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Heterogeneous effects of weather extremes on different dimensions of poverty in Kyrgyzstan

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Abstract

Weather extremes become more frequent and intense with climate change, but how weather extremes impact household wealth in the Global South remains elusive in many regions. We combined nationally representative quarterly household panel data with climate data to evaluate the impact of weather extremes on household poverty in Kyrgyzstan between 2013 and 2020. We evaluated multiple dimensions of poverty by quantifying changes in nutrition, education, health, and living standards. We used a linear quantile mixed model to relate the poverty dimensions with four salient weather extremes: cold winters, hot summers, excessive rains, and dry spells. Our findings show that all weather extremes harmed household wealth but with substantial spatial variation. Cold winters were the most detrimental, with negative consequences that continued into the subsequent year. Poor households suffered disproportionally more from extremes than rich ones. Our results underscore the need to initiate place-based adaptation options to cushion the adverse effects of extreme weather events on household wealth.

1. Introduction

With climate change, weather extremes become more frequent, which jeopardizes household livelihoods, particularly in the Global South (Spilker *et al* 2020, Soergel *et al* 2021). More frequent and intense extreme weather events, such as cold winters, hot summers, excessive rains, and dry spells, already substantially impact ecosystems and humans (Barrett *et al* 2011, Sandhu and Sandhu 2014). The suddenness and variability of weather extremes exacerbate social and economic inequalities, especially for unprepared and marginalized rural communities (Tenzing and Conway 2022, Rao *et al* 2023). Therefore, it is essential to understand the effects of weather extremes on household wealth, particularly for vulnerable households with limited resilience to external shocks.

Developing countries are particularly vulnerable to climate change due to their heavy dependence on natural resources and the challenges posed by low-income levels for timely adaptation (Arouri *et al* 2015, Salvucci and Santos 2020). Previous research has demonstrated that climate change has a greater negative impact on income in the Global South compared to the Global North (Tol 2009, Azzarri and Signorelli 2020). Furthermore, evidence suggests that climate change disproportionately affects impoverished individuals, particularly in disadvantaged regions (Hallegatte and Rozenberg 2017, Barbier and Hochard 2018, Hallegate *et al* 2020). However, how climate change, particularly weather extremes, impacts multiple dimensions of wealth and poverty and how these effects vary across space remains understudied in many regions (Adenle *et al* 2017).

Poverty encompasses more than just income and consumption; it includes deficits in well-being, positive emotions, relationships, social freedoms, and opportunities for personal development (Adger *et al* 2022). To effectively address poverty, interventions must consider these multiple dimensions and target them accordingly (Dika *et al* 2021). Empirical evidence further suggests that the effects of climate change and adaptation options to these changes differ substantially between households and regions (Bryan *et al* 2013, Thornton and Herrero 2014, Carman and Zint 2020).

The existing empirical literature focuses on analyzing the effect of weather extremes on poverty on the sample mean but often neglects within-sample heterogeneity. People living in poverty are more susceptible to weather shocks and recover more slowly than affluent population segments. Evidence testifies that poor households receive less support from friends, family, and social safety nets after a natural disaster than wealthier households (Hallegatte and Rozenberg 2017). Quantifying the effects of weather-related shocks on poverty requires a disaggregated perspective to account for socioeconomic heterogeneity within countries and regions (Nguyen *et al* 2020).

Spatial targeting and wealth mapping are critical to determine how the effects of climate change impact poverty by region and district (Marcinko *et al* 2022). Spatially disaggregated analyses are, therefore, especially paramount for countries that suffer disproportionately from the effects of changing weather patterns. However, subnational analysis in developing countries remains limited due to high data requirements, such as georeferenced household panel data, which allow overlaying meteorological data and control for unobserved individual and household characteristics.

Central Asia is a blind spot in analyses of spatially disaggregated impacts of weather on the multiple dimensions of poverty. Recent research has elucidated the adverse impacts of how extreme weather increases the probability of stunting of children and reduces birth outcomes in Kyrgyzstan, where extreme weather, such as droughts, floods, and cold spells, severely affect children under 20 months of age and rainfall damaged prenatal birth weights (Freudenreich *et al* 2022, Nguyen and Le 2022). Our analysis aims to evaluate the effects of weather extremes on poverty with nationally representative, location-matched, quarterly household panel data from Kyrgyz households. We use a linear quantile mixed model (LQMM) to quantify how four types of weather extremes (extreme winter cold, extreme summer heat, excessive rainfall, and drought) affect the different dimensions of poverty and how these effects are distributed throughout Kyrgyzstan.

Kyrgyzstan is an interesting case because almost 70% of the population lives in rural areas, and nearly 25% of the population was below the national poverty line in 2020 (Nguyen and Le 2022). Additionally, the country suffers from frequent and variable extreme rainfall, heat waves, and harsh winters (World Bank 2021). Weather extremes and the lack of adaptive capacity to these extremes make Kyrgyzstan one of the most vulnerable countries in Central Asia (UNICEF 2017).

2. Methods

2.1. Identifying poverty

Poverty measures such as the Human Development Index, the Human Poverty Index, and the Multidimensional Poverty Index (MPI) (Alkire and Santos 2014) define poverty as a multidimensional phenomenon. Our MPI for Kyrgyzstan, MPI_{KGZ}, comprises ten deprivation indicators that proxy poverty along four dimensions: *nutrition, education, health*, and *living standards* (see figure 1 and table A1 for a detailed definition). Each dimension was linked to the Millennium Development Goals at the time and is equally weighted across dimensions (Alkire and Santos 2014). The MPI_{KGZ} is continuous and ranges from 0 to 1, with higher values indicating a wealthier household status. However, the original MPI was designed for low-income contexts.

We adapt the original MPI to the conditions prevalent in Kyrgyzstan to account for the local specificities due to the Soviet past (see A1 for a detailed description of the method). The original MPI includes nutrition and child mortality indicators as part of the health dimension. However, child mortality in Kyrgyzstan is very low, comparable to high-income countries, and does not show variation between regions. Consequently, we exclude *child mortality* from MPI_{KGZ} and isolate *nutrition* as a separate dimension.

The general energy intake of the Kyrgyz people is sufficient and there is no undernourishment in the country. However, the quality of the diets of low-income households suffers from a low variety (Rodriguez-Cruz *et al* 2022). Consequently, we measure the dimension of *nutrition* by relying on the degree of diversification. We aggregated food expenditure shares into ten groups: cereals, flour products, edible oils, fruits & vegetables, processed food, eggs, & meat, & fish, dairy products, drinks, sugar, and miscellaneous items (Kimsanova *et al* 2023). These groups form the Berry Index, which shows the degree of food diversification as

$$BI = 1 - \sum_{i=1}^{10} \omega_i^2, \tag{1}$$

where ω_i is the share of expenditures on food group i in the household's total consumption expenditure (Thiele and Weiss 2003, Herzfeld *et al* 2014). The value of the Berry Index is between 0 and 1, with higher values indicating a more varied diet.

The second dimension of the original MPI is *education*, with *years of schooling* and *school attendance* as indicators. The education level in Kyrgyzstan is higher than in African countries due to nine years of compulsory schooling. Consequently, we replace

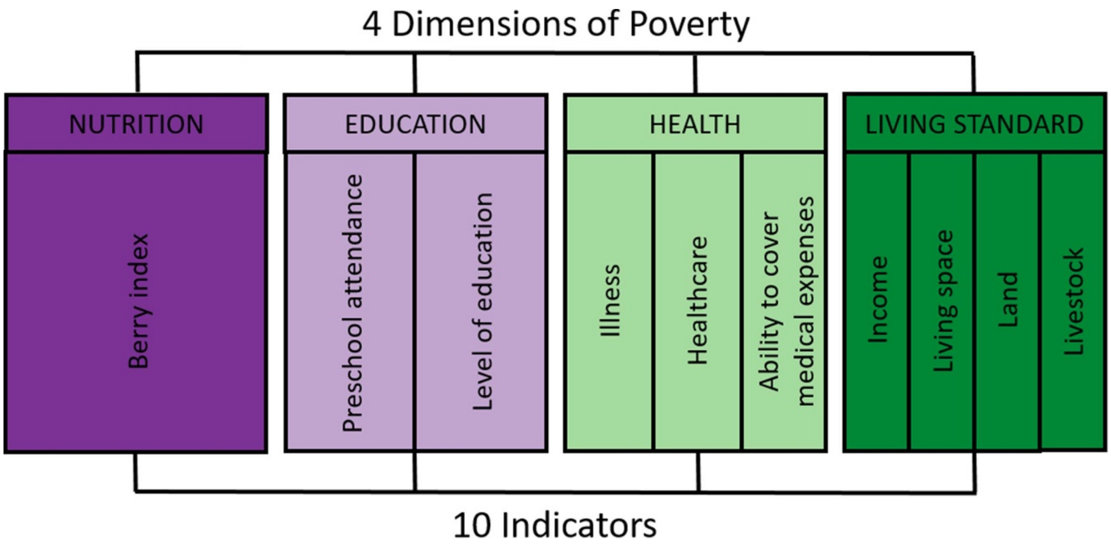

Figure 1. Multidimensional Poverty Index for Kyrgyzstan (Alkire and Santos 2014). Source: Authors' figure.

the original indicators of *school attendance* and *years of schooling* with *preschool attendance* and *level of education*, where the latter includes household heads without 11 years of education.

We include *health* as a separate dimension with three indicators: *illness, healthcare*, and *ability to cover medical expenses*. These focus on identifying the inability to receive medical assistance (Bambrick *et al* 2015). Kyrgyz households can suffer from severe health problems due to the country's lack of health insurance (Moldoisaeva *et al* 2022). In addition, medical treatment is expensive and unaffordable for poor households.

Finally, *living standard* in the original MPI includes *cooking fuel, sanitation, drinking water, electricity, housing*, and *assets* as a welfare measure. However, these are basic needs and are satisfied by each Kyrgyz household, thus failing to distinguish the level of welfare. Therefore, our *living standard* measure consists of *income* and *living space* for urban and rural subsamples and of *land* and *livestock* for rural households. *Income* and *living space* are normalized and standardized for urban and rural subsamples to avoid discrimination against rural households. We measure the existence of *livestock* and *agricultural land* only for rural households, as those are unavailable for urban households.

2.2. Household survey data

We use data from the Kyrgyz Integrated Household Survey (KIHS), conducted quarterly each year by the Kyrgyz Republic's National Statistical Committee for 2013–2020. The KIHS is a rotating panel that forms a nationally representative sample of nearly 5000 households each quarter since its inception in 2003. The sampling procedure is stratified into urban and rural areas within the seven provinces and the capital city of Bishkek, resulting in sampling strata. In 2013, the sample was renewed with additional information on the location of households in 206 districts. Therefore, our analysis is based on households included in the survey in 2013, and our sample runs until 2020 (for more details of the panel characteristics, see table A2).

The survey provides information on a broad set of individual, household, and community characteristics, including demographics, education, health, employment, monthly expenditures, durable goods, land, livestock, housing conditions, income, and transfers. The means of indicators used in the $\mathrm{MPI}_{\mathrm{KGZ}}$ assessment at the household level, separating the sample into three subsamples (terciles), are presented in table 1. The sample is skewed to the right with a mean of .69 (minimum = .29, maximum = .93). All variables are linearly related across terciles except income, living space, and agricultural land. The distribution of households by poverty level is illustrated in figure 2.

2.3. Identifying weather extremes

We selected three types of extreme weather events that were self-reported by Kyrgyz households in the national household survey 'Life in Kyrgyzstan' (LiK study 2010–2019). These are cold winters (reported by 25% of interviewed households), excessive rainfalls (33%), and dry spells (16%). We also include hot summer waves, which pose an additional challenge for Kyrgyzstan (Lee *et al* 2023).

To define dry spells, we use the standardized precipitation index (SPI), a commonly used index to estimate deviations of recorded precipitation from long-term average levels (WMO 2012). The SPI ranges from −3 to +3 and is calculated by normalizing the precipitation at a predefined time scale after fitting it to its long-term probability density function (McKee *et al* 1993).

Table 1. Means of indicators used in MPI_{KGZ} computation.

		Poor	Middle	Rich
	MPI	.61	.71	.75
1	Berry Index	.75	.76	.81
2	Children out of preschool due to financial constraints (%)	9	3	0
	Household heads without a secondary education (%)	33	0	0
3	People who cannot afford medical care (%)	22	6	2
	People who cannot afford hospital treatment (%)	19	7	1
	People who cannot cover medical expenses (%)	76	43	10
4	Monthly household income (1000 KGS)	56.27	45.22	69.63
	Living space per person (m^2)	18.04	16.48	23.73
	Agricultural land (ha)	.83	.68	.70
	Livestock (LSU)	1.64	1.44	1.62
	Number of households	2616	3099	2833
	Number of observations	32 010	32 010	33 980

Note: poor = lowest tercile, middle = second tercile, rich = highest tercile.

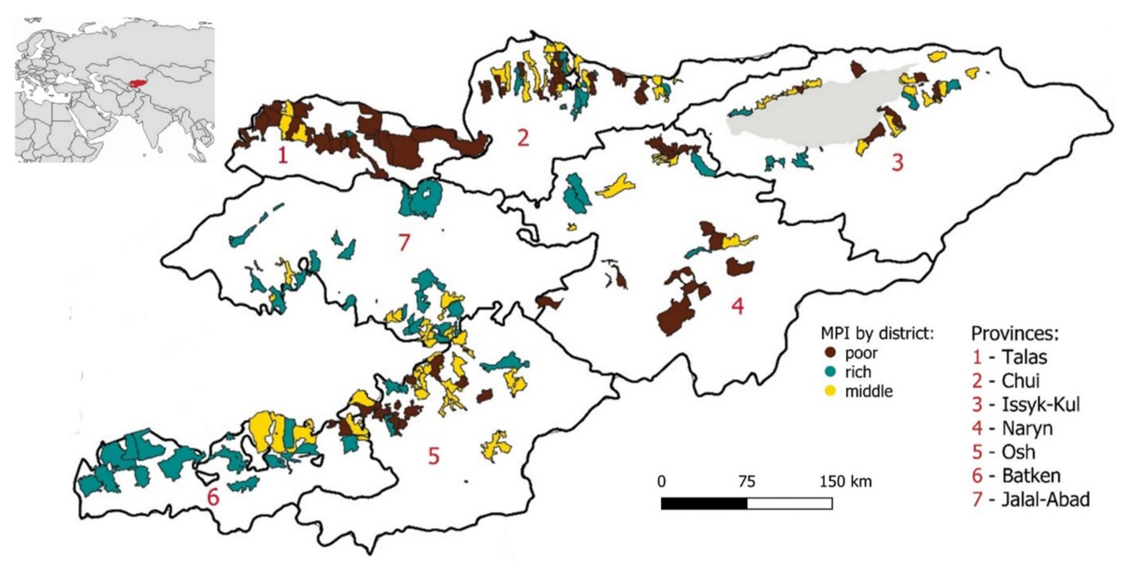

Figure 2. Distribution of households by poverty level.
Note: Tercile I is represented in brown, tercile II in yellow, and tercile III in blue (table A3 presents the MPI by province).

In Kyrgyzstan, water availability during the summer largely depends on rainfall that accumulates as snow during winter in the upstream parts of river basins (Apel *et al* 2018, Cowherd *et al* 2023). We determined dry spell events by calculating the 12 month SPI at the provincial level for a hydrological year that starts in October of the previous year and ends in September. We classified an annual SPI value of less than −1 as a dry spell event corresponding to moderate to severe dry conditions (McKee *et al* 1993). We also calculated a 1 month SPI time series for each district to determine extreme rain events and classified values above +2 during the spring months as excessive rainfall.

We used the standardized temperature index (STI) to capture the effect of temperature extremes. We calculated a time series of 1 month district-level STIs and classified cold winter when the observed STI was less than −2 (severely cold) in January, February, or March. We used these three months to describe winter conditions because, in addition to being cold, long periods of cold and snow in early spring can increase mortality and reduce the productivity of livestock (Kaziev 2021). Hot summers are events in which monthly STI values surpass +2 in July or August. Table 2 summarizes the resulting extreme weather events considered in the following analysis.

2.4. Climate data

We calculated all SPI and STI indices using precipitation and temperature data from the ERA5-Land

Table 2. Derivation of weather extremes.

Variables	Explanation	Spatial resolution
Dry spell (DS)	SPI<-1 for the hydrological year	Province
Excessive rain (ER)	Monthly SPI in spring >2	District
Cold winter (CW)	Monthly STI for January, February, and March <-2	District
Hot summer (HS)	Monthly STI for July, and August >2	District

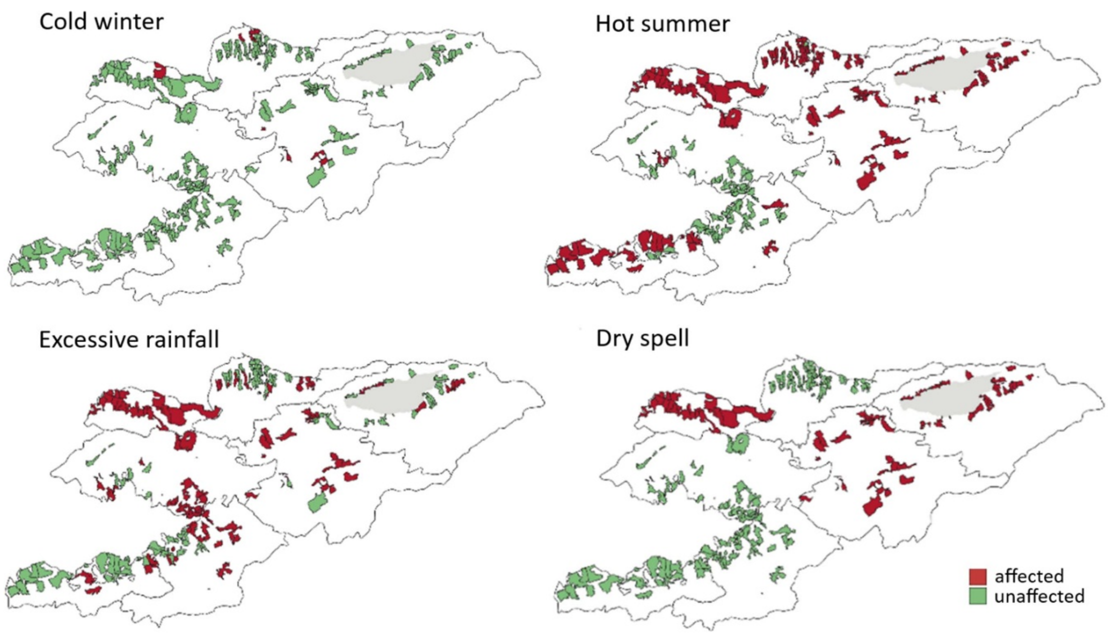

Figure 3. Districts where weather extremes occurred at least once during 2014–2020. *Note*: figure A1 displays the frequency of weather extremes across the country.

global reanalysis dataset (Muñoz-Sabater *et al* 2021), available at a resolution of approximately 9 km. We used the entire 1950–2020 ERA5 Land period to establish long-term climatological averages and calculate the time series of the SPI and STI indices for the boundaries of each district of Kyrgyzstan derived from OCHA (2022). Figure 3 depicts the distribution of districts where we detected at least one instance of a weather extreme.

2.5. Specification of the econometric model

The effects of weather extremes on a household's wealth can be heterogeneous in space and time. We are particularly interested in understanding whether weather extremes affect the poorest households more than more affluent ones. Therefore, we need an estimator that divides our sample into three subsamples, representing the three terciles of the MPI distribution. Additionally, household wealth and weather shocks are clustered in districts that are likely to correlate with unobserved location characteristics, which we account for in the estimations.

We use the LQMM of Geraci and Bottai (2014). The LQMM allows us to model the relationship between independent and dependent variables for each subsample. Furthermore, the model accounts for the potential correlation of household wealth within districts. We use the *lqmm* package of R to analyze the model specified as

$$\mathrm{MPI}_{ij}^{\mathrm{KGZ}} = \alpha^{\tau} + \gamma_i^{\tau} + (\beta^{\tau} + \lambda_i^{\tau})\left(\sum_{n=-3}^{0} \mathrm{CW}_{ij}^{n} + \sum_{n=-3}^{0} \mathrm{HS}_{ij}^{n} + \sum_{n=-2}^{0} \mathrm{ER}_{ij}^{n} + \mathrm{DS}_{ij} + A_{ij} + R_{ij} + \mathrm{AAR}_{ij}\right) + \varepsilon_{ij}^{\tau}, \quad (2)$$

where $\mathrm{MPI}_{ij}^{\mathrm{KGZ}}$ is an $\mathrm{MPI}_{\mathrm{KGZ}}$ of the household i in the district j. CW_{ij}^{n}, HS_{ij}^{n}, ER_{ij}^{n}, and DS_{ij} are the climate variables where n represents lagging values. A_{ij}, R_{ij}, and AR_{ij} signal if a household is farm, rural, or both, as farming infers MPI. α^{τ} and β^{τ} are the fixed intercept and slope of the τth quantile level of interest, respectively. γ_i^{τ} and λ_i^{τ} are the random intercept and slope for the ith household, respectively. ε_{ij}^{τ} is an unexpected error associated with $\mathrm{MPI}_{ij}^{\mathrm{KGZ}}$.

3. Results

3.1. Weather extremes harm household welfare

Weather extremes harm household wealth, with cold winters being the most destructive (figure 4). Poor

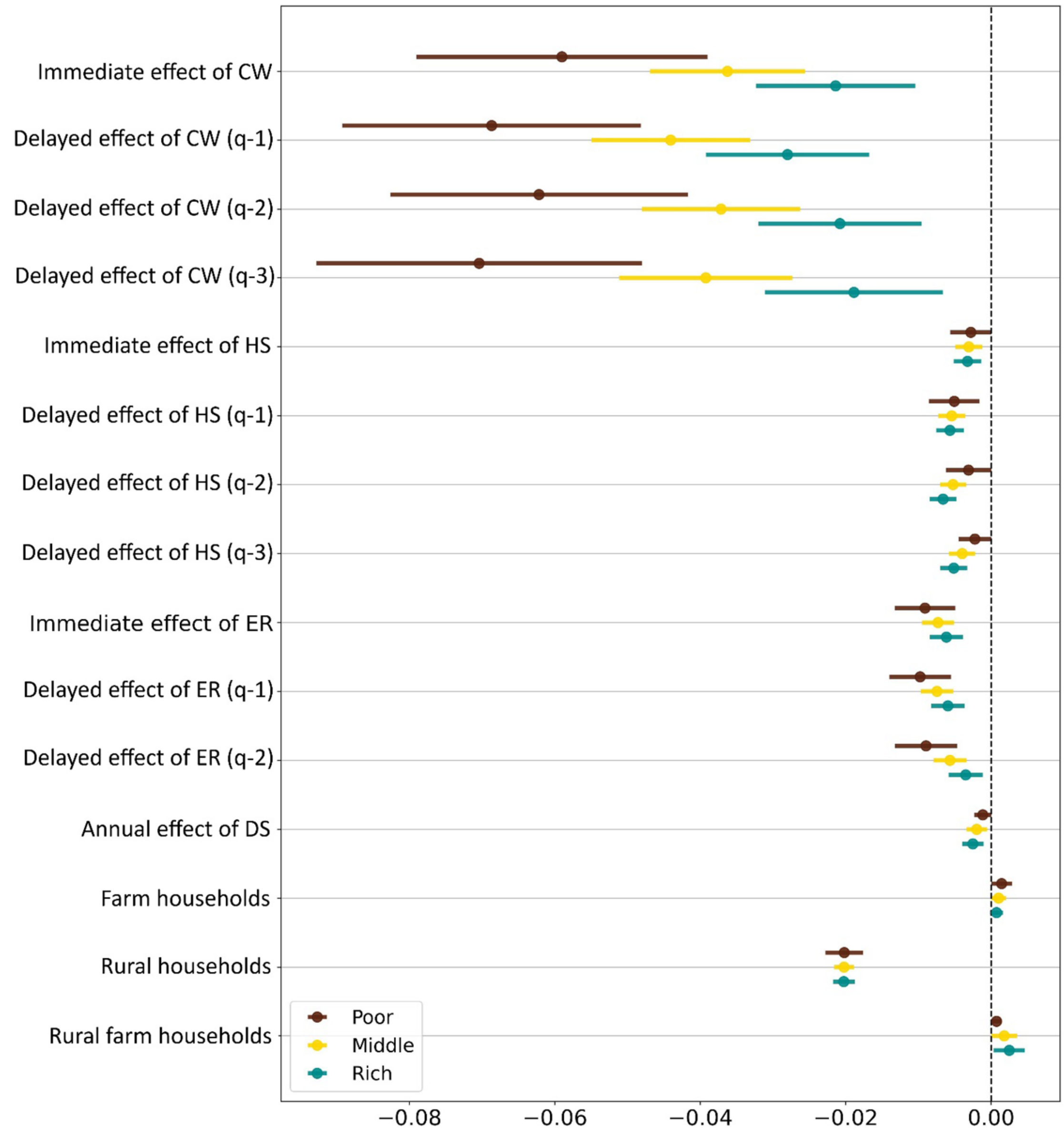

Figure 4. The average partial effects of weather extremes on MPI.
Note: The length of the lines shows the 95% confidence intervals. Immediate and delayed effects of weather extremes on MPI are displayed for up to 3 subsequent quarters (q) and the respective control variables.

households are particularly vulnerable to cold winters and excessive rainfall. The delayed effects of weather shocks over a quarter-year period vary between different types of shocks and poverty classes.

The average partial effect estimates of −.06 for the lowest tercile, −.04 for the second tercile, and −.02 for the highest tercile imply that an immediate cold winter was associated with a 6 percentage points reduction of the MPI for the poor, 4 for the middle, and 2 for the rich. The delayed effects of cold winters in spring and fall further exacerbate poverty, especially for the poor, with a 7 percentage point increase. Overall, the delayed effects of cold winters are greater for the poor and middle classes.

Hot summers, excessive rainfall, and dry spells have comparatively less detrimental effects throughout the year. The immediate effect of hot summers was similar for all households and below 1%, while the delayed effects of hot summers were more harmful to wealthy households. The immediate and delayed effects of excessive rainfall are the same for all households. The annual effect of a dry spell is negligible.

Rural households consistently exhibit lower MPI than urban households in all subsamples. Farm households, in general, are, on average, slightly wealthier than non-farm households, with rural farm households notably surpassing their urban counterparts in wealth.

3.2. Large regional differences in the impact of weather extremes

We calculate the marginal and gross effects of weather shocks by summing the immediate and delayed effects of each weather event by province over the

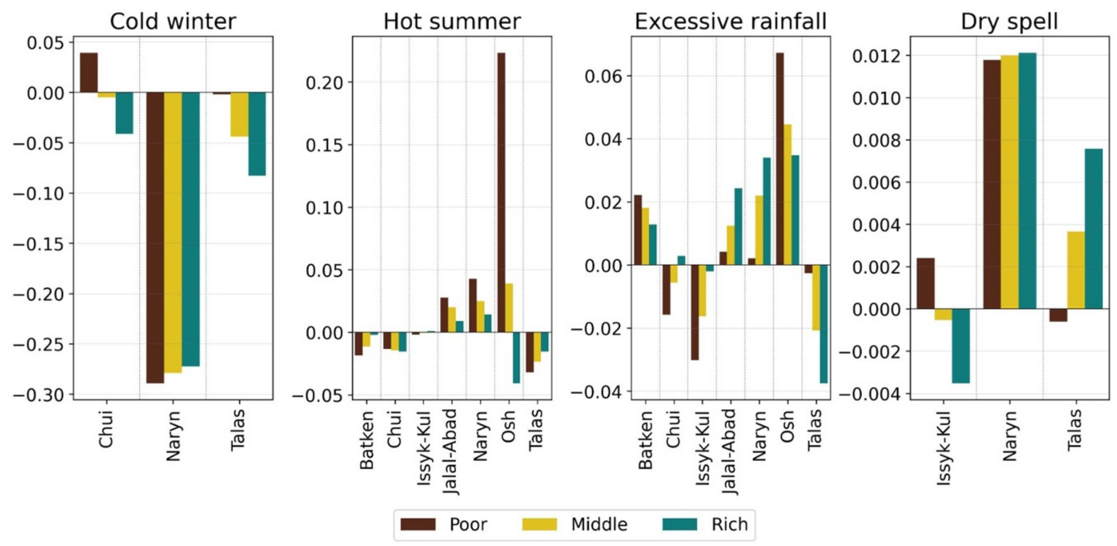

Figure 5. Marginal changes in MPI by province and population segment.

year (figure 5). Compared to the main specification (figure 4), the results show larger effects due to the increased focus on specific provinces and the higher proportion of affected households within those provinces.

Weather shocks demonstrated varying impacts on specific population segments across different provinces. Notably, hot summers and excessive rainfall showed various consequences, albeit of lesser magnitude compared to cold winters and dry spells. Cold winters had an overall detrimental effect on individuals throughout all provinces, reducing up to .3 points in their MPI. Conversely, dry spells tended to yield favorable outcomes.

Naryn (see districts locations in figure 2), a poverty-stricken province with harsh winters, experienced a significant .3-point decline in its MPI due to cold weather, affecting all components of the MPI (figure 5). Most households in Naryn depended on the rearing of livestock and were forced to sell or slaughter their livestock, resulting in substantial losses. Tragically, some livestock perished due to extreme cold. This finding aligns with the research by Sultakeev and Petrick (2021), highlighting the crucial role of livestock as the primary asset for Naryn pastoralists in breaking the cycle of poverty.

The favorable impact of dry spells on the well-being of the Naryn and Talas families is linked to the distinctive geographical and agricultural characteristics of these provinces. Their elevated terrain and reliance on upstream river basins indicate a lower vulnerability to droughts than regions heavily dependent on irrigated agriculture. Additionally, these provinces focus predominantly on livestock farming rather than irrigated crop cultivation, contributing to their resilience to dry spells. Although dry spells adversely affect irrigated crop production, their impact on other agricultural activities in these areas is less pronounced.

Naryn households benefit from hot summer events, taking advantage of their high elevation and generally colder setting. The occasional warmth contrasts with their typical cooler climate, providing residents with a temporary reprieve from chilly conditions and potentially improving overall well-being during the summer months.

Unlike mountainous regions, Osh, Jalal-Abad, and Batken provinces in low-elevation valleys possess different climates and susceptibilities to weather-related risks. Their hot and arid climate provides advantages over their mountain counterparts, particularly in managing hydroclimatic extremes. This climatic distinction reduces vulnerability to excessive rainfall episodes, a significant benefit in rugged terrain.

3.3. Heterogeneous effects of weather extremes on the different dimensions of poverty

We estimated four separate regressions to analyze the effects of the province and MPI dimensions on the sample mean (figure 6). The results reveal slight differences from the pooled sample, as different subsamples have different distributions. In particular, households in provinces with an average MPI closer to the national average exhibit results similar to those of the pooled sample.

Weather events had varying impacts on MPI components, with education, health, and nutrition accounting for 95% of MPI (see figure A2). The findings reveal a positive correlation between MPI and hot summers in Naryn, driven by health improvements. In Osh, a noticeable positive impact of around .1 points is observed on overall MPI during

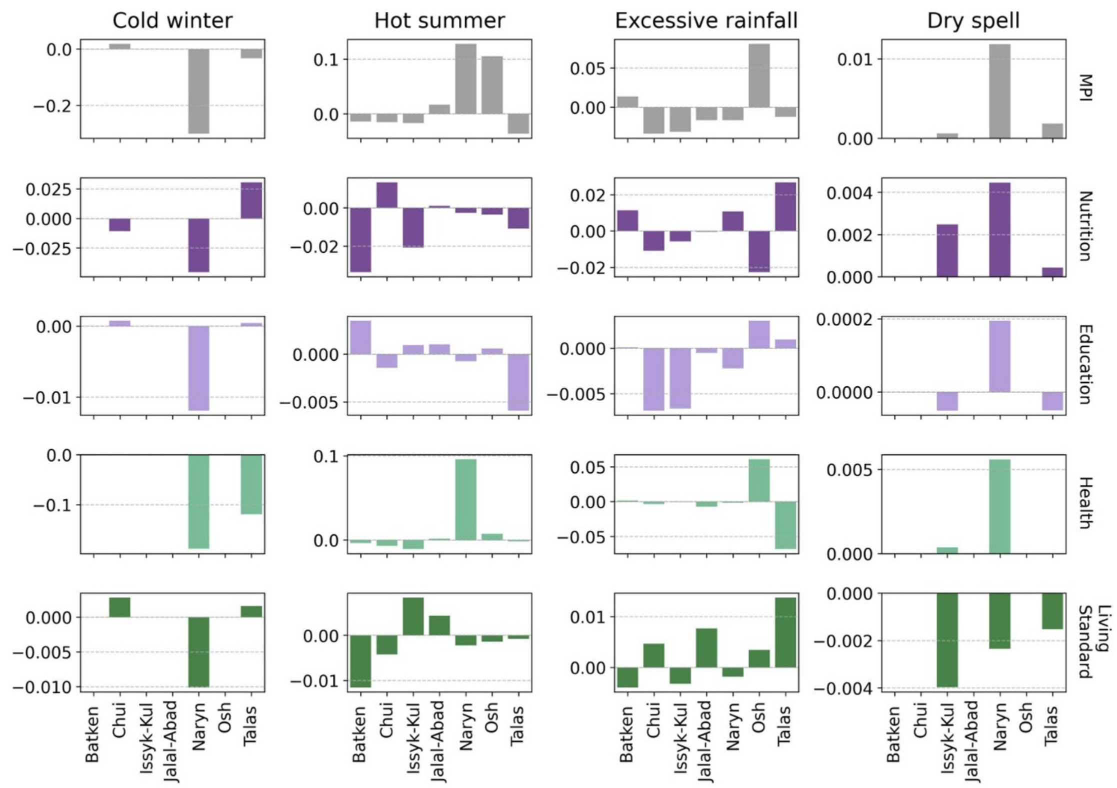

Figure 6. Marginal changes in MPI and its components by province on the sample mean.

hot summers, with negligible effects on individual dimensions. This underscores the nuanced disparities within subsample distributions and accentuates the intricate interplay between climatic variables and poverty dimensions.

The positive impact of excessive rains on MPI in Osh is related to improvements in education, health, and living standards. Presumably, households in Osh favor more rainfall due to the severe aridity in the region. Similarly, the positive impact of dry spells on MPI in Naryn and Talas is associated with improvements in nutrition, education, and health, possibly influenced by warm weather. A comprehensive exploration is warranted to discern the causal mechanisms, particularly given the long-term nature of these dimensions.

4. Discussion

Our analysis offers a comprehensive understanding of the impact of increasingly frequent weather extremes on the various dimensions of poverty in Kyrgyzstan. We revealed the regional specifics of the weather extremes on the poverty dimensions and explored the varied impacts of the extremes on different wealth segments.

We show how the poorer population segments suffer disproportionally more from weather extremes than the richer segments. This finding corroborates empirical evidence that weather extremes predominantly jeopardize the livelihoods of the poor and thus tend to increase inequality (Diffenbaugh and Burke 2019, Capelli *et al* 2021). The delayed impact of weather extremes appeared to aggravate poverty by compounding the extent and probability of increased economic inequality arising from climate change (Schewe *et al* 2019). Our results suggest that existing adaptation measures, though partially effective, do not fully alleviate the regressive impact of weather extremes on economic inequality in Kyrgyzstan. Similar worrying developments have also been found in other countries, particularly in the Global South, such as the Caribbean island (Friedman 2023) and the Philippines (See and Wilmsen 2020).

We also reveal that the impacts of extreme weather on the local population exhibit considerable geographic variability, highlighting the importance of spatially explicit analysis. It also underscores that climate adaptation efforts must respond to this spatial variation and encompass locally adapted strategies, which fall within the responsibility of local governments and communities (Mathew *et al* 2012). However, weak government institutions, limited research and development capacity, and fragile state bureaucracies often impede effective climate adaptation actions and fail to reach some population groups, especially marginal ones (Garschagen and Doshi 2022).

Approximately 1.2 billion people worldwide live in acute poverty, as measured by the MPI (UNDP 2022). The United Nations uses MPI to monitor progress toward Sustainable Development Goal 2 of reducing global poverty by half, covering all dimensions of poverty (UN 2022). Our econometric findings underscore the importance of tailored policies that consider regional disparities and that account for the various dimensions of poverty between households. These go beyond monetary measures, such as income, and include education, health, and nutrition as critical indicators. Our comprehensive approach effectively addresses how weather shocks affect these multiple dimensions, which is critical to achieving the desired reduction in poverty in the face of ongoing climate change.

Empirical impact functions, as used here, are based on historical data. While providing important lessons from historical developments, we know that such approaches are only of limited use to accurately predict long-term impacts and adaptations in the face of increasing climate variability (Lee *et al* 2023). Our analysis can also not fully account for additional multifaceted inequalities such as gender, race, and the large variation in the adaptive capacities of households. Moreover, we caution readers to generalize our results to different climatic conditions and other socioeconomic contexts.

5. Conclusion and policy implications

Previous studies have documented an increase in the frequency, duration, and severity of droughts, floods, heatwaves, mudslides, and wildfires globally and in Central Asia. This trend is projected to continue due to accelerating climate change and is likely to jeopardize the well-being of households, particularly in the global South. In Kyrgyzstan, the results of our analysis underline that weather extremes have a heterogeneous effect on various dimensions of poverty.

The cold winter in the northern part of the country in 2014 was particularly critical to poor households, mainly by reducing education levels and health conditions. If these extremes persist, households in these regions will be in danger of a downward spiral of reducing levels of education and health. Policymakers should particularly target these vulnerable people and risk areas by supporting education and health infrastructure.

With climate change, heat waves are intensifying and rainfall events become more extreme in Central Asia. It is crucial for the Kyrgyz government to implement effective measures to mitigate the adverse consequences, particularly in regions where these shocks have severe impacts. Priority should be given to disadvantaged and impoverished households, as they bear a disproportionate burden of these effects.

Data availability statement

The data cannot be made publicly available upon publication because they are owned by a third party and the terms of use prevent public distribution. The data that support the findings of this study are available upon reasonable request from the authors.

Appendix

A1. Description of MPI modification.
The MPI's mathematical structure corresponds to one member of a family of multidimensional poverty measures proposed by Alkire and Foster (2011). Constructing this measure entails the following steps in our study:

- **Identification of deprivations:** Define and identify the key dimensions of poverty, such as nutrition, education, health, and living standards.
- **Selection of indicators:** Choose specific indicators within each dimension that accurately capture the extent of deprivation (Berry Index, preschool attendance, level of education, illness, healthcare, ability to cover medical expenses, income, living space, land, and livestock).
- **Threshold determination:** Set appropriate thresholds for each selected indicator to distinguish between the deprived and non-deprived population. In establishing deprivation thresholds, our study employs specific criteria across dimensions. Within the food diversification dimension (Berry Index), ranging from 0 to 1, higher values indicate a more diverse diet, designating households with higher values as non-deprived. The education dimension considers preschool attendance and level of education, categorizing households with children unable to attend preschool due to financial constraints or with uneducated heads as deprived (assigned 0), while others are non-deprived (assigned 1). In the healthcare dimension, binary variables (illness, healthcare, and ability to cover medical expenses) dictate that households unable to pay for medical care, hospital treatment, or cover medical expenses are classified as deprived (assigned 0). The living standard dimension, comprising continuous variables (income, living space, land, and livestock), undergoes standardization and normalization between 0 and 1 for a precise

Table A1. Dimensions and sub-dimensions comprising MPI for Kyrgyzstan.

Dimension	Sub-dimension	Explanation of sub-dimensions	Survey question	Weights
Nutrition	Berry Index	Food diversity is measured by Berry Index as follows: $BI = 1 - \sum_{i=1}^{10} \omega_i^2$, where ω_i is the share of expenditures on food group i in the household's total consumption expenditure.	What kind of food products were consumed by members of your household during the surveyed 14 d?	Berry Index/4
Health	a. Illness b. Healthcare c. Coverage of medical expenses	a. Identify the need for medical assistance and determine the reason for refusing medical services. We considered it poor if a family could not pay for medical care or buy medicine due to a lack of money. b. Identification of the need for inpatient treatment and determination of the reasons for refusal of inpatient treatment. We considered it poor if a family could not pay for hospital treatment due to a lack of money. c. Identification of financial difficulties in covering medical expenses.	a. Have you needed medical assistance in the past year? If yes ⇒ were there any cases during the year when you could not use medical services? If yes ⇒ for what reason did you not use medical services during the year? b. Have you been referred to a hospital or needed hospital treatment but did not go to the hospital in the past year? If, Yes, I was referred but did not go to the hospital, or/and Yes, I needed hospital treatment but did not go to the hospital. ⇒ Reasons why you did not go to the hospital. c. What did you have to do to use medical services over the past year?	Illness/12 Healthcare/12 Coverage of medical expenses/12
Education	a. Pre-school attendance b. Level of education	a. Identification of children who do not attend preschool and whether this is due to financial difficulties. b. Identification of the household head's level of education and consider uneducated if the household head does not have 11 years of primary education.	a. Does (NAME) attend preschool? If no ⇒ what is the reason (NAME) is not attending preschool? b. What is the highest level of education you have received?	Pre-school attendance/8 Pre-school attendance/8

(Continued.)

Table A1. (Continued.)

Dimension	Sub-dimension	Explanation of sub-dimensions	Survey question	Weights
Living standard	a. Urban income b. Urban living space c. Rural income d. Rural living space e. Rural land f. Rural livestock	a.&c. The total household income (urban and rural) is calculated as the sum of recorded and deflated individual earnings that are aggregated into three main groups: wages, social transfers, and remittances. Values are standardized by the following formula: $z_i = \frac{x_i - \mu}{\sigma}$, then normalized by $n_i = \frac{x_i - \min(x)}{\max(x) - \min(x)}$. b.&d. The living space available to each household member is calculated as the ratio of the living space to the number of household members. The obtained values are also standardized and normalized. e. Amount of land owned by rural households, which is also standardized and normalized. f. Livestock from various species is unified by the Livestock unit https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Livestock_unit_LSU and multiplied by the amount of livestock, then normalized and standardized.	a.&c. What income did you receive over the past month and the amount of this income? b.&d. What is your family's living space (sq. m.)? e. Do you have any land in use? If yes ⇒ what is the plots' total area (with the house) (sq. m.)? e. What livestock, poultry, or other animals do you have?	Income/16 Living space/16 Land/16 Livestock/16

Table A2. The panel structure of KIHS (%), 2013–2020.

	2013	2014	2015	2016	2017	2018	2019
2013							
2014	91						
2015	83	90					
2016	78	85	93				
2017	72	78	85	91			
2018	69	75	82	87	95		
2019	66	72	78	83	90	95	
2020	63	68	74	79	86	90	95

Table A3. MPI by province.

	Poor	Middle	Rich
MPI by province:	.61	.71	.75
Talas	.66	.71	.83
Chui	.69	.73	.84
Issyk-Kul	.70	.73	.87
Naryn	.63	.71	.83
Osh	.65	.72	.85
Batken	.71	.73	.86
Jalal-Abad	.72	.74	.93

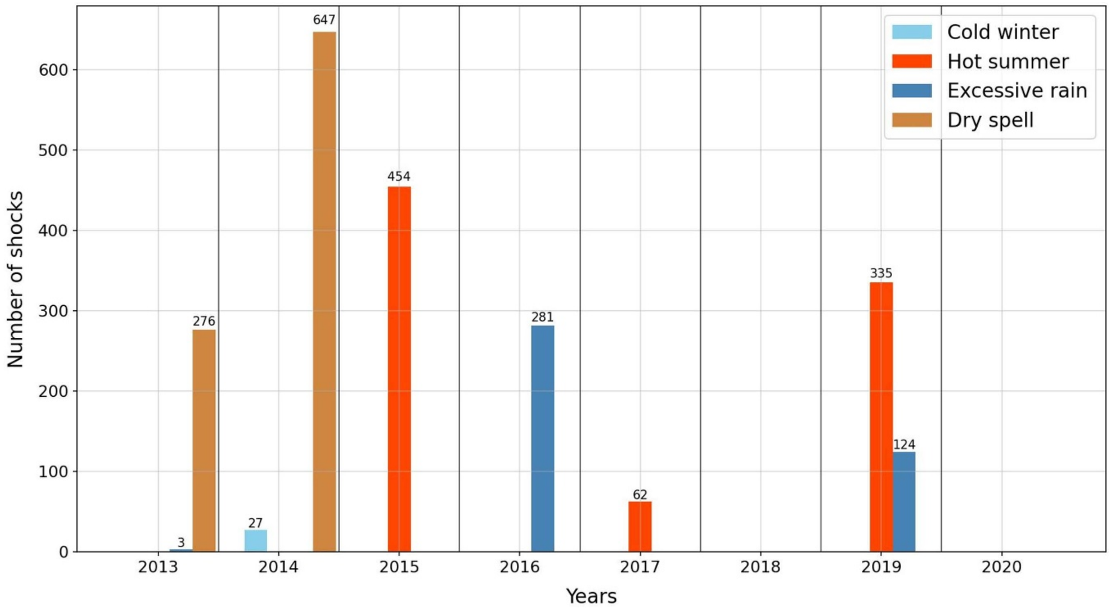

Figure A1. Frequency of weather extremes across the country.

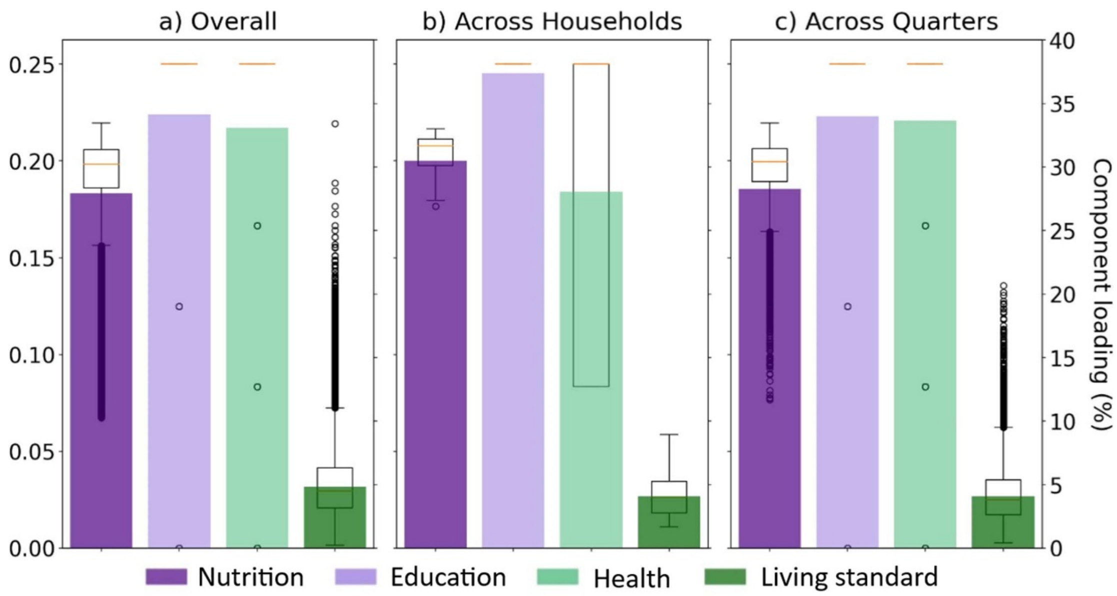

Figure A2. Variation and component loadings of MPI.

distinction between deprived and non-deprived categories.

- **Selection of weights:** We focus on selecting relative weights for each indicator such that they sum to one as $\frac{\text{Nutrition}}{4} = \frac{\text{Berry Index}}{4}$, $\frac{\text{Education}}{4} = \frac{\text{Preschool education}}{8} + \frac{\text{Level ofeducation}}{8}$, $\frac{\text{Health}}{4} = \frac{\text{Ilness}}{12} + \frac{\text{Healthcare}}{12} + \frac{\text{Ability tocover medicalexpenses}}{12}$, $\frac{\text{Living standard}}{4} = \frac{\text{Income}}{16} + \frac{\text{Living space}}{16} + \frac{\text{Land}}{16} + \frac{\text{Livestock}}{16}$.
- **Calculation of deprivation score:** In calculating the deprivation score, we compute the weighted proportion of deprivation for each household.
- **Poverty classification:** A household is categorized as multidimensionally poor if deprivation score falls within the first tercile, identified as middle if in the second tercile, and classified as rich if situated in the third tercile. This approach succinctly stratifies households based on their level of multidimensional deprivation.

By following these steps, the constructed measure captures the nuanced aspects of multidimensional poverty and provides a comprehensive assessment of well-being beyond a unidimensional approach.

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