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Floods, food security, and coping strategies: Evidence from Afghanistan

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Abstract

In this paper, we assess the long-term effect of floods on food security (as measured by calorie and micronutrient consumption) by applying an instrumental variable approach to data from the Afghanistan National Risk and Vulnerability Assessment survey. To identify the determinants of this effect, we also estimate how floods affect per capita yearly household income and poverty status. We find that exposure to flooding during a 12-month period decreased daily calorie consumption by approximately 60 kcal while increasing the probability of iron, vitamin A, and vitamin C deficiency by 11, 12, and 27 percentage points, respectively. Controlling for price shocks and income only marginally reduces this flood effect on food security, suggesting that impaired livelihoods (rather than price hikes) are its primary driver. We further determine that exposure to this natural disaster decreases income by about 3% and makes flood-affected households about 3 percentage points more likely to be poor. Lastly, we show that experience of floods is strongly and significantly associated with lower diet quality and quantity, and with engaging in consumption smoothing coping strategies, such as buying food on credit and taking loans. These findings underscore the serious direct impact of floods on both diet and effective behavioral responses to such shocks while emphasizing the need for targeted micronutrient supplementation in disaster relief and food aid measures even after the period of natural disaster emergency.

KEYWORDS
Afghanistan, coping strategies, floods, food security, nutrition, instrumental variables

JEL CLASSIFICATION
Q18, Q54, I32

1 | INTRODUCTION

Despite some progress in combating global hunger and malnutrition, approximately two billion individuals worldwide—around a third of the world's population—suffer from food insecurity (Wheeler & Von Braun, 2013) as broadly defined by the FAO (2002).[1] In fact, for the first time since the turn of the century, hunger has actually increased with 821 million people classified as

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[1] This definition encompasses the availability of sufficient food quantities, access to adequate resources, food utilization, and stability of food access.

undernourished, mostly as a result of conflicts and weather shocks (FAO, IFAD, WHO, WFP, & UNICEF, 2018). Because many of these adverse events result from climate change, a large body of literature has emerged that addresses this phenomenon's potential effect on food security (e.g., Fischer, Shah, Tubiello, & van Velhuizen, 2005; M. Parry, Rosenzweig, & Livermore, 2005; M. L. Parry, Rosenzweig, Iglesias, Livermore, & Fischer, 2004; World Bank, 2010). However, although all these studies agree that climate change will definitely increase food insecurity, they offer substantially different projections dependent on scenario.

As a consequence of rising temperatures, floods have become more frequent and devastating because raised temperatures not only change rainfall patterns but also increase the frequency and severity of extreme weather (Ahern, Kovats, Wilkinson, Few, & Matthies, 2005; Costello et al., 2009; Haines & Patz, 2004; Ramin & McMichael, 2009). Hence, although the evidence on climate change's effect on flooding frequency is inconsistent, all projections point to its strong potential to substantially change human exposure to flood hazards (Arnell & Gosling, 2016), an exposure that increases with rapid urbanization (Du, FitzGerald, Clark, & Hou, 2010). Because the floods themselves have severe consequences for the health and well-being of affected individuals (Ahern et al., 2005; Alderman, Turner, & Tong, 2012; Sekulova & van den Bergh, 2016; Von Möllendorff & Hirschfeld, 2016), as well as a direct effect on all food security dimensions (De Haen & Hemrich, 2007), they are often associated with malnutrition and stunting among children, especially when malnutrition levels are high (Del Ninno & Lundberg, 2005; Goudet, Faiz, Bogin, & Griffiths, 2011). This present study thus applies a two stage least squares (2SLS) approach to microdata from the 2011/2012 Afghanistan National Risk and Vulnerability Assessment (NRVA) cross-sectional survey to assess the effect of floods on food security in Afghanistan. To achieve the main study objective of quantifying flooding's longer term effects on household food access, we measure flood exposure in the year before interview using household-level calorie and micronutrient consumption or deficiency indicators as dependent variables.

Our analysis of the flood-food security nexus is novel in two ways: First, while most extant studies on flooding's effect on food security focus only on calorie shortages (the study by Del Ninno, Dorosh, & Smith, 2003 is an exception; Wheeler & Von Braun, 2013), we explore the size of this shock's effect on the micronutrients that are particularly relevant for the Afghan population (vitamins A and C and iron). Understanding the determinants of these deficiencies is also of value in light of their related health effects, which can impair physical and mental capacities and lead to loss of productivity, permanent mental disability, blindness, depressed immune system function, and increased infant and maternal mortality (Kennedy, Nantel, & Shetty, 2003). Second, we test the hypothesis that flood-related effects on food security last far beyond the actual disaster's occurrence, as supported by ample evidence of floods being responsible for the disruption of crops (Zhang, Gu, Singh, Liu, & Kong, 2016), roads and other physical infrastructures (Winter et al., 2016), household assets (Afriyie, Ganle, & Santos, 2018), as well as for higher unemployment (Sarmiento, 2007). To pinpoint possible transmission mechanisms for this flood-induced impact while also identifying household strategies for coping with it, we first measure flooding's effects on household yearly income and poverty, and then estimate the enactment probability of different responses (e.g., reducing consumption or quality of food consumed, taking out loans, and seeking community assistance). The most notable finding from this entire analysis is that, dependent on econometric specification, flood exposure decreases household calorie consumption by only 57 or 69 kcal a day but is responsible for a 0.11, 0.12, and 0.27 higher probability of deficiency in iron, vitamin A, and vitamin C, respectively.

2 | BACKGROUND

The effect of climate change on flooding is likely to be especially severe in South Asia where climate change appears to be influencing both the monsoon and tropical cyclones, the two main drivers of flooding in the region (Douglas, 2009). At the same time, higher temperatures are expected to generate more rapid melting of snow and glacier ice, thereby increasing the seasonal peak flows of Himalayan headwaters. One country strongly affected by such flooding is Afghanistan, in which about 70% of all natural disasters are attributable to floods (OCHA, 2014), with around 400,000 individuals displaced and 5,000 killed by flooding between 1988 and 2006 (Hagen & Teufert, 2009). According to a report by the World Food Program and UN Environment Program (WFP & UNEP, 2016), Afghanistan is already facing severe climate-change-related flooding caused by heavy rainfall over a short period and rapid melting of snow and ice in highland areas during the spring. In 2017 alone, climate shocks (floods and droughts) negatively affected the food security status of 7.8 million Afghans (FAO et al., 2018). In fact, Afghanistan is classified among the nations with the most climate-sensitive agricultural production, and in the 2011–2016 period, the country faced high exposure to climate extremes in terms of interseasonal variability, frequency, and intensity (FAO et al., 2018). At the same time, widespread suffering, death, and displacement results from the flooding engendered by precipitation events, whose severity has increased by 10–25% in the past 30 years (WFP & UNEP, 2016). According to a descriptive analysis of the NRVA data used in this study, over a fifth of Afghans were negatively affected by floods within a 12-month period between 2011 and 2012.

Nonetheless, despite extensive evidence that flood exposure reduces household calorie consumption (e.g., Del Ninno et al., 2003), neither floods nor climate change in general influence food security solely through short-term availability and food prices; floods may also be responsible for lowering household income and assets (Del Ninno et al., 2003). As a result, flooding can be expected to have detrimental effects on calorie and micronutrient consumption also in the longer term. For example, Del Ninno, Dorosh, and Islam (2002), in their study of the 1998 Bangladeshi flooding, observe that although households were able to smooth their food consumption in the disaster's aftermath, when shortages caused a rise in food prices (especially for rice and vegetables), the average calorie consumption decreased. In fact, the ability of natural disasters in general to detrimentally impact both national economies (Nordhaus, 2006) and local labor markets (Mueller & Quisumbing, 2011) may at least partly account for the positive relation documented between disaster damage, poverty, and vulnerability (De Silva & Kawasaki, 2018). In these contexts, children and women are usually those disproportionally affected (Del Ninno et al., 2003).

In the case of Afghanistan, the severe effects of conflict and price shocks on household food security are well documented. For example, while a one percent increase in wheat flour price may induce a 0.07% decline in calorie consumption (and 0.25% decline for proteins; D'Souza & Joliffe, 2012), a 1% increase in violence (fatalities per 10,000 inhabitants, 2SLS model) can reduce this consumption by 9.2% (D'Souza & Jolliffe, 2013). Most important, these shocks are responsible for a food quantity–quality trade-off (D'Souza & Jolliffe, 2012), leading Afghanistan to experience severe micronutrient deficiency, as reflected in the 2002 scurvy epidemic (Cheung et al., 2003) and in large portions of the population (especially women of reproductive age) suffering from anemia and iron and vitamin A deficiency (Cheung et al., 2003; Levitt, Kostermans, Laviolette, & Mbuya, 2010; Mihora et al., 2004; Oskorouchi, Nie, & Sousa-Poza, 2018). These latter deficiencies, together with inadequate intake of vitamins B12 and B9, are the principal nutrition-related causes of anemia, a health condition responsible for nearly 20% of all maternal deaths in South Asia (Noronha, Khasawneh, Seshan, Ramasubramaniam, & Raman, 2012).

Despite growing concerns about increased climate change-related flooding in much of South Asia (Douglas, 2009), surprisingly little research examines the negative effects of floods on household food security in this area. In fact, for Afghanistan we know of only one other paper that examines the negative impacts of flooding on anemia (Oskorouchi et al., 2018). Hence, not only does this current analysis of the flood-food security nexus and its long-term effects contribute usefully to the knowledge pool, it has the potential to improve aid intervention effectiveness and targeting capacities for regions in protracted crisis, such as Afghanistan and South Asia in general.

3 | DATA

3.1 | Dataset

Our primary data source is the 2011–2012 Afghanistan National Risk and Vulnerability Assessment (NRVA) survey,[2] which provides detailed information on quantities and consumption frequencies in the week prior to interview for 91 food items (including market-bought, self-produced, and other sources of food like gifts and aid). It also contains sociodemographic, income, and labor and assets data, as well as a detailed module on shocks experienced and coping strategies enacted by the household during the previous year. Because the sampling frame relies on the 2003 Afghanistan Central Statistical Office (CSO) household listing, last updated in 2009, the sample, obtained using a two-stage clustering technique, is representative at the national, seasonal, and first administrative levels (34 provinces) for both urban and rural households.

3.2 | Dependent variables

3.2.1 | Equivalized calorie consumption

Our main outcome variable is a measure of equivalized nutritional consumption comprising both per capita calorie and micronutrient consumption. Because our analysis is based on household data, it is subject to the common caveat that the nutrition-related measures do not account for intrahousehold disparities in food distribution. We thus adjust both energy and micronutrient consumption for household size, taking into account that the recommended daily consumption varies by age group, sex, and level of physical activity. More specifically, using the calorie consumption guidelines and energy requirement tables from Smith and Subandoro (2007), we construct a set of scales for each nutritional outcome variable based on the daily consumption of a moderately active male aged

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[2] Although the CSO released the Afghanistan Living Condition Survey 2013–14 and a National Nutrition Survey 2013 in 2015, these contain only a food group frequency recall module and thus provide no detailed food expenditure information.

30–60. After computing the recommended energy consumption for each household member (dependent on personal characteristics) as a share of the kcal/day recommended for the reference adult (i.e., 2,900 kcal/day), we sum these shares in each household to yield household size measured in adult equivalent.

To estimate the physical activity level for each individual aged 18 years or older, we exploit the NRVA 2011–12 labor module to create a moderate physical activity variable equal to 1 if that individual engages in security work, food processing, or sales/trade, and 0 otherwise. We proxy heavy physical activity by a dummy variable equal to 1 for individuals working in construction/mining, transportation, farming, metal/wood sectors, shepherding, or as a plant or machine operator, with all remaining work activities specified in our data (i.e., teaching, handicrafts, and employment in the service or health sector) coded as light.

To obtain weekly household energy consumption, we multiply each food item quantity by its calorie content, as listed in Sabry and Rizek (1982), and sum the calorie consumption over all food items. To obtain daily values, we first divide this result by the household size in adult equivalent and then by 7 days. Lastly, we drop any observations with a daily energy consumption per capita lower than 500 kcal (43 cases) or above three standard deviations (350 cases) as implausible and classify all households failing to meet the 2,100 kcal/day per adult equivalent as calorie deficient (FAO & WHO, 2004; World Bank & CSO, 2012). When computing calorie consumption, in line with prior literature (USDA, 2011), we consider neither the potentially higher minimum calorie requirement during winter nor meals consumed outside the home or by guests, whose number in the NRVA 2011/2012 dataset is negligible (1% and 2% of total household meals, respectively).

3.2.2 | Equivalized micronutrient consumption

Only recently, a substantial amount of relatively high-quality nutritional data has become available for Afghanistan, enabling more accurate estimation of malnutrition in the country and generating a growing number of studies on the prevalence, consequences, and determinants of regional micronutrient deficiency (Ahmad, 2002; Cheung et al., 2003; Levitt et al., 2010; Oskorouchi et al., 2018). While these studies concentrate on certain population subgroups such as women and children, our analysis covers the entire population. It also focuses specifically on the micronutrients that present the greatest public health challenges in Afghanistan; namely, vitamins A and C and iron. As in the computation of calorie consumption, we use FAO and WHO (2004) equivalency scales and deficiency thresholds to calculate household-level micronutrient consumption, identifying household vitamins A and C deficiencies as (adult equivalent) consumption lower than 600 μg/day and 45 mg/day, respectively, and iron deficiency as under 27.4 mg/day.

A major motivation for sampling the entire population is that analyzing different subgroups does not guarantee comparability of the estimated prevalence of micronutrient deficiency. In fact, some groups may be biologically more prone to specific deficiencies. For example, women are more likely to be iron deficient because of menstrual cycle-related blood losses, hormonal changes during lactation or menopause, and the presence of health conditions such as uterine fibroids. Men, in turn, are more likely to be deficient in vitamin C in both high- and low-/middle-income countries, possibly because of their greater use of tobacco and lower consumption of vitamin C-rich foods (Ravindran et al., 2011; Schleicher, Carroll, Ford, & Lacher, 2009). At the same time, some discrepancy in the prevalence of a specific deficiency may be due to the measurements employed. For example, a major difference between the NNS 2013 data and our estimates of micronutrient deficiency stems from the former's use of blood biomarkers (which account for food utilization) whereas our study focuses on consumption (and thus food access). In light of these considerations, divergence between our estimates and those of other studies are to be expected. For instance, the NNS 2013 finds that when iron deficiency is measured by blood levels of ferritin (a protein that proxies iron storage), 24% and 26% of Afghan women and children, respectively, suffer from it. We, in contrast, estimate a prevalence of 17% among the whole Afghan population (15% of households), probably because of our comprehensive sample and disregard of intrahousehold food distribution and iron absorption inhibitors such as tea (Zijp, Korver, & Tijburg, 2000).

3.2.3 | Poverty and income

Because poverty and income are two important determinants of food access, we employ these two measures as dependent variables in a series of auxiliary analyzes, and when appropriate, as control variables in the main econometric models estimating flooding's effect on food access. Given that our aim is to estimate the flood-food security nexus in the long term, we measure both variables in the longer term (i.e., in the year prior to the interview for income). To construct our measure of equivalized yearly household income, we apply the Oxford equivalence scale[3]

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[3] The Oxford equivalence scale (also called the old OECD equivalence scale) assigns a value of 1 to the household head, 0.7 to each extra adult

to data from the NRVA 2011–12 household income module; more specifically, the amount in Afghani (2011 prices) of the main income source and its share of total income. Hence, although the survey does not explicitly report the total yearly household income, we can easily calculate it by dividing the amount earned from the main activity by its share of total income. Admittedly, because the multiple income-earning activities typical of Afghan households tend to be conducted by several household members, the household head's calculation of how much each activity contributes to total household income may be subject to some degree of misreporting. However, we judge the risk of systematic underreporting (and related bias) because of perceived income question intrusiveness (Tourangeau & Yan, 2007) to be smaller when respondents are asked about income shares rather than the exact monetary compensation for each activity.

Even so, to mitigate any concerns about income measurement reliability, we employ an additional consumption-based measure of poverty originally computed by CSO Afghanistan and the World Bank and included in the NRVA 2011–12 data release (for the technical details, see Section B.1 of the Online Appendix). We also limit the importance of extreme observations in the regression analysis with income as the dependent variable by transforming this measure by means of inverse hyperbolic sine (IHS). This transformation, first introduced in econometrics by Burbidge, Magee, and Robb (1988) and usefully applied in other studies like ours (e.g., D'Souza & Jolliffe, 2014), provides an alternative to taking logs that still allow the coefficient interpretation in percentage change while raising no concerns in the presence of zero values.

3.2.4 | Coping strategies

The NRVA 2011–12 data also report 15 coping strategies[4] enacted by survey households during the 365 days prior to interview. We retain the six most effective for compensating a food access shock and the most likely to be adopted in response to a flood: (a) reducing diet quality, (b) reducing food quantity or skipping meals, (c) purchasing food on credit from traders, (d) taking out loans, (e) receiving help from others in the community, and (f) selling assets. For each of these, we create a dummy variable equal to 1 if the household enacted the coping strategy during the year prior to interview (previous year), and 0 otherwise.

3.3 | Independent variables

3.3.1 | Floods

Our main independent variable of interest is based on an item in the NRVA 2011–12 household shocks and coping strategies module, which asks whether, in the year before interview, the household was negatively affected by any of 30 listed shocks. This list includes natural disasters (e.g., avalanches, earthquakes, floods, and hailstorms), violence and conflict, death or illness of a family member, loss of employment, and agriculture-specific and price shocks. To proxy exposure to floods at the household level, we create a dummy equal to 1 if the household reported being negatively affected by a flood in the year prior to interview, and 0 otherwise.

Unlike Oskorouchi et al. (2018), who use satellite precipitation-driven modeling to measure flood exposure, we rely on a measure derived from individuals' direct responses on whether they have been negatively affected by floods. On the one hand, such a survey question has the distinct advantage over satellite-derived flood assessment of allowing exact identification of flood-affected households. Hence, although satellite precipitation-driven modeling offers a valid objective measure, it raises the risk of household misclassification and fails to differentiate between households that are negatively versus positively affected by (mild) floods. On the other hand, the subjective nature of this measure may admittedly be problematic for isolating unbiased effects; that is, as extensively discussed in Section 4 (and in the Online Appendix), households less able to cope with floods are more likely to report shock exposure, and vice versa. Another seeming weakness of our flooding measure is its inability to determine the exact period of shock exposure. However, because the survey is seasonally representative (i.e., data collection lasted from April 2011 to August 2012), we can safely claim that, on average, our coefficient measures flood exposure in the long term (months to years) as opposed to the immediate (when the flood occurs) or medium-term recovery phase (days to a few weeks; Du et al., 2010). It should also be noted that, because of the protracted occurrence of flooding in Afghanistan, our proxy for this natural disaster might correlate with, and thus, capture the effect of,

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in the household, and 0.5 to each child. It should be noted, however, that no country-specific equivalence scale exists for Afghanistan and that the Afghanistan CSO uses only the household size as a deflator, meaning that its poverty measures do not account for economies of scale.

[4] The NRVA 2011–12 lists the following coping strategies: reducing diet quality; reducing food quantities or skipping meals; decreasing expenditures; purchasing food on credit from traders; taking out loans; receiving help from others in the community; selling assets; renting out or mortgaging land; selling a house, land, or female reproductive livestock; working for relief programs; joining the military; taking children out of school; increasing child labor; selling child brides; and begging.

particularly, calamitous flooding events that occurred more than 1 year prior to interview.

3.3.2 | Instrumental variable

We construct our instrumental variable to correlate with the self-assessed flood exposure without directly affecting the outcome variables via channels other than the shock of interest. This variable relies on the provincial-level count (for each observation in our sample) of flood affected households and each time excluding the observations belonging to the same community from this count. Hence, for a household living in community A of province X, we count all flood-affected households in province X except those residing in community A. This variable thus takes a different value for each community. Our dataset comprises 34 provinces and 2,083 communities. Not only is this measure highly correlated with the suspected endogenous flood regressor (a Spearman correlation coefficient of 0.50), it poses no concerns about the subjective nature of the original flood variable. We further discuss and test the exogeneity of this instrument in the Methods section.

3.3.3 | Other shocks

We also construct dichotomous variables for two other shocks that may be correlated with flooding: experiences of insecurity or violence and unusually high increases in food prices. As we do not know what motivated such price spikes (e.g., whether flood or conflict), using the price shock measure in our regressions could either attenuate the possibility of omitted variable bias or capture part of the flood effect (if flooding led to higher prices). This measure is thus likely to be both a confounder and a transmission channel of the flood-food security nexus, prompting us to estimate all models both with and without it. In addition, because conflict may be more likely when a natural disaster occurs (Nel & Righarts, 2008), we include a violence variable in our set of regressors to limit the risk of omitted variable bias.

3.3.4 | Other relevant constructs

To further limit any risk of omitted variable bias, all our regressions control for a wide range of confounding factors measured at different levels. In addition to household characteristics (age, gender, literacy, employment status, and marital status of household head; household size; and rural residency), we denote community crop land topography by a four-level categorical variable: open valley (reference), valley, valley and hills, and hills (no valley cultivation). We also include the distance in kilometers from the household's community to the nearest drivable road and provincial fixed effects.

4 | METHODOLOGY

This study has the major goal of establishing the nexus between floods and nutritional consumption (as well as related deficiencies). An additional aim is to identify which coping strategies Afghan households enact in response to floods. Finally, we support the above-mentioned relation between floods and food security by running a transmission channel analysis of the flood-related impact on household income and poverty status. Although many transmission channels drive the flood-food security nexus, estimating the effects of flooding on income and poverty status measured in the year prior to interview is likely to provide valuable evidence on the hypothesis that this disaster affects livelihoods in the longer term.

Like other studies on similar natural disasters (droughts and floods), we assume that the occurrence of floods is quasi-random (Kumar, Molitor, & Vollmer, 2016; Oskorouchi et al., 2018). However, because some mechanisms could invalidate a causal interpretation of our results, we also estimate the flood effects on food security, poverty, and income within a 2SLS framework able to address the different sources of endogeneity. In Section B.2 of the Online Appendix, we detail the issues that could invalidate a causal interpretation of the Ordinary Least Squares (OLS) results.

4.1 | Basic econometric model

Our basic identification strategy relies on the estimation of OLS models that control for possible confounders of the food security/poverty-flood and coping strategy-flood nexuses expressed in Equation (1):

$$Y_i = \alpha + \beta_1 Flood_i + \beta_2 Violence_i + \beta_h \boldsymbol{HC} + \boldsymbol{T_t} + \boldsymbol{P_p} + \varepsilon_i. \tag{1}$$

Here, the dependent variable *(Y)* is a measure of either food access (i.e., consumption of calories, vitamin A, vitamin C, or iron), poverty status/income, or a variety of coping strategies. The variable of interest (*Flood*) is a dummy variable of self-reported exposure to a flood in the year before interview. In all models, we employ a wide range of control variables: a dichotomous measure of self-reported conflict exposure in the year prior to interview (*Violence*) and a vector of household demographic and socio-economic characteristics (***HC***), namely:

head of household's age, whether married, male, literate, employed; household size; equivalized household income; distance (in km) from the household's community to the closest drivable road; and urban residency. Finally, a categorical variable of community topographic characteristics (***T***) and provincial fixed effects (***P***) control for time-invariant unobserved heterogeneity related to the characteristics of a community crop land and of the first administrative unit of residence, respectively. Finally, ϵ is a household-level idiosyncratic error term. Moreover, we estimate regression (1)additionally controlling for per capita yearly income and for a dichotomous measure capturing the occurrence of price shocks. All models correct for survey design (i.e., two-stage clustering and sampling weights) and standard errors are clustered at the district level (345 districts).

4.2 | Instrumental variable approach

To adequately address omitted variables, sample selection, and possible measurement errors in the flood variable, we estimate a 2SLS model that uses both synthetic heteroskedastic and standard instrumental variables. Our standard instrument is a measure of the average number of flood-affected households in each observation's province of residence, exclusive of those in its own local community. In addition to posing no concerns about heterogenous perceptions of shock severity, this instrument strongly correlates with the endogenous flood variable (a Spearman correlation coefficient of 0.50). Given that all models control for time-invariant provincial heterogeneity by including a set of 33 dummy variables, the possibility of the IV picking up time-invariant structural differences across provinces (e.g., poverty status or infrastructures) is limited. Moreover, because our use of a standard excluded instrument together with several heteroskedastic ones allows formal testing for Instrumental Variables (IV) exogeneity (when at least one instrument is exogenous), we are able to formally demonstrate that, in all regressions, the instrumental variables pass the J-Sargan overidentification test of exogeneity. Likewise, in a formal test of instrument nonweakness via partial *F*-statistics (corrected for the sample's clustered nature), we show that in no model does this statistic fall below 10 (the threshold suggested in the literature), except in regressions that use iron deficiency as the dependent variable (whose *F*-statistic is approximately 9).

We employ this instrumental variable within a heteroskedasticity 2SLS model (Klein & Vella, 2010; Lewbel, 2012), an approach successfully used to deal with a variety of empirical issues, such as disentangling the moral hazard effect on body weight from that on having health insurance (Kelly & Markowitz, 2009), estimating how access to domestic and international markets affects household consumption levels in China (Emran & Hou, 2013), and assessing the causal impact of microfinance program coverage on moneylender interest rates in northern Bangladesh (Mallick, 2012).

This estimation technique does not rely on standard exclusion restrictions and it is able to achieve identification in the presence of endogeneity when errors are heteroskedastic and there exists a vector X of exogenous variables. Moreover, the approach proposed by Lewbel (2012) can be applied together with a standard excluded instrument (Baum & Lewbel, 2019). Consider the triangular system in Equations (2) and (3)—where Y_1 and Y_2 are endogenous, X is a vector of exogenous predictors, and ε_1 and ε_2 are unobserved errors that may be correlated with each other—the exogeneity assumption is satisfied when $E(\varepsilon,X) = 0$. However, although this assumption suffices for identification of the reduced-form equation, in the absence of identifying restrictions (i.e., when the instruments do not directly affect the outcome variable), no causality can be claimed for the structural equation's parameters.

$$Y_1 = \beta_1 \boldsymbol{X}' + \beta_2 Y_2 + \varepsilon_{1,} \tag{2}$$

$$Y_2 = \beta_1 \boldsymbol{X}' + \varepsilon_2. \tag{3}$$

In the Lewbel (2012) approach, in the presence of first-stage heteroskedasticity (i.e., when $E(\varepsilon\varepsilon'|X)$ is not a matrix of constants), identification can be achieved by employing information from within the specified model. The instruments are generated by exploiting the first-stage regressions' residuals, which take the form presented in Equation (4).

$$Z_k = \left(X_{k,i} - \bar{X}_{k,i}\right) \varepsilon_{i.} \tag{4}$$

The instruments are the product of each (mean-centered) regressor multiplied by the residual vector from the first-stage regression of the endogenous variable on all exogenous predictors, including a constant vector (Baum, Lewbel, Schaffer, & Talavera, 2012). The underlying rationale is that the first-stage regression heteroskedasticity leads to higher moment conditions of ε, making identification possible via the assumption $\mathrm{Cov}(X,\varepsilon^2) = 0$ (i.e., in the presence of a set of exogenous regressors), and $\mathrm{Cov}(Z, \varepsilon_1\varepsilon_2) = 0$, where instrument weakness is inversely related to the degree of scale heteroskedasticity in the error process (Lewbel, 2012). In this study, we implement the Lewbel (2012) procedure by means of the *ivlewbel* R package (Fernihough, 2014), which provides a partial first-stage statistic for testing weak instruments, and the J-Sargan overidentification test.

Lastly, to test the exogeneity of our standard instrumental variable, we run a series of falsification tests that regress the outcome variable(s) on the set of original regressors with the excluded instrument included, but using only the subsample of unexposed observations. Because these observations are not treated, an instrument's coefficient that is statistically different from zero would signal that the IV is affecting the outcome of interest via channels other than flooding and vice versa. However, given that our purpose in using a 2SLS strategy is to address the erroneous inclusion of flood-exposed resilient households in the control group, this test would be meaningful only if there exists a subset of dependent variables that are free from this measurement error. In fact, because the measurement error relates to the subjective nature of the flood variable—and ultimately to household heterogeneity in coping—it could be pronounced depending on the specific outcome variable employed. We thus anticipate that in an ex-post comparison of the OLS and 2SLS results, the flood coefficient will stay virtually unchanged when calorie and iron consumption (deficiency) are the dependent variables. These results are in line with the assumption that heterogeneous coping abilities are more likely to exist for some micronutrients (i.e., vitamins A and C) than for calorie and iron consumption. Hence, because we judge the risk of group misassignment to be minimal when calories and iron are taken into account, our falsification tests regress these outcomes on the IV using the sample of self-declared unexposed households.

As Table A.1 in the Online Appendix shows, the coefficient of the IV in these falsification tests is always statistically insignificant, confirming the overidentification test results of instrument exogeneity. At the same time, directly plugging the IV into the first-stage (falsification) regressions not only prevents inclusion of the provincial dummies but reveals strong multicollinearity with the instrument.[5] Nonetheless, because excluding the provincial dummy variables from the set of controls only raises the probability of the IV picking up the effect of provincial differences, it likely only increases the likelihood of wrongly detecting instrument endogeneity, not the reverse. Finally, in Section B.3 of the Online Appendix, we discuss additional robustness checks that estimate the effect of floods while additionally controlling for a household enaction of relevant coping strategies.

5 | RESULTS

5.1 | Descriptive statistics

As Table 1 (column (1)) shows, the households in the study sample are mostly rural (84%), with the majority headed by males (99%), who are on average 41 years old, married (96%), and employed (88%). Only a relatively small share of the household heads is literate (34%). Forty-nine percent of the households live on open plains, 30% on terrain with valleys and hills, and 18% in valleys, with communities located on average 3 km from the nearest drivable road. The average yearly per capita Afghan income is 19,629 Afghani (in 2011 prices).

Although the average Afghan household consumes an adequate number of calories (3,054 kcal), the consumption of a relevant portion does not meet the daily minimum requirement of 2,100 kcal (22.3%). We also observe worrying levels of vitamin A and C deficiency (67% and 46%, respectively). The prevalence of iron deficiency, in contrast, is much lower and affects only 15% of Afghan households. A fifth of these reported being negatively affected by a flood[6] and/or violence, confirming that conflict and climate-related disasters are very common in the country. It is thus not surprising that almost half the sample reported being affected by price shocks. To offset the negative consequences of one or more shocks, the households had opted for the following coping strategies: reducing food quality (39%), taking out loans (27%), and/or purchasing food on credit (18%). A 10th of the households (especially rural households) had skipped a meal and/or asked for help from their community, and a small number had been forced to sell off assets (2.9%).

In Table 1, we report the sample characteristics for non-flood-affected and flood-affected households (columns (3) and (5), respectively), as well as the difference in mean values and its statistical significance (column (7)). According to these estimations, households reporting a flood are worse off in terms of both calories and micronutrient consumption/deficiency, with the two subsamples differing statistically on all control variables except household size and household head being male, married, and literate. As expected, the mean of the instrumental variable is considerably higher for households that self-reported exposure to

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[5] We cannot determine the exact degree of multicollinearity because the Stata variation inflation factor command only indicates that the models have aliased coefficients.

[6] It is worth noting that while our results indicate that in the year prior to interview, 23% of our sample was negatively affected by floods, and satellite imagery in Oskorouchi, Nie, and Sousa-Poza (2018) suggests that 32% of the observations in the sample experienced at least a day of flooding in the 2 months before interview. Although the two samples are not entirely comparable, these percentages imply that the satellite-based results overestimated the number of individuals affected by floods.

TABLE 1 Sample characteristics

Variable	Full sample Mean (1)	Full sample SD (2)	Non-flood affected Mean (3)	Non-flood affected SD (4)	Flood affected Mean (5)	Flood affected SD (6)	Difference (7)
	Dependent variables (food security analysis)						
Kcal/pc	3,054	1,280	3,270	1,893	2,965	1,535	305.00***
Kcal deficiency (≤2,100 kcal/day)[a,b]	0.23	0.42	0.23	0.42	0.24	0.43	−0.02**
Iron/pc (mg/day)	600.60	497.10	675.97	640.92	543.86	506.39	132.11***
Iron deficiency (≤27.4 mg/day)[a,b]	0.15	0.36	0.14	0.35	0.18	0.38	−0.04***
Vit. A/pc (μg/day)	610.80	782.90	791.95	1,352.00	581.85	1,101.64	210.10***
Vit. A deficiency (≤600 μg/day)[a,b]	0.66	0.47	0.63	0.48	0.72	0.45	−0.09***
Vit. C/pc (mg/day)	73.78	74.87	85.06	186.20	64.48	175.99	20.59***
Vit. C deficiency (≤45 mg/day)[a,b]	0.45	0.50	0.41	0.49	0.55	0.50	−0.15***
	Independent variables						
Flood[a,c]	0.23	0.42	—	—	—	—	—
IV	0.22	0.24	0.15	0.17	0.49	0.28	−0.34***
Violence[a]	0.21	0.41	0.20	0.40	0.23	0.42	−0.02***
Price shock[a]	0.58	0.49	0.53	0.50	0.70	0.46	−0.17***
Rural[a]	0.84	0.37	0.81	0.39	0.93	0.25	−0.12***
Household size	7.69	3.38	7.63	3.37	7.68	3.44	−0.05
Income/pc (1,000 Afg)	19.63	19.43	20.49	20.13	17.05	16.43	3.44***
Household head male[a]	0.99	0.08	0.34	0.47	0.35	0.48	−0.01
Age of household head	41.55	13.58	41.00	13.47	42.93	13.89	−1.93***
Household head literate[a]	0.34	0.47	0.34	0.47	0.35	0.48	−0.01
Household head employed[a]	0.89	0.32	0.89	0.31	0.87	0.33	0.02**
Household head married[a]	0.96	0.19	0.96	0.20	0.96	0.19	0.00
Nearest drivable road (in km)	2.91	6.59	3.18	6.94	2.41	5.53	0.77***
Open plain[a]	0.49	0.50	0.55	0.50	0.28	0.45	0.27***
Valley and hills[a]	0.30	0.46	0.25	0.43	0.48	0.50	−0.23***
Valley[a]	0.18	0.39	0.18	0.38	0.20	0.40	−0.02***
Hills (no valley cultivation)[a]	0.03	0.16	0.02	0.15	0.05	0.21	−0.03***
	Coping strategies						
Food on credit[a]	0.18	0.38	0.12	0.32	0.40	0.49	−0.28***
Loans[a]	0.27	0.44	0.21	0.41	0.46	0.50	−0.24***
Sold assets[a]	0.03	0.17	0.02	0.15	0.06	0.23	−0.04***
Reduced quality[a]	0.40	0.49	0.34	0.47	0.60	0.49	−0.26***
Skipped meals[a]	0.12	0.32	0.10	0.30	0.18	0.38	−0.08***

(Continues)

TABLE 1 (Continued)

Variable	Full sample Mean (1)	Full sample SD (2)	Non-flood affected Mean (3)	Non-flood affected SD (4)	Flood affected Mean (5)	Flood affected SD (6)	Difference (7)
Help from community[a]	0.10	0.30	0.06	0.24	0.22	0.41	−0.15***
Number of provinces	34						
Number of districts	345						
Number of observations	20,325[d]						

Notes: Results are based on NRVA 2011–12 data. SD stands for standard deviation.

[a] Dummy variables.

[b] Deficiencies are measured at the household level in adult equivalents.

[c] Based on a survey item that asks respondents whether in the year prior to interview, the household was negatively affected by a flood.

[d] The dependent variable computations exclude observations with values above three standard deviations (and below 500 kcal for calorie consumption). The exact numbers of observations are 20,325 for kcal, 20,368 for iron, 20,301 for vitamin A, and 20,520 for vitamin C. The independent variable computations are based on the sample nonmissing in the variable kcal (20,325 observations).

*$p < .1$.

**$p < .05$.

***$p < .01$.

TABLE 2 Flood effect on Kcal consumption and deficiency (2SLS)

	Kcal/pc. (1)	Kcal deficiency (2)	Kcal/pc. (3)	Kcal deficiency (4)
Flood[a]	−69.334***	0.017**	−57.183***	0.013
	(21.061)	(0.007)	(20.792)	(0.008)
Income/pc (1,000 Afg.)			7.958***	−0.001***
			(0.612)	(0.0001)
Price shock[b]			−195.355***	0.042***
			(19.828)	(0.007)
Constant	3,359***	0.445***	3,235***	0.438***
	(76.863)	(0.029)	(8.985)	(0.031)
Household controls	**Yes**	**Yes**	**Yes**	**Yes**
Topography FE	**Yes**	**Yes**	**Yes**	**Yes**
Province FE	**Yes**	**Yes**	**Yes**	**Yes**
Observations	20,325	20,325	20,246	20,246
Weak Instrument (F.stat)	23.567	23.567	24.559	26.753
J-test (*p*-value)	.227	.605	.330	.550

Notes: Results are based on NRVA 2011–12 data, with deficiency defined as kcal <2,100. All regressions control for household characteristics, topography, and province fixed effects and are estimated using sampling survey weights. Standard errors (in parentheses) are clustered at the district level.

[a] Dummy variable equal to 1 if the household was negatively affected by a flood in the past year; 0 otherwise.

[b] Dummy variable equal to 1 if the household was affected by a price shock in the past year; 0 otherwise.

*$p < .1$.

**$p < .05$.

***$p < .01$.

floods, who are also 27 percentage points (pp) less likely to live in open plain areas and 23 pp more likely to reside in a valley or in hills. Households living in flooded areas also reported more frequent engagement in all of the six coping strategies.

5.2 | Effects of flooding on food consumption

Table 2 reports the 2SLS estimates for the effect of flood exposure in the 12 months before interview on equivalized

TABLE 3 Flood effect on iron consumption and deficiency (2SLS)

	Iron/pc. (1)	**Iron deficiency** (2)	**Iron/pc.** (3)	**Iron deficiency** (4)
Flood[a]	−58.119***	0.107***	−52.030***	0.113***
	(8.405)	(0.013)	(8.414)	(0.012)
Income/pc (1,000 Afg.)			0.249	−0.0009***
			(0.176)	(0.0001)
Price shock[b]			−102.337***	0.044***
			(8.227)	(0.005)
Constant	343.332***	0.137***	429.310***	0.102***
	(27.397)	(0.019)	(29.011)	(0.012)
Household controls	**Yes**	**Yes**	**Yes**	**Yes**
Topography FE	**Yes**	**Yes**	**Yes**	**Yes**
Province FE	**Yes**	**Yes**	**Yes**	**Yes**
Observations	20,368	20,368	20,281	20,281
Weak Instrument (F.stat)	15.209	9.645	15.082	8.995
J-test (*p*-value)	.566	.497	.574	.513

Notes: Results are based on NRVA 2011–12 data, with iron deficiency defined as <27.4 mg/day. All regressions control for household characteristics, topography, and province fixed effects and are estimated using sampling survey weights. Standard errors (in parentheses) are clustered at the district level.

[a] Dummy variable equal to 1 if the household was negatively affected by a flood in the past year; 0 otherwise.

[b] Dummy variable equal to 1 if the household was affected by a price shock in the past year; 0 otherwise.

$^{*}p < .1$.

$^{**}p < .05$.

$^{***}p < .01$.

per capita calorie consumption (columns (1) and (3)) and the probability of inadequate consumption (kcal < 2,100; columns (2) and (4)). When the dummy for price shock exposure and household income are excluded (included), flood exposure lowers the per capita consumption by 69.33 kcal (57.18 kcal). Floods also increase the probability of a household being calorie deficient by 1.7 pp, but this effect becomes insignificant once we control for income and the price shock variables.

When we estimate the 2SLS flood coefficients using the equivalized consumption of iron and vitamin A and related deficiency as the dependent variables (see Tables 2 and 3), exposure to floods leads to 58.2–52.0 mg lower iron consumption (Table 3, columns (1) and (3)) and a 10.7–11.3 pp higher probability of being deficient in this micronutrient (columns (2) and (4)). Likewise, when vitamin A in micrograms is the outcome variable (Table 4), flood exposure in the year before interview results in a 373.2–332.0 μg reduction in equivalized vitamin A consumption (columns (1) and (3)) and a 11.9–21.3 pp higher probability of being deficient (columns (2) and (4)). Floods are similarly responsible for a 35.4–29 mg decrease in equivalized vitamin C consumption (Table 5, columns (1) and (2)) and a 30.3–26.7 pp higher probability of deficiency in this micronutrient (columns (3) and (4)). We also compute iodine consumption, but as expected, because Afghanistan is an area of endemic iodine deficiency (Levitt et al., 2010), we find no flooding effect on equivalized iodine levels.

5.3 | Effects of flooding on poverty status and income

To provide evidence for flooding's long-term effects on food security, we explore the effect of this shock on two important dimensions of food access measured over the 12-month period before interview; namely, a poverty status dummy (calculated using a cost of basic needs approach) and per capita yearly monetary income. As Table 6 shows, households exposed to floods in the year before interview are 2.5–3.1 pp more likely to be deemed poor (columns (1) and (2)). Hence, although we do not believe that selection bias (when flood-affected households differ systematically from unaffected households) is likely to be a major problem for our Afghan sample, we account for possible differences by including household income as a covariate in the poverty regression. We find that the flood coefficient does indeed remain significant and stable at 0.26 (column (3)): in fact, flood exposure decreases per capita yearly income by around 3% (column (4)).

TABLE 4 Flood effect on vitamin A consumption and deficiency (2SLS)

	Vit. A/pc. (1)	Vit. A deficiency (2)	Vit. A /pc. (3)	Vit. A deficiency (4)
Flood[a]	−373.238***	0.213***	−332.055***	0.119***
	(22.086)	(0.014)	(23.484)	(0.015)
Income/pc (1,000 Afg.)			3.725***	−0.002***
			(0.366)	(0.0002)
Price shock[b]			−16.223	−0.0009
			(11.759)	(0.007)
Constant	1,072***	0.397***	429.310***	0.199***
	(22.986)	(0.025)	(29.011)	(0.015)
Household controls	**Yes**	**Yes**	**Yes**	**Yes**
Topography FE	**Yes**	**Yes**	**Yes**	**Yes**
Province FE	**Yes**	**Yes**	**Yes**	**Yes**
Observations	20,258	20,258	20,179	20,179
Weak Instrument (*F*-stat)	25.864	16.284	22.166	18.166
J-test (*p*-value)	.067	.113	.072	.157

Notes: Results are based on NRVA 2011–12 data, with vit. A deficiency defined as <600 μg/day. All regressions control for household characteristics, topography, and province fixed effects and are estimated using sampling survey weights. Standard errors (in parentheses) are clustered at the district level.

[a] Dummy variable equal to 1 if the household was negatively affected by a flood in the past year; 0 otherwise.

[b] Dummy variable equal to 1 if the household was affected by a price shock in the past year; 0 otherwise.

*$p < .1$.

**$p < .05$.

***$p < 0.01$.

TABLE 5 Flood effect on vitamin C consumption and deficiency (2SLS)

	Vit. C/pc. (1)	Vit. C deficiency (2)	Vit. C /pc. (3)	Vit. C deficiency (4)
Flood[a]	−35.407***	0.303***	−29.017***	0.267***
	(2.133)	(0.015)	(2.173)	(0.015)
Income/pc (1,000 Afg.)			0.565***	−0.002***
			(0.043)	(0.0001)
Price shock[b]			−5.978***	0.041***
			(1.058)	(0.008)
Constant	155,771***	0.061**	140.905***	0.058**
	(4.067)	(0.025)	(4.089)	(0.025)
Household controls	**Yes**	**Yes**	**Yes**	**Yes**
Topography FE	**Yes**	**Yes**	**Yes**	**Yes**
Province FE	**Yes**	**Yes**	**Yes**	**Yes**
Observations	20,575	20,575	20,493	20,493
Weak Instrument (*F*-stat)	20.225	12.418	17.536	14.693
J-test (*p*-value)	.066	.043	.335	.0668

Notes: Results are based on NRVA 2011–12 data, with vit. C deficiency defined as <45 mg/day. All regressions control for household characteristics, topography, and province fixed effects and are estimated using sampling survey weight. Standard errors (in parentheses) are clustered at the district level. [a] Dummy variable equal to 1 if the household was negatively affected by a flood in the past year; 0 otherwise. [b] Dummy variable equal to 1 if the household was affected by a price shock in the past year; 0 otherwise.

*$p < .1$.

**$p < .05$.

***$p < .01$.

TABLE 6 Flood effect on poverty and yearly household income (2SLS)

	Poverty		Income (IHS)	
	(1)	(2)	(3)	(4)
Flood[a]	0.031***	0.025***	0.026**	−0.030**
	(0.009)	(0.009)	(0.009)	(0.013)
Price shock[b]		0.097***	0.081***	
		(0.007)	(0.007)	
Income/pc (1,000 Afg)			−0.004***	
			(0.0002)	
Constant	0.261***	0.171***	0.359***	4.283***
	(0.031)	(0.032)	(0.033)	(0.042)
Household controls	**Yes**	**Yes**	**Yes**	**Yes**
Topography FE	**Yes**	**Yes**	**Yes**	**Yes**
Province FE	**Yes**	**Yes**	**Yes**	**Yes**
Observations	19,505	19,505	19,419	20,647
Weak Instrument (*F*-stat)	10.127	9.898	9.920	10.225
J-test (*p*-value)	.417	.498	.418	.148

Notes: Results are based on NRVA 2011–12 data, with the poverty line calculated using a cost of basic needs approach and household income measured in Afghani per capita per year. All regressions control for household characteristics, topography, and province fixed effects and are estimated using sampling survey weights. Standard errors (in parentheses) are clustered at the district level.

[a] Dummy variable equal to 1 if the household was negatively affected by a flood in the past year; 0 otherwise.

[b] Dummy variable equal to 1 if the household was affected by a price shock in the past year; 0 otherwise.

*$p < .1$.

**$p < .05$.

***$p < .01$.

5.4 | Floods and coping strategies

As regards the association between flood exposure in the year before interview and engaging in one of the six coping strategies (Table 7), when confronted with the negative shock of a flood, households are more likely to smooth their calorie consumption by opting for lower food quality (10.6 pp), taking out loans (7.4 pp), and/or purchasing food on credit (4.9 pp). They are only 2.4–2.5 pp more likely, however, to invoke the coping strategies of skipping meals, selling assets, and accepting community help, probably because selling assets, especially means of production, may trap households into poverty for years, whereas asking for community help may be ineffectual in the circumstances. That is, floods (like economic crises) affect entire groups of the population, so informal mitigation and community-based coping mechanisms may be infeasible (Skoufias, 2003). These results are in line with those of previous research, including the finding in Akampumuza and Matsuda (2017) of no causal relation between weather shocks in urban Uganda and the likelihood of selling assets or livestock. Rather, as in our sample, the Ugandan households hit by such shocks are 11.6 pp more likely to rely on credit. Likewise, in research for Nepal, access to credit enhances the probability of adaptation by enabling better household implementation of adaptive strategies (Khanal, Wilson, Hoang, & Lee, 2018).

In Section A of the Online Appendix, we report the OLS estimations of flood exposure on calorie (Table A.2) and micronutrient (Tables A.3–A.5) consumption/deficiency, and yearly income and poverty status (Table A.5). The most noteworthy aspect of these tables is that the OLS flood estimates using calorie and iron consumption/deficiency (Tables A.2 and A.3) and income/poverty (Table A.6) as dependent variables are virtually identical to those from the corresponding 2SLS models (Tables 2, 3, and 6), a coefficient stability that confirms the appropriateness of our 2SLS strategy. Comparing the OLS and 2SLS results for vitamins A and C, in contrast, indicates that the uninstrumented models (Tables A.4 and A.5) understate flood exposure effect. These results thus support our assumption that the greater heterogeneity in micronutrient-related coping abilities (vitamins A and C) is more common in relation to easily perishable foods (e.g., fresh fruit and vegetables). In fact, a lower likelihood of the more resilient households reporting flood exposure would increase the average observed control group outcome and, in an OLS setting, produce downwardly biased estimates.

TABLE 7 Flood effect on the probability of adopting coping strategies (OLS)

	Skip meals (1)	Lower quality (2)	Take loans (3)	Use credit (4)	Sell assets (5)	Community help (6)
Flood[a]	0.024**	0.106***	0.074***	0.049***	0.024**	0.025*
	(0.012)	(0.018)	(0.021)	(0.015)	(0.010)	(0.014)
Violence[b]	0.069***	0.166***	0.105***	0.040***	0.009	0.031***
	(0.020)	(0.024)	(0.025)	(0.013)	(0.007)	(0.011)
Income/pc	−0.001***	−0.002***	−0.002***	−0.001***	−0.0002*	−0.0001
(1,000 Afg)	(0.0001)	(0.0003)	(0.0004)	(0.0002)	(0.0001)	(0.0001)
Constant	0.821***	0.961***	0.484***	0.742***	0.119***	0.269***
	(0.042)	(0.031)	(0.043)	(0.067)	(0.024)	(0.030)
HH controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Topogr. FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Province FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Observations	20,627	20,627	20,627	20,627	20,627	20,627
Adjusted R^2	0.369	0.336	0.281	0.363	0.077	0.321
Res. std. error	3.162	5.108	5.015	3.815	1.940	2.842
F statistic	***	***	***	***	***	***

Notes: Results are based on NRVA 2011–12 data for six coping strategies: reducing food quantity or skipping meals, reducing diet quality, taking out loans, purchasing food on credit from traders, accepting help from the community, and selling assets. All regressions control for household characteristics, topography, and province fixed effects and are estimated using sampling survey weights. Standard errors (in parentheses) are clustered at the district level. [a]Dummy variable equal to 1 if the household was negatively affected by a flood in the past year; 0 otherwise. [b]Dummy variable equal to 1 if the household was affected by violence in the past year; 0 otherwise.

*$p < .1$.

**$p < .05$.

***$p < .01$.

6 | DISCUSSION

This analysis of data 2011/2012 Afghanistan National Risk and Vulnerability Assessment (NRVA) survey data clearly demonstrates a significant flood effect on food security in the long term, not only on calorie but also on micronutrient consumption. These long-term effects are not surprising, not only because flooding in Afghanistan is particularly catastrophic, but also in the light of the protracted occurrence of such disasters in the country.

According to our analysis, households negatively affected by floods suffer a reduction in calorie consumption of approximately 60 kcal per day per adult equivalent. Although this deficit amounts to only about 3% of the recommended daily requirement, such small changes in daily calorie consumption can have negative long-term effects on body weight (Hill et al., 2003). This reduction of about 60 kcal per day is also remarkable, given that our flooding exposure measure has two characteristics likely to dilute flooding's negative effects on calorie consumption: first, it is a relatively long-term indicator (i.e., over the year prior to interview), and second, it does not record the severity of the flood exposure. Moreover, as indicated by Del Ninno et al. (2003) in their analysis of the effect on child health of the severe Bangladeshi floods of 1998, even small changes in calorie consumption can have lasting effects on populations with a low baseline level of resources. Taken together, the relatively small effect of flood exposure on calorie consumption (deficiency) and the more pronounced detrimental effect that this disaster has on the probability of poverty (2.5–3.1 pp) and nominal income (3%) suggest that flood-affected households reallocate financial resources in favor of calorie consumption (cf. Akampumuza & Matsuda, 2017). Because the effect of floods on micronutrients is of significant magnitude, we further assume that any smoothing of this food consumption largely favors staples, a quality-for-quantity trade-off corroborated by D'Souza and Jolliffe (2012) in their analysis of the 2007/2008 rise in Afghan food prices.

At the same time, by showing flood exposure's negative effect on the consumption of important micronutrients like vitamin A, vitamin C, and iron, our analysis underscores its negative impact on food diversity. In fact, the flood effects for all three of these micronutrients are relatively strong, with the probabilities of iron and vitamin A and C deficiency increasing by 11, 12, and 27 pp, respectively. Given that the Afghan households in our sample are 10.6 pp more likely to reduce food quality while about 2.4 pp to skip meals in response to a negative flood shock, this latter's strong effects on micronutrient consumption may even result from coping strategies that reduce a household's food diversity. This conclusion is in line with previous evidence that coping strategies do not improve micronutrient consumption (see Skoufias, 2003, for a review).

One important mechanism through which floods affect food security in the longer term is their effect on income and poverty. In fact, flood-affected households in our sample had a 3.1 pp higher probability of falling below the poverty line as determined by a cost of basic needs approach. It is especially noteworthy that this effect only falls to 2.5 pp when we control for price shocks, suggesting that flooding's effect on poverty is driven primarily by its impairment of livelihood (e.g., the loss of livestock, agricultural production, and employment) and only to a lesser extent by its negative effect on prices.

The effect size of reduced calorie consumption is also in line with those of other studies with a longer than immediate perspective (i.e., months to years), albeit somewhat smaller. For example, Del Ninno et al. (2002) estimate that the calorie consumption of Bangladeshi flood-exposed households decreased by 227 kcal a few months after being affected by the 1998 flooding. In D'Souza and Jolliffe (2013), each extra fatality per 10,000 inhabitants in the year before interview decreased household calorie consumption by about 2–9% (as compared to our 2% reduction). Although we are aware of no studies whose assessment of a natural disaster's effects on micronutrient consumption/deficiency permits direct comparison, Del Ninno et al. (2003) finding that the 1998 Bangladeshi flooding reduced the budget share for rice, milk, and fruits accords with our evidence for increased micronutrient deficiencies and lower diet quality among flood-affected households. It should nonetheless be noted that while these authors observe substantial recovery within 8 months of the flood, the case of Afghanistan is likely to differ based on the interaction of a variety of protracted and frequent shocks (e.g., violence and natural disasters) that country has suffered over many years.

As relevant as the above observations are, however, and as promising as self-reported flood exposure may be as a way to assess flooding's influence on food security, we acknowledge that our data are subject to certain limitations; in particular, the inability to identify flood severity or assess the exact measurement (or recollection) error in responses. Yet, the former would assumedly impose only a downward bias on our results, while the richness of our dataset and the 2SLS approach employed greatly reduce the potential for endogeneity from either omitted variables or measurement error. We do nonetheless acknowledge that using an objective flood index to measure flooding (as in Del Ninno et al., 2003) would overcome the problems related to both satellite and self-reported exposure measures but unfortunately, we know of no such data source for Afghanistan.

One important contribution of our study is that it highlights the need for proactive policy measures at all levels of government and at the household level, an approach already elaborated by both academic researchers and international organizations (e.g., Devereux, 2007; Douglas, 2009; WFP & UNEP, 2016) and proved successful in other contexts (e.g., Khandker, 2007). At the national level, such measures would include grain storage, investment, and changes in agricultural policies to adapt crop mixtures and agricultural practices to changing climate. At the local level, they might take the form of small-scale infrastructure investment for groundwater recharge, irrigation and flood protection, local seed banks, and coordination of adaptive responses. Households themselves could mitigate the negative effects of flooding by diversifying livelihoods, investing in human and physical capital, and changing agricultural practices. However, in a context of protracted physical insecurity such as the Afghan one, it could be challenging to adopt these household-level responses. Nonetheless, disaster relief and food aid at all levels of government are crucial because although the long-term effect of flooding on calorie consumption appears limited, the same is not true for micronutrients. Not only does this latter imply that disaster relief should incorporate micronutrient supplementation beyond the natural disaster emergency, it underscores that, based on the severe micronutrient deficiency in Afghanistan, targeted supplementation of micronutrients is of paramount importance.

7 | CONCLUSIONS

Afghanistan is particularly strongly affected by climate-change related flooding, with over a fifth of the population impacted in just one 12-month period between 2011 and 2012. According to our analysis, such flooding has a significant effect on both calorie and micronutrient consumption. These long-term effects are further confirmed by the analysis of the detrimental effects of flood on income and poverty measured in the year before interview. Moreover, even though households seem relatively efficient in implementing various coping strategies to mitigate calorie deficiency in their diets, there is evidence of a diet quantity-quality trade-off against micronutrient consumption. Lastly, we suspect that had our study design enabled estimation of the flooding effect net of preshock household adaptation to climate change and government or NGO intervention, the true effect of flooding would be even more severe.

Based on the above observations, targeted disaster relief and food aid should consider micronutrient supplementation for vulnerable population groups. At the same time, because interventions are more effective when based on mitigation policies already in place before the shock occurs (Skoufias, 2003), local governments and households should be guided in better identifying disaster-prone areas to limit the potential exposure to these shock events. To date, several programs have been developed aimed at reducing both the risk and detrimental effects of natural disasters on the various dimensions of Afghan human development. For example, the World Bank Afghanistan Disaster Risk Management and Resilience Program has implemented an irrigation restoration and development project, as well as an Afghanistan rural access project. Nevertheless, more robust microlevel empirical analysis is needed to uncover the dynamics between risk exposure and adaptation to or coping with climate change outcomes.

DATA APPENDIX AVAILABLE ONLINE

A data appendix to replicate the main results is available in the online version of this article. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.

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CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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