228	-1.626***	2.574***
	(0.06)	(0.05)	(0.15)	(0.437)	(0.228)
Landscape (0/1, 1=plain)	-0.659***	0.178***	-0.132	-1.692***	2.715***
	(0.06)	(0.05)	(0.22)	(0.412)	(0.218)
Price shock (0/1, 1=yes)	0.139***	0.053***	0.051	-0.273	-0.132*
	(0.02)	(0.01)	(0.06)	(0.206)	(0.071)
Weather shock (0/1, 1=yes)	0.867***	0.266***	0.194	0.994***	-1.984***
	(0.03)	(0.03)	(0.29)	(0.203)	(0.092)
Precipitation	0.001	0.000	-0.000	-0.005	0.007***
	(0.00)	(0.00)	(0.00)	(0.004)	(0.002)
Temperature	-0.009	0.014***	0.070***	-0.175**	-0.017
	(0.01)	(0.00)	(0.01)	(0.078)	(0.025)
Incidents (N)	-0.004***	0.000*	-0.001**	-0.011***	0.004***
	(0.00)	(0.00)	(0.00)	(0.003)	(0.001)
Resident code (0/1, 1=urban)	-0.319***	-0.432***	0.225	4.342***	1.830***
	(0.10)	(0.10)	(0.14)	(0.745)	(0.348)
Resident code (0/1, 1=Rural)	-0.068	-0.416***	0.283**	4.185***	1.215***
	(0.09)	(0.10)	(0.12)	(0.645)	(0.333)
Time to market (0/1, 1=2-6 hrs)	-0.037	-0.251***	-0.183***	-0.044	-0.177
	(0.04)	(0.03)	(0.05)	(0.276)	(0.119)
Time to market (0/1, 1= <2 hrs)	-0.126***	-0.285***	-0.160**	-0.610**	-0.265**
	(0.04)	(0.03)	(0.07)	(0.291)	(0.119)
IV (LoM)	7.863***	X		X	
	(0.35)				
Lewbel IV1	-0.005	X		-	
	(0.01)				
Lewbel IV2	0.020***	-		X	
	(0.00)				
_cons	-1.070***	1.132***	0.535	-1.809**	-1.789***
	(0.12)	(0.11)	(0.80)	(0.801)	(0.404)
Diagnostics					

Sigma		15.778***	0.823***	5.554***	4.593***
		(0.166)	(0.090)	(.067)	(.026)
Rho		0.425***	-0.031***	.108***	.994***
		(0.029)	(0.018)	(.001)	(0.014)
LR Test	3864.04***	27.31***		64.01***	
Log likelihood	-7087.27	-30923.11		-59989.52	
Wald		765.82***		10521.25***	
Pseudo R2	0.214				
Observation	18,960	3,467	15,493	3467	15486

Notes: Estimated using the *movestay* command in Stata. Variables and significance as for Table A14.

Tables A14 and A15 presents results from the preferred ESR model, with the first stage focusing on the incidence of natural disasters as the binary dependent variable in column one. The two-stage equation independence LR test (bottom of Tables A14 and A15) rejects the null hypothesis of mutual independence between the selection equation and the outcome equation at the 1% significance level. The correlation coefficients of error terms (rho_1 and rho_2) are both significant at the 1% level, indicating that there is sample self-selection bias in the outcome models. Wald statistics, also significant at the 1% level, confirm that explanatory variables are collectively statistically significant ($p < 0.01$). The instrumental variables are all statistically significant in the first stage, indicating that the IVs are strongly correlated with the binary endogenous variable of natural disasters. There is a significant association between district-level measures of temperature and precipitation and the likelihood of natural disasters. Exposure to weather and price shocks and violence (both the HH self-reported and number of incidents at district) increases the likelihood of households being affected by natural disasters. More mountainous and rural areas experience more frequent natural disasters.

In the second stage for the outcome equations, positive coefficients are consistently observed for household characteristics such as head employment, age, and education. Head literacy shows a positive association with HFSC and expenditures, but it is statistically insignificant for income and farm revenue. The dependency ratio exhibits a negative impact (though insignificant for some outcomes), and HH size consistently shows a negative effect except for HFCS. Livestock ownership consistently shows a positive correlation, indicating that households with more livestock achieve higher levels of food security and welfare.

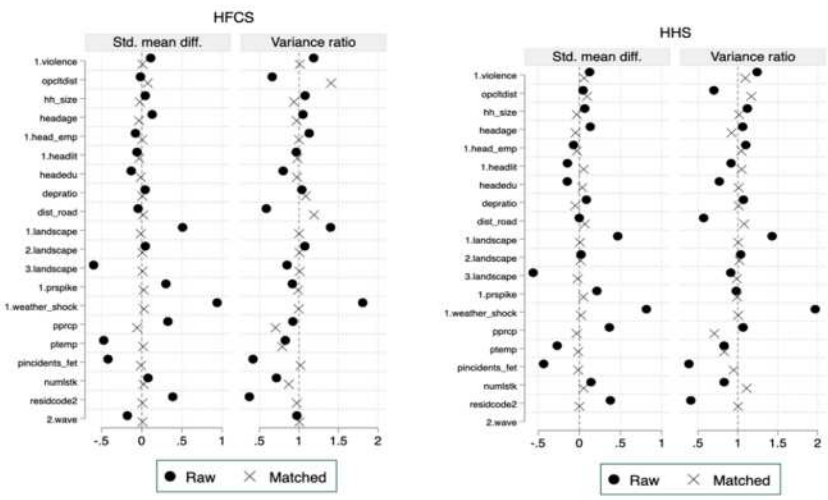
Exposure to shocks significantly influence the outcome variables. Price shocks consistently show a negative correlation with all outcomes. Weather shocks exhibit a positive impact on HFCS and farm revenues but a negative effect on expenditures and income. Self-reported violence shows a positive association with HFCS, household income, and farm revenues. The number of incidents at the district level (USDP measure) is positively correlated with almost all outcomes, except for HFCS and income for households affected by floods. Climate variables, including district-level pooled temperature and precipitation, prove significant across all models, with temperature showing a positive association with HFCS but consistently exhibiting a negative impact on other outcomes. Precipitation is positively linked to HFCS and food expenditures but negatively affects income and revenue. Opium cultivation has a negative impact except for food expenditures and income of households that have not experienced natural disasters. The coefficients on the rural dummy are negative except for farm revenue (insignificant). The estimated coefficients reveal considerable variation in the impact of landscape variables on different outcomes. Households residing in areas with a plain landscape tend to achieve higher outcomes, except for farm households affected by natural disasters, where they attain significantly lower farm revenues (flooding may be a determining factor affecting yields).

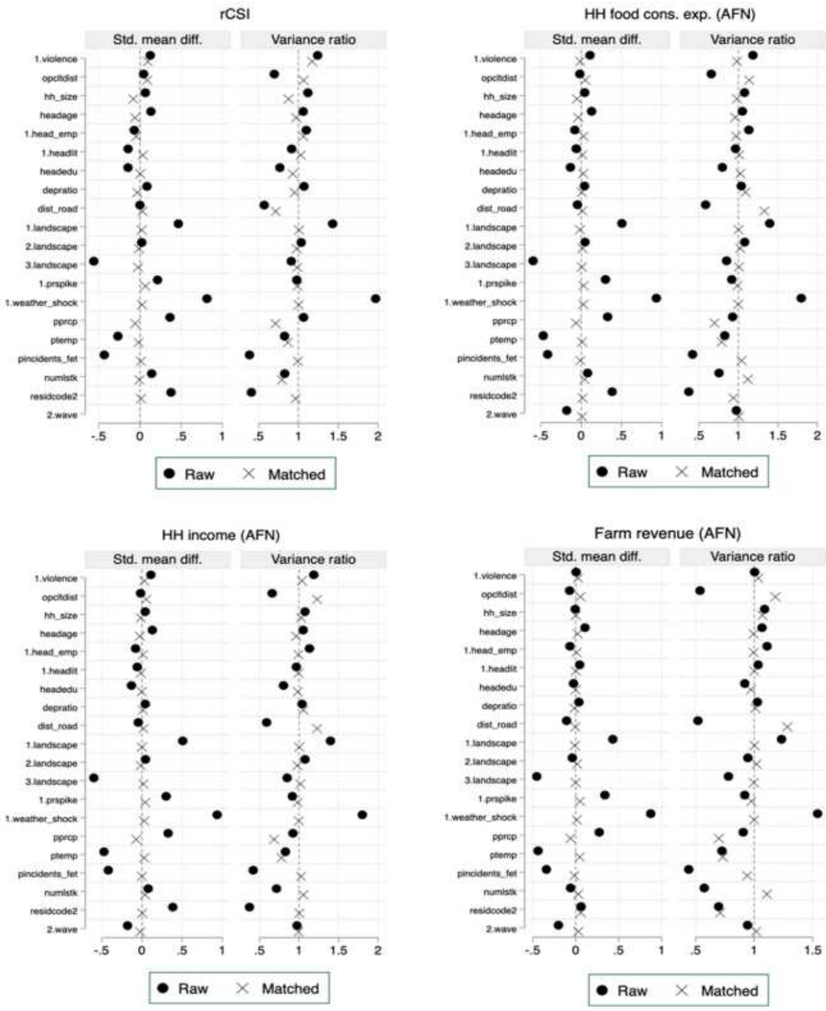
Table A16 PSM results using various matching techniques

Outcome variable	Treatment effect	Mean of outcome variables based on matched observations					
		Nearest neighbour matching (NNM 5)			Multivariate distance matching (MDM)		
		Affected	Unaffected	Difference	Affected	Unaffected	Difference
HFCS	ATT	40.32	43.05	-2.73***	40.34	43.06	-1.276***
	ATU	41.65	43.06	-1.405***	40.39	41.67	-2.106***
	ATE	41.37	43.05	-1.684***	40.81	42.74	-1.932***
HHS	ATT	0.66	0.59	0.070**	0.66	0.54	0.115***
	ATU	0.51	0.46	0.049**	0.53	0.46	0.072***
	ATE	0.53	0.48	0.053**	0.55	0.47	0.079***
RCSI	ATT	2.93	2.47	0.464***	2.90	2.44	0.465***
	ATU	2.27	2.14	0.311	2.289	2.137	0.153
	ATE	2.39	2.20	0.191*	2.40	2.19	0.209**
Log real HH food cons. exp (AFN)	ATT	7.033	6.97	0.062***	7.03	6.98	0.051***
	ATU	7.111	7.04	0.068***	7.08	7.04	0.038***
	ATE	7.095	7.03	0.067***	7.07	7.03	0.041***
Share of food cons. exp. in total cons. exp (%)	ATT	0.774	0.76	0.011***	0.774	0.768	0.006***
	ATU	0.767	0.76	0.008**	0.776	0.759	0.018***
	ATE	0.768	0.76	0.009**	0.776	0.761	0.015***
Log real HH income	ATT	10.08	10.15	-0.074***	10.08	10.19	-0.113***
	ATU	10.20	10.30	-0.107***	10.17	10.30	-0.136***
	ATE	10.17	10.27	-0.100***	10.15	10.28	-0.131***
Log real farm revenues	ATT	8.53	8.60	-0.075***	8.53	8.71	-0.184***
	ATU	88.82	8.89	-0.066***	8.65	8.89	-0.239***
	ATE	8.74	8.81	-0.068**	8.61	8.84	-0.223***

Notes: NMM5 refer to five nearest neighbouring matching algorithm. *, **, and *** denotes significance level at 10%, 5% and 1%, respectively.

Figure A1: Standardized differences plots before matching (all data) and after matching (matched data)



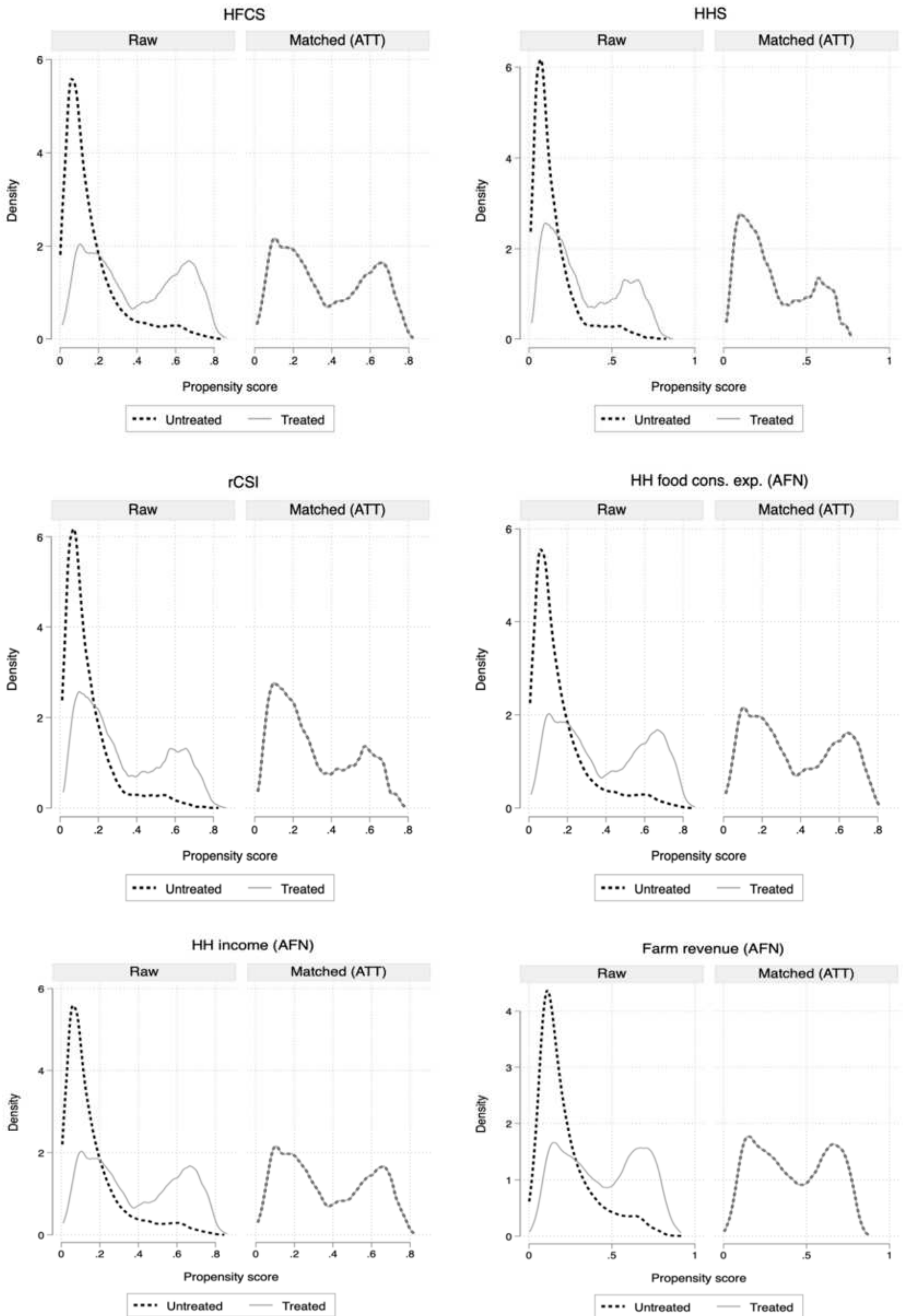


Notes: Covariates listed on the y axis The dotted vertical line indicates a commonly used cut-off for absolute standardized difference (0) and variance ratio (1). A covariate balance ≤0.25 in absolute standardized difference and variance ratio between 0.5 and 2 are considered acceptable.

Figure A1 shows the standardized differences and the treated-to-control variance ratio of confounders (covariates) between affected and non-affected groups in both the unmatched and matched samples. For optimal variable balance, the absolute standardized mean difference should be ≤ 0.25, and the variance ratio should be between 0.5 and 2 (Stuart, 2010).[6] Matching significantly reduced the standardized differences and variance ratios, bringing them within the acceptable ranges. Figure A2 presents kernel density estimates of the propensity scores for affected and non-affected households in both the unmatched and matched samples. A visual examination of the density distributions reveals that the common support condition is satisfied, indicating substantial overlap in the distribution of propensity scores for both groups. Common support ensures that persons with the same X-values have a positive probability of being both treatment and non-treatment. This overlap in the propensity score distributions does not guarantee sufficient balance on individual covariates, but Figure A1 shows balance.

[6] Stuart, E.A., 2010. Matching methods for causal inference: A review and a look forward. *Statistical Science* **25**, 1–21. https://doi.org/10.1214/09-STS313

Figure A2: Propensity score density plots before and after matching



Notes: Compare affected and non-affected households before and after matching For optimal variable balance, the absolute standardized mean difference should be ≤ 0.25, and the variance ratio should be between 0.5 and 2.

Appendix B Community Level Analysis

Table B1 Summary statistics by survey year (commune/*Shura* level)

Natural disaster	Wave 2011-12	Wave 2013-14	Pooled
Non-affected	1,037	1,097	2,134
	51.08	*54.25*	*52.67*
Affected	993	925	1,918
	48.92	*45.75*	*47.33*
Total	2,030	2,022	4,052

Note: First row has *frequencies* and second row has *column percentages*

Table B2 Summary statistics (commune/Shura level)

Variables	Affected Mean	Non-affected Mean	Difference	All sample Mean	All sample Std. Dev.
Outcome variables					
HFCS	41.245	43.518	-2.273***	42.442	11.283
HHS	.621	.394	.227***	.498	.531
rCSI	2.653	2.032	.621***	2.316	3.635
Total cons exp (AFN)	1,750.431	1,885.56	-135.13***	1,821.58	762.834
Food cons exp (AFN)	1,317.636	1,386.63	-68.991	1,353.96	566.606
Food cons exp/total exp (%)	.773	.754	.018***	.763	.112
HH income (AFN)	33,385.60	41,115.33	7,729.73***	37,455.59	1,9195.29
Farm revenue (AFN)	10,461.48	15,150.87	-4,689.40***	12,741.97	15,354.44
Explanatory variables					
Natural disaster (dummy)				.473	.499
Natural disaster (proportion)	.444	0		.21	.306
Flood (dummy)	.975	0		.462	.499
Flood (proportion)	.42	0		.199	.297
Other natural disasters (dummy)	.325	0		.154	.361
Other natural disasters (proportion)	.117	0		.055	.176
HH size (n)	7.649	7.557	.091	7.6	1.833
Dependency ratio	1.296	1.244	.052***	1.269	.38
Head edu. (years)	2.63	3.139	-.510***	2.898	2.833
Violence (proportion)	.216	.148	.069***	.18	.288
Price shock (proportion)	.586	.487	.098***	.534	.368
Weather shock (proportion)	.394	.115	.279***	.247	.332
Total land (Jeribs)	6.449	7.492	-1.044**	6.975	16.298
Input expense (AFN)	8,205.83	11,521.94	-3,316.11***	9,833.32	1,2362.95
Crops grown (n)	1.737	1.725	.013	1.731	.594
Livestock owned (n)	9.17	6.96	2.210***	8.006	11.621
Distance to road (km)	2.297	2.614	-.317***	2.464	7.315
Rural (proportion)	.921	.775	.146***	.844	.363
Observations	1,918	2,134		4,052	

Notes: All continuous variables, including all outcome variables and household characteristics are commune/shura level averages. The variable natural disasters cover both floods + other natural disasters. Other natural disasters are only earthquakes landslides, and avalanches (not flood). Dummy variables indicate the incidence of a natural disaster), with a value of 1 indicating the presence of a shock if at least one household reported a natural disaster and 0 otherwise. Proportions represent the proportion or percentage of household being affected by the natural disaster shocks in a commune. A total of 2,030 and 2,022 communities or local *Shura* were surveyed in the 2011-12 and 2013-14 surveys, respectively. *, **, and *** denotes significance level at 10%, 5% and 1%, respectively.

Table B3 Commune-level analysis of natural disasters and household outcomes

	(1) HFCS	(2) HHS	(3) rCSI	(4) Log of food exp. (AFN)	(5) Share of food exp (%)	(6) Log of HH income (AFN)	(7) Log of farm rev. (AFN)
Panel A: Commune-level estimates from OLS							
Natural dis.	-1.908***	.073***	.424**	.081***	.018***	-.101***	-.148***
	(.393)	(.027)	(.196)	(.018)	(.004)	(.018)	(.028)
Controls	Y	Y	Y	Y	Y	Y	Y
Wave FE	Y	N	N	Y	Y	Y	Y
Panel B: Commune-fixed effect estimates							
Natural dis.	-1.385**	-	-	.109***	.010	.026	-.067*
	(.64)			(.029)	(.007)	(.027)	(.043)
Controls	Y			Y	Y	Y	Y
Wave FE	Y			Y	Y	Y	Y
Comm FE	Y			Y	Y	Y	Y
Panel C: Commune-fixed effects estimates (floods and other disasters included separately)							
Flood	-1.262**	.062**	.387**	.101***	.010	-.009	-.083**
	(.654)	(.028)	(.2)	(.03)	(.007)	(.028)	(.044)
Other dis.	-.336	.003	.322	.081**	-.001	.153***	.007
	(.835)	(.04)	(.291)	(.038)	(.009)	(.035)	(.056)
Controls	Y	-	-	Y	Y	Y	Y
Wave FE	Y			Y	Y	Y	Y
Comm FE	Y			Y	Y	Y	Y
Observations	3469	1649	1649	3469	3469	3469	3465

Notes: estimates for HHS and rCSI are based on 2013-14 survey round. Variable natural dis. In panels A and B is a dummy, with value 1 indicating incidence of natural disasters within the community in the past year, and 0 otherwise. Variables flood and other dis. in panel C are dummy that take value of 1 if flooding or other disasters including earthquake, landslide, and avalanches occurred in the commune in the past year. Description for all dependent and control variables are as per Table B2. Control variables included are: household characteristics (e.g., log of HH size, dependency ratio, head education), other shocks (weather, price, and violence), log of total land, log of input expense, number of crops, log of total livestock owned, distance to the nearest road, and proportion of household living in rural areas. Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

Table B4 Estimates from Difference-in-Difference model (Commune-level)

VARIABLES	HFCS	Log of food cons. exp. (AFN)	Log of HH income (AFN)	Log of farm revenue (AFN)
Diff-in-diff	-5.139***	-0.309***	-0.0874**	-0.084*
	(0.964)	(0.046)	(0.0431)	(0.075)
Observations	3,494	3,494	3,494	3,489
R-squared	0.702	0.645	0.727	0.769
Mean control t(0)	52.04	6.321	10.96	9.525
Mean treated t(0)	53.79	6.593	11.03	9.502
Diff t(0)	1.747	0.272	0.0754	-0.0231
Mean control t(1)	48.45	6.633	10.88	9.676
Mean treated t(1)	45.05	6.596	10.87	9.569
Diff t(1)	-3.392	-0.0371	-0.0119	-0.107

Notes: As for Tables B3.

Map B1 District level maps of self-reported natural disasters