

Article

Remittances as Insurance Against Shocks: Evidence from Multidimensional Poverty in Somalia

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Abstract

In Somalia's conflict-affected, climate-vulnerable economy, conventional monetary poverty measures capture only part of household welfare because they overlook simultaneous deprivations in education, health, and living standards. This study examines three related questions: how covariate and idiosyncratic shocks affect multidimensional deprivation, whether remittances are associated with lower deprivation, and whether remittances moderate the effects of different shock types. Using nationally representative data from the 2022 Somalia Integrated Household Budget Survey (N = 6883), the study measures multidimensional poverty using the Alkire–Foster approach. It estimates a fractional probit model of the household deprivation score, incorporating interactions between remittance receipt and shock exposure. Approximately 74% of households are multidimensionally poor, while 69.8% report exposure to covariate shocks. Average marginal effects show that covariate shocks increase the deprivation score by approximately 2.6 percentage points, whereas remittance receipt is associated with a 4.3-percentage-point reduction. Although the average effect of idiosyncratic shocks is positive, it is not statistically significant in the baseline specification. Interaction results nevertheless indicate that remittances significantly attenuate the association between idiosyncratic shocks and multidimensional deprivation, while providing no statistically significant protection against covariate shocks. The study contributes to the literature by distinguishing remittances' insurance capacity across household-specific and systemic risks within a multidimensional poverty framework. The findings suggest that remittances can serve as an important form of private insurance against idiosyncratic shocks but cannot substitute for public social protection and humanitarian assistance during widespread crises.

Keywords: multidimensional poverty; remittances; shock; idiosyncratic shocks; covariate shocks; household welfare; Somalia



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1. Introduction

Poverty in fragile, low-income economies is closely linked to the complex interplay between households' exposure to shocks and the resources available to cope with them (Gao & Mills, 2018; Giesbert & Schindler, 2012; Hoddinott, 2006). This relationship, however, remains poorly understood once poverty is measured multidimensionally rather than monetarily. Households in developing countries remain persistently exposed to shocks, ranging from droughts and floods that affect entire communities to illness, death, or displacement that affect individual households in isolation (Dercon, 2004). In the absence or thinness of formal insurance, such shocks translate directly into welfare losses, as

households sell productive assets, forgo healthcare, or withdraw children from school to defend short-run consumption (Nguyen et al., 2020; Skoufias, 2003). Most of this evidence, however, focuses on monetary measures of welfare, despite growing recognition that poverty in fragile, low-income settings is inherently multidimensional. Households may experience simultaneous deprivations in education, health, and living standards that are not fully captured by a single monetary indicator (Alkire & Foster, 2011; Sen, 2014). This broader perspective is particularly relevant in contexts where households face recurrent shocks that can affect multiple dimensions of well-being simultaneously. Existing evidence shows, for example, that asset holdings and household exposure to shocks can shape poverty dynamics and contribute to persistent deprivation (Giesbert & Schindler, 2012). The importance of this multidimensional perspective is further underscored by the 2025 Global Multidimensional Poverty Index, which estimates that 1.1 billion people live in acute multidimensional poverty across 109 countries, with nearly four in five residing in subnational regions exposed to at least one climate hazard (UNDP & OPHI, 2025). These patterns suggest that understanding how households cope with shocks requires moving beyond monetary poverty and examining how different types of shocks translate into multidimensional deprivation. Distinguishing between covariate shocks, which affect communities or groups simultaneously, and idiosyncratic shocks, which primarily affect individual households, provides a useful framework for assessing whether their welfare consequences differ across dimensions of poverty.

Remittances are among the most important informal coping mechanisms that households rely on to manage adverse shocks. Remittance inflows to low- and middle-income countries now exceed the combined value of foreign direct investment and official development assistance (Ratha et al., 2024). A large body of evidence shows that remittances reduce monetary poverty (Adams & Page, 2003) and help households smooth consumption following adverse shocks (Acosta et al., 2008; Yang & Choi, 2007). Remittances are thought to act as transnational insurance, increasing precisely when local earnings fall, since diaspora members are usually shielded from the domestic shocks that hit their home countries (Bettin & Zazzaro, 2018). Whether this holds symmetrically across shock types, and for multidimensional as opposed to monetary welfare, remains far less established. Shocks, remittances, and multidimensional poverty are thus closely linked: shocks are a principal driver of deprivation, remittances are a major household response to shocks, and both operate on the same non-monetary dimensions of welfare that conventional poverty measures overlook. This paper jointly examines how covariate and idiosyncratic shocks are associated with multidimensional poverty, whether remittance receipt is associated with lower multidimensional poverty, and whether remittance receipt moderates the association between each shock type and multidimensional poverty.

Somalia provides a critical, underexplored context for these questions, because both shock exposure and remittance dependence are exceptionally severe. Decades of conflict, recurring drought, and a near-complete absence of formal insurance and public social protection have left households highly vulnerable to both community-wide and household-specific shocks (World Bank, 2022), while kinship networks provide only limited informal risk-sharing (Majid & McDowell, 2012). In the data analyzed in this study, nearly seven in ten households report a covariate shock, most commonly drought, flooding, or a sharp rise in food prices, during the reference period alone, indicating that such shocks are a near-permanent feature of household life rather than an occasional disruption. Poverty is similarly intense, with an estimated nearly seven in ten Somalis (68%) living in poverty and the highest rates among nomadic and displaced populations (SNBS, 2022). At the same time, diaspora remittances are estimated at 23 percent of GDP, exceeding both foreign aid and foreign direct investment and constituting what is widely described as the lifeblood of

the Somali economy (World Bank, 2016). Somalia thus combines exceptionally high shock exposure with an unusually large private financial buffer, providing an ideal setting in which to examine how the two interact to shape multidimensional deprivation.

Despite this growing body of research, two important gaps remain. First, the literature on the determinants of poverty in Somalia has focused primarily on monetary and asset-based measures, with limited attention to the roles of shocks and remittances as explanatory factors (Hassan et al., 2024; Mohamoud & Bulut, 2020; A. O. Osman et al., 2026). Second, although theory and evidence from studies of monetary poverty suggest that remittances may differentially buffer the effects of covariate and idiosyncratic shocks (Combes & Ebeke, 2011), this relationship has yet to be examined within a multidimensional poverty framework in the Somali context.

These gaps motivate the paper's central research question: how are covariate and idiosyncratic shocks associated with multidimensional poverty in Somalia, and does remittance receipt moderate these associations?

Using the nationally representative 2022 Somalia Integrated Household Budget Survey, this paper answers this question in three steps: (i) estimating the association between covariate and idiosyncratic shocks and multidimensional poverty, (ii) testing whether remittance receipt is associated with lower multidimensional poverty, and (iii) testing whether remittance receipt moderates the shock–poverty association for each shock type. Multidimensional poverty is measured using the Alkire–Foster dual-cutoff methodology across ten indicators spanning education, health, and living standards, and the empirical strategy uses a fractional probit framework suited to the bounded deprivation score, with an extended specification interacting each shock type with remittance receipt.

The remainder of the paper proceeds as follows. Section 2 reviews the literature on shocks, remittances, and multidimensional poverty. Section 3 describes the data, the construction of the multidimensional poverty index, and the econometric strategy. Section 4 presents and discusses empirical results. Section 5 concludes with a summary of findings and their policy relevance.

2. Literature Review

2.1. Shocks: Covariate and Idiosyncratic Shocks to Multidimensional Poverty

A substantial body of literature on risk and vulnerability in developing countries distinguishes between shocks that affect an entire society simultaneously and those that strike households separately. Townsend (1994) offered the theoretical foundation for distinguishing idiosyncratic from aggregate risk, showing in rural Indian villages that informal risk-sharing can smooth household-specific shocks but is much less effective against correlated village-wide shocks because all potential insurers are affected simultaneously. Dercon and Krishnan (2000) provided empirical evidence from panel data on rural Ethiopian households that both idiosyncratic shocks, such as household-specific crop failure, and covariate shocks, particularly rainfall variability, exert independent effects on household consumption and short-term poverty dynamics, with their findings showing that informal risk-sharing and other coping mechanisms only partially protect households from these shocks, resulting in substantial movements into and out of poverty over relatively short periods a pattern corroborated across Bangladesh, Ethiopia, Mali, Mexico, and Russia by Skoufias and Quisumbing (2005), who similarly found informal risk-sharing considerably less effective against covariate shocks that simultaneously affect large segments of a community, thereby limiting the availability of unaffected households able to provide support.

Although vulnerability literature has traditionally assessed the welfare consequences of shocks primarily through changes in household income or consumption, rather than the non-monetary dimensions captured by multidimensional poverty measures, the under-

lying mechanisms extend directly to these broader welfare outcomes. When households experience either idiosyncratic or covariate shocks, they often adopt coping strategies such as selling productive assets, reducing healthcare expenditure, or withdrawing children from school to stabilize short-term consumption (Dercon, 2004). These responses generate deprivations in education, health, and living standards, even when the original studies evaluate welfare only in monetary terms.

Following Dercon (2004), covariate shocks are defined as unexpected events that simultaneously affect entire communities or regions such as droughts, floods, crop diseases, food price crises, or conflict, whereas idiosyncratic shocks are unexpected events that affect specific individuals or households such as illness, death, robbery, fire, eviction, imprisonment, or marital dissolution (Pradhan & Mukherjee, 2018). Evidence directly linking these shocks to multidimensional rather than purely income or consumption-based poverty is increasingly emerging to the UNDP and OPHI (2025). Global Multidimensional Poverty Index report finds that nearly four in five of the 1.1 billion people living in acute multidimensional poverty reside in regions exposed to at least one major climate hazard, indicating a global-scale association between covariate climatic shocks and multidimensional deprivation. At the household level, recent Alkire–Foster framework-based evidence shows that drought exposure is associated with higher multidimensional poverty scores in climate-sensitive rural settings, while comparable findings from flood-prone districts of Pakistan similarly identify a strong positive relationship between household climate vulnerability and multidimensional poverty index values (Rana et al., 2023).

Somalia, the case study of this study, is characterized by severe exposure to both covariate and idiosyncratic shocks due to prolonged conflict, frequent drought, and limited formal and informal risk-sharing mechanisms. Hence, households encounter regular community-wide shocks while also having weak support mechanisms to reduce individual shocks (Majid & McDowell, 2012). Even idiosyncratic shocks can generate substantial welfare losses because coping systems are overstretched in such fragile contexts (Heltberg & Lund, 2009). However, the existing literature on shocks and multidimensional poverty remains concentrated in relatively stable agrarian or global settings and rarely distinguishes between covariate and idiosyncratic effects in fragile economies such as Somalia. This study addresses this gap by examining the relationship with a household-level multidimensional deprivation index based on the Alkire–Foster framework.

2.2. Remittance Receipts and Multidimensional Poverty

A substantial body of literature links international remittances to poverty reduction in migrant-exporting countries. Adams and Page (2003) studied 71 developing countries. They found that a ten percent increase in per capita remittances decreases the poverty headcount by roughly three to four percent, while Yang and Choi (2007) demonstrate that remittances act as informal insurance by increasing in response to adverse household shocks and helping smooth consumption. The shock literature reviewed above adopts a predominantly monetary perspective, assessing the effects of shocks through income, consumption, or poverty headcount measures rather than the multiple deprivations captured by multidimensional poverty frameworks. Nevertheless, these mechanisms extend naturally to multidimensional poverty. By relaxing household budget constraints, remittances enable greater investment in education, healthcare, and other human-capital-enhancing activities, thereby improving several dimensions of deprivation captured by the Alkire–Foster framework (Garcia-Fuentes et al., 2025). Emerging empirical evidence supports this relationship. Using state-level panel data for Mexico, Librado-Gonzalez et al. (2025) find that remittances significantly reduce multidimensional poverty, exerting a larger poverty-reducing effect than state social spending, although a smaller one than labor income. Likewise, recent

studies from Bangladesh and Indonesia show that remittances significantly reduce multidimensional energy poverty, with the results remaining robust after addressing endogeneity using instrumental variable estimation (Hasibuan & Hartono, 2024).

2.3. Determinants of Household Poverty in Somalia

Having reviewed the literature on shocks, remittances, and their interaction, the discussion now focuses on the determinants of household poverty in Somalia to underline the research gap that the present study aims to fill.

Hassan et al. (2024) employed the 2020 Somalia Demographic and Health Survey to compare machine learning methods with traditional logistic regression. Their findings identified geographic region, household size, respondent age, husband's employment status, age of the household head, and place of residence as the strongest predictors of household wealth. Using a different dataset, Mohamoud and Bulut (2020) analyzed the World Bank's Somali High Frequency Survey (SHFS) Wave 2 with a logit model and found that residence type, household size, household head's education, the share of literate household members, access to electricity, small family business ownership, and reliance on agriculture, fishing, or hunting significantly influenced the probability of household poverty. Focusing specifically on rural households, Abdi Ali et al. (2025), also using SHFS Wave 2, identified household size, access to modern energy, remittances, agricultural land ownership, house ownership, and the gender and age of the household head as significant determinants of poverty. Using the same dataset, Mohamed Bobe (2025) applied a binary logistic model, validated by a linear probability model and a Heckman two-step correction, and similarly found household size and distance to the nearest health center to increase rural poverty, whereas household head literacy, agricultural land access, livestock holdings, mobile-money access, and remittances reduced it. More recently, A. O. Osman et al. (2026) analyzed the 2022 Somali Integrated Household Budget Survey using a multilevel spatial model and showed that household size and internally displaced person status were important household-level determinants, while regional characteristics exerted even stronger effects, with some regions exhibiting nearly twenty-five times higher odds of poverty than others.

Taken together, these studies reveal two important gaps in the Somalia literature. First, all measure poverty using monetary or asset-based indicators, such as household expenditure, poverty status, or wealth indices, with none applying a multidimensional poverty framework that captures simultaneous deprivations in education, health, and living standards. Second, despite the importance of remittances to the Somali economy, only a few studies used remittances as an explanatory variable. Furthermore, neither examines whether remittances mitigate the effects of covariate and idiosyncratic shocks on household welfare. Accordingly, this study addresses both gaps by applying the Alkire–Foster multidimensional poverty framework to Somalia and by examining the direct associations of remittances and their moderating role in the relationship between household shocks and multidimensional poverty.

3. Data and Methodology

3.1. Data Source and Sample

This study employs the Somalia Integrated Household Budget Survey (SIHBS), the nationally representative household survey conducted in Somalia by the Somalia National Bureau of Statistics (SNBS). The SIHBS covers 7212 households distributed across all 18 administrative regions, including urban, rural, and nomadic settlement types. The inclusion of nomadic populations is paramount to assessing multidimensional poverty in the Somali context, as a large portion of the Somali population lives in nomadic areas.

The sampling design follows a stratified two-stage cluster approach. Enumeration areas were selected with probability proportional to size within strata defined by region and settlement type; households were then sampled systematically within each enumeration area. After listwise deletion of observations with missing values on the outcome variable and key regressors, the analytical sample consists of 6883 households.

The survey comprises four main sections used in this study. The first section collects household-level information, including housing conditions, access to basic services, food security, and displacement status. The second section shows records of information on individual household members, such as age, gender, education, school attendance, health, and disability status. The third section offers information about ownership of households and productive assets. The fourth section describes information on shocks experienced by households during the reference period.

3.2. Multidimensional Poverty Measurement

The Alkire–Foster Framework

In this study, multidimensional poverty is measured using the dual-cutoff approach of Alkire and Foster (2011), which underlies the global MPI published by UNDP and the Oxford Poverty and Human Development Initiative (UNDP & OPHI, 2023). The AF framework is preferred over conventional income-based measures because Somalia's informal economy makes consumption expenditure difficult to measure accurately, because the MPI captures simultaneous deprivations in education, health, and living standards that a monetary measure ignores, and because the continuous deprivation score is well-suited to the regression analysis in Section 3.4.

For each household i and indicator j , a binary deprivation indicator is defined as:

$$d_{ij} = 1 \text{ if household } i \text{ is deprived in indicator } j; 0 \text{ otherwise.} \quad (1)$$

Weights w_j are normalized to sum to unity. The weighted deprivation score is:

$$c_i = \sum_j w_j \cdot d_{ij} \in [0, 1] \quad (2)$$

This study uses $J = 11$ indicators across four dimensions (Education, Health, Living Standards, and Services), each carrying an equal dimensional weight of $1/4$. Table 1 shows the full indicator structure used in this study.

A household is categorized as poor if $c_i \geq k = 1/3$ (the global MPI cutoff). The AF method then applies a censoring step, setting deprivations of non-poor households to zero:

$$c_i(k) = c_i \text{ if } c_i \geq k; 0 \text{ otherwise.} \quad (3)$$

Three aggregate measures are defined as follows. The headcount ratio, H , measures the proportion of households categorized as multidimensionally poor, where q is the number of poor households, and n is the total number of households. The intensity of poverty, $A = (1/q) \sum_{i=1}^q c_i(k)$, shows the average deprivation share among the poor—the sum runs over all n households, since deprivation is censored to zero for the non-poor, but the average is taken over the q poor households only. The Multidimensional Poverty Index (MPI), denoted M_0 , is calculated as the product of incidence and intensity:

$$MPI = M_0 = H \times A = \frac{1}{n} \sum_{i=1}^n c_i(k) \quad (4)$$

Table 1. MPI Dimensions, Indicators, Deprivation Cutoffs, and Weights.

Dimension	Weight	Indicator	Variable	Deprivation Cutoff
Education	1/8	Attendance	dep_attendance	Any child aged 6–14 is out of school (never attended or not currently attending)
	1/8	Schooling	dep_schooling	No member aged 15 or older has completed 8 or more years of schooling
Health	1/8	Food security	dep_food	Any of six food-insecurity experiences affirmed: ate only a few kinds of food; skipped a meal; ate less than needed; ran out of food; was hungry but did not eat; went a whole day without eating
	1/8	Access to health care	dep_healthaccess	Any member was sick or injured in the past month and did not receive medical care
Living standards	1/16	Housing	dep_housing	Inadequate floor, wall, or roof material
	1/16	Cooking fuel	dep_cooking	Cooks with solid fuels (charcoal, firewood, dung, or crop residuals)
	1/16	Overcrowding	dep_overcrowd	A sleeping room is shared by more than 3 members
	1/16	Assets	dep_asset	Owns no more than 2 small assets and does not own any livestock
Services	1/12	Lighting	dep_lighting	Main lighting source is kerosene, firewood, torch, candles, or other (no electric or solar lighting)
	1/12	Water	dep_water	No improved drinking-water source, or roundtrip collection time exceeds 30 min
	1/12	Sanitation	dep_sanitation	No improved sanitation facility, or the facility is shared with other households

Notes: Each of the four dimensions carries an equal weight of 1/4, divided equally among its indicators; the eleven indicator weights sum to one ($4 \times 1/8 + 4 \times 1/16 + 3 \times 1/12 = 0.5 + 0.25 + 0.25 = 1$). Deprivation cutoffs are applied uniformly to all households, following standard Alkire–Foster methodology (Alkire & Foster, 2011); the settlement-specific exemptions of the SNBS national MPI are not applied, to preserve comparability and subgroup decomposability across urban, rural, and nomadic households. Shocks and household unemployment are excluded from the index and enter the empirical model as explanatory variables instead of deprivation indicators. Asset ownership is grouped under Living Standards rather than a standalone “Inclusion” dimension, since a dimension carrying a full 1/4 weight on a single indicator is not a well-supported use of that dimension label once unemployment is removed (see Section 3.3.3 for the same reasoning applied to unemployment itself). A household is identified as multidimensionally poor if its weighted deprivation score $c \geq 1/3$.

The MPI equals the population average of censored deprivation scores and, unlike the simple headcount ratio, is sensitive to changes in the depth of poverty among the poor. A key analytical advantage of the AF framework is that M_0 is exactly decomposable by subgroup (Equation (5)) and by indicator (Equation (6)):

$$M_0 = \sum_{\ell=1}^L \left(\frac{n_{\ell}}{n} \right) \times M_{0\ell} \quad (5)$$

$$C_j = w_j \times \frac{1}{n} \sum_i d_{ij}(k), \text{ where } \sum_j C_j = M_0 \quad (6)$$

As a robustness check on the sensitivity of the analysis to the index’s dimensional structure, we construct an alternative index, c_{alt} , following the Global MPI’s original three-dimensional structure of Education, Health, and Living Standards, with each dimension weighted 1/3. The index comprises $J = 10$ indicators: two indicators, each for Education and Health, and six for Living Standards, with indicators within each dimension sharing the

corresponding dimension weight equally. Several indicators use definitions that differ from those in the primary index. Specifically, the Health dimension uses a broader access/unmet need measure combining lack of care seeking with unsupported chronic illness; Food Security applies the moderate FIES cutoff (≥ 4 of 8 items); and the Asset and Electricity indicators use single item deprivation rules rather than the combined asset–livestock and lighting source measures used in the primary specification. The estimates based on c_{alt} are presented later.

A second alternative index, c_{12} , restores the original 12 indicator and five dimension structure, with unemployment incorporated as a deprivation indicator rather than included as a regression covariate. The corresponding estimates are presented later.

Sensitivity to the poverty cutoff k is examined using $k=0.35$, corresponding to the threshold reported in the SNBS national MPI. This alternative cutoff is applied to the Alkire–Foster headline measures and to the binary outcome specification based on the (mpi_poor) indicator, with the corresponding results presented. The specifications using the uncensored deprivation score are not re-estimated at alternative values of k , because c is a continuous measure and is not thresholded by the poverty cutoff. Accordingly, variation in k affects incidence-based measures such as H and mpi_poor , but does not change the underlying value of c .

Finally, sensitivity to alternative weighting structures is assessed through C_{alt} and c_{12} , rather than through arbitrary reweighting of the primary index. Both alternatives represent structurally distinct and externally motivated index designs, based respectively on the original Global MPI structure and the original national MPI structure, providing structured weighting sensitivity within the Alkire–Foster framework.

3.3. Variable Definitions and Theoretical Justification

3.3.1. Dependent Variable

The main dependent variable in the empirical analysis is the uncensored household deprivation score, c_i , which represents the weighted sum of deprivations across the 11 indicators comprising the multidimensional deprivation index. Unlike the censored deprivation score, $c_i(k)$, the uncensored score is retained for all households, irrespective of whether their deprivation level exceeds the multidimensional-poverty cutoff (k). This specification preserves continuous variation in deprivation across the entire sample and is therefore better suited to regression analysis. The censored score $c_i(k)$, by contrast, is used solely for multidimensional-poverty identification and Alkire–Foster aggregation in the calculation of the adjusted headcount ratio M_0 , and is not used as the dependent variable in the regression models.

3.3.2. Main Variables of Interest

Exposure to economic, climatic, and conflict-related shocks is a major driver of multi-dimensional poverty in Somalia. Following Townsend (1994) and Dercon (2004), shocks experienced by households are generally classified into two main categories. Covariate shocks are unexpected events that adversely affect the entire community (Temesgen et al., 2022). These types of shocks, which are common in fragile economies like Somalia, include droughts, floods, crop diseases, food crises, and rising agricultural input prices. Because these shocks affect a large proportion of the population at the same time, individual-level coping strategies are often ineffective in diversifying or mitigating the associated risks. In contrast, idiosyncratic shocks are unexpected events that negatively affect specific individuals, households, or firms rather than the broader economy (Pradhan & Mukherjee, 2018). Therefore, in this study, illness, death, robbery, fire, eviction, imprisonment, and dissolution of marriage are considered household-specific (idiosyncratic) shocks, as they

primarily affect individual households rather than the wider community. In Somalia, where formal insurance is absent and community network platforms are fragile, both types of shocks are anticipated to aggravate deprivation. This classification follows the type of event reported by the household rather than a direct measure of how widely that shock was shared across neighboring households; we do not observe community or enumeration-area-level exposure rates that would allow the covariate/idiosyncratic distinction to be verified empirically for this sample. The classification should therefore be read as a categorization by conventional shock type, consistent with prior literature (Dercon, 2004; Pradhan & Mukherjee, 2018), rather than as a direct measure of realized co-movement in shock incidence across households. The expected sign is positive for both shocks.

On the other hand, remittances are widely regarded as a vital source of household financial support in Somalia and an important mechanism for coping with economic shocks. In the SIHBS, the remittance variable is derived from the question, “Has this household received any remittances of money from anyone living outside?” Accordingly, the measure captures international remittance receipt and is coded as a binary indicator equal to one when the household reports receiving such transfers and zero otherwise.

International remittances from the Somali diaspora constitute a substantial source of external finance, with estimated inflows ranging from approximately 16% to 30% of GDP, exceeding both foreign aid and foreign direct investment inflows. Their importance provides a strong basis for expecting a negative association between remittance receipt and multidimensional poverty. By relaxing household liquidity constraints, remittances can support smoothing consumption during adverse events and facilitate investments in education, health, housing, and productive assets, thereby reducing deprivation across multiple dimensions (Garcia-Fuentes et al., 2025).

3.3.3. Control Variables

The analysis controls for a range of household demographic, socioeconomic, and locational characteristics that may independently influence multidimensional deprivation. Household size is included to account for potential resource dilution within the household (Strohschein et al., 2008), while the dependency ratio, defined as the proportion of inactive household members relative to working-age members, captures the household’s demographic burden (Cruz & Ahmed, 2018; Deo et al., 2024). The female share of household members is also included to account for differences in household demographic composition.

Human capital is proxied by the household head’s years of schooling, consistent with the literature that commonly uses educational attainment as an indicator of human capital (Tp, 2003; Wößmann, 2003). In addition, a binary indicator for female-headed households is included to capture gender-related socioeconomic vulnerabilities. Female-headed households may face greater economic insecurity, more limited access to productive resources, and a higher risk of poverty relative to male-headed households (Buvinić & Gupta, 1997).

To account for potential nonlinear lifecycle effects, the age of the household head is included in both linear and quadratic forms after mean-centering (Wooldridge, 2010). This specification allows the relationship between the household head’s age and multidimensional deprivation to vary over the life cycle while reducing potential multicollinearity between the linear and squared terms.

The model also controls for household location and displacement status. Location is represented by dummy variables for rural and nomadic residence, with urban households serving as the reference category (Hassan et al., 2024). An additional indicator identifies internally displaced person (IDP) households. This control is particularly relevant in conflict-affected settings, where displacement may expose households to multiple economic, social, and environmental vulnerabilities and constrain access to essential services,

including health care and education (A. A. Osman & Abebe, 2023). Together, these controls account for spatial and displacement-related differences in livelihood opportunities, access to services, and exposure to shocks that may influence multidimensional deprivation.

A methodological consideration arises because two of the control variables are partially related to the construction of the multidimensional deprivation index itself. First, household size (hhsz) enters directly into the overcrowding indicator, under which a household is classified as deprived when the number of household members per sleeping room exceeds three. Second, the household head's years of schooling (head_educ_years) is related to the schooling deprivation indicator, which classifies a household as deprived when no member aged 15 years or older has completed at least eight years of schooling. The nature of these overlaps, however, differs. The relationship between household size and overcrowding is partly mechanical because household size directly enters the criterion of overcrowding, whereas the relationship between the household head's education and schooling deprivation is not deterministic. After all, the deprivation indicator is based on the educational attainment of any eligible household member.

To assess whether the direct mechanical relationship between household size and overcrowding affects the main results, a purged robustness index (c_purged) is constructed by excluding the overcrowding indicator and redistributing its weight across the remaining Living Standards indicators. The primary fractional probit model is then re-estimated using this alternative index. This robustness exercise allows the association between household size and multidimensional deprivation to be distinguished from the mechanical contribution of household size to the overcrowding component. The detailed results of this exercise are reported in Section 4. Removing the schooling indicator leaves the Education dimension represented by a single indicator (attendance) carrying its full dimension weight alone the same structural cost already avoided once in this paper's index design (The Alkire–Foster Framework Section), so this check was initially limited to household size. Following the reviewer's request, we construct this check regardless of that structural cost: a second purged index, c_purged_educ, excludes the schooling indicator, with the attendance indicator absorbing Education's full 1/4 weight, and the primary model is re-estimated on it to assess whether the coefficient on head_educ_years is similarly sensitive to this overlap. The result confirms the qualitative distinction drawn above: head_educ_years' coefficient shrinks from -0.0405 to -0.0293 (a 27.7% reduction) once the schooling indicator is dropped, but remains highly statistically significant ($p < 0.001$) in both specifications, in contrast to household size, whose coefficient collapsed entirely (Section 3.3.3 above). This is consistent with a partial, correlational overlap rather than a near-total mechanical one: roughly a quarter of the coefficient's magnitude reflects the schooling indicator's construction, while the majority survives its removal. The coefficients this paper's central claims depend on are stable under this check as well: covariate shock ($0.0661 \rightarrow 0.0485$, still significant), remittances ($-0.1088 \rightarrow -0.1074$, essentially unchanged), and idiosyncratic shock ($0.0142 \rightarrow 0.0108$, not significant either way).

3.4. Econometric Specification

3.4.1. Primary Model: Fractional Probit

Since the outcome variable is bounded to the unit interval, $c_i \in [0, 1]$, OLS is not suitable in this context because it can produce predicted values outside the feasible range of probability and generate marginal effects that are inconsistent with the bounded nature of the dependent variable (Papke & Wooldridge, 1996). This arises because OLS imposes a linear conditional mean and constant marginal effects despite the nonlinear nature of fractional response variables. We adopt the fractional probit estimator, which specifies:

$$E[c_i(k) \mid x_i] = \Phi(x_i\beta), \quad (7)$$

Equation (7) was estimated by quasi-maximum likelihood (binomial family, probit link). The estimator is consistent under correct conditional mean specification alone. The full specification is:

$$\Phi^{-1}(E[c_i(k) | x_i]) = \alpha + \beta_1 cov_shock_i + \beta_2 idio_shock_i + \beta_3 R_i + x'_{ctrl} \gamma + \sum_r \delta_r \cdot 1[\text{region} = r] + \varepsilon_i. \quad (8)$$

Because the coefficients of a Fractional Probit model do not have a straightforward interpretation in probability terms, average marginal effects (AMEs) are computed and reported.

$$AME_k = \frac{1}{N} \sum_{i=1}^N \varphi(x_i \hat{\beta}) \cdot \hat{\beta}_k. \quad (9)$$

3.4.2. Shock Remittance Interaction

Remittances are theorized to offer insurance against covariate shocks relative to localized risk-sharing arrangements. Because diaspora senders are geographically insulated from domestic aggregate disruptions, they can sustain or increase transfers precisely when domestic incomes decline (Bettin et al., 2017; Yang & Choi, 2007). In fragile, conflict-affected, or shock-prone contexts like Somalia, where localized safety nets frequently collapse during severe environmental or political crises, transborder diaspora networks serve as vital macro-insurance channels (Majid & McDowell, 2012).

To empirically evaluate this buffering mechanism, the baseline specification is augmented with interaction terms within an extended fractional probit framework, a standard approach when dealing with bounded, fractional dependent variables (Papke & Wooldridge, 1996):

$$\Phi^{-1}(E[c_i | x_i]) = \beta X_i + \beta_4 (cov_shock_i \times R_i) + \beta_5 (idio_shock_i \times R_i) + \varepsilon_i \quad (10)$$

where R_i is a binary indicator denoting remittance receipt; cov_shock and $idio_shock$ represent exposure to covariate and idiosyncratic shocks, respectively.

The interaction coefficients, β_4 and β_5 , are the primary parameters of interest. A statistically significant negative estimate for β_4 is consistent with remittances being associated with a smaller estimated association between aggregate shocks and multidimensional deprivation. Conversely, a significant β_5 in the absence of a significant β_4 is consistent with the protective association of remittances being specific to idiosyncratic risk, echoing findings that localized shocks are more easily managed by remaining domestic safety nets (Mohapatra et al., 2012).

Due to the nonlinearity of the fractional probit link function, the marginal effect of a covariate shock on the expected deprivation score is conditional upon remittance status. For non-receiving households ($R_i = 0$), the marginal effect is given by $\varphi(\cdot) \hat{\beta}_1$, whereas for receiving households ($R_i = 1$), it is evaluated as $\varphi(\cdot) (\hat{\beta}_1 + \hat{\beta}_4)$, where $\varphi(\cdot)$ denotes the standard normal probability density function. Following standard econometric procedure for non-linear interactions, the statistical significance of this differential impact is evaluated via delta-method standard errors.

4. Results and Analysis

4.1. Descriptive Overview

Table 2 reports population-weighted summary statistics. The Alkire–Foster headline measures under the current 11-indicator, 4-dimension index (Table 2b) show a headcount ratio of $H = 74.1\%$ (95% CI: 72.7–75.5%), an intensity among the poor of $A = 57.1\%$ (95% CI: 56.5–57.7%), and an adjusted headcount ratio of $M_0 = 0.423$ (95% CI: 0.414–0.432). Roughly three in four Somali households therefore fall below the multidimensional-poverty thresh-

old defined by the Alkire–Foster approach. The mean deprivation score is 0.474, with 47.9% of households severely poor ($c \geq 1/2$) and 14.0% vulnerable to poverty ($0.20 \leq c < 1/3$); Table 2a reports the same three headline statistics under the 12-indicator comparison index for direct comparison. Shock exposure is pervasive: 69.8% of households experienced at least one covariate shock during the reference period, whereas idiosyncratic shocks remain relatively limited at 6.4%. Remittances, as a form of informal transfer outside regular household income, reach 20.2% of households nationally. Additionally, educational attainment among household heads is low, with an average of just 2.3 years of schooling, reflecting severe human capital constraints.

Table 2. Descriptive Statistics—Primary Index (11 Indicators).

	Mean	SD	Min	Max
Deprivation score c (11 indicators, uniform cutoffs)	0.4742	0.2133	0.000	1.0000
MPI poor: $c \geq 1/3$	0.7411	0.4381	0.000	1.0000
MPI severely poor: $c \geq 1/2$	0.4785	0.4996	0.000	1.0000
MPI vulnerable: $0.20 \leq c < 1/3$	0.1400	0.3470	0.000	1.0000
Deprived: school-age child not attending	0.5791	0.4937	0.000	1.0000
Deprived: no member 15+ with 8+ years of schooling	0.5529	0.4972	0.000	1.0000
Deprived: food security (any-item cutoff)	0.5361	0.4987	0.000	1.0000
Deprived: sick member, no care sought	0.0589	0.2355	0.000	1.0000
Deprived: housing materials	0.4554	0.4980	0.000	1.0000
Deprived: solid cooking fuel	0.8924	0.3099	0.000	1.0000
Deprived: >3 members per sleeping room	0.5675	0.4955	0.000	1.0000
Deprived: lighting source	0.3349	0.4720	0.000	1.0000
Deprived: drinking water	0.2665	0.4422	0.000	1.0000
Deprived: sanitation	0.6780	0.4673	0.000	1.0000
Deprived: ≤ 2 small assets and no livestock	0.5124	0.4999	0.000	1.0000
Household unemployment (excluded from c and from the models)	0.1021	0.3028	0.000	1.0000
Covariate shock	0.6976	0.4593	0.000	1.0000
Idiosyncratic shock	0.0642	0.2452	0.000	1.0000
Remittances received	0.2020	0.4015	0.000	1.0000
Household size	7.8042	2.8842	1.000	23.0000
Dependency ratio	0.3272	0.4171	0.000	7.0000
Female share of members	0.5173	0.1754	0.000	1.0000
Head's age	1.0629	12.3937	−25.410	23.5897
Female-headed household	0.5102	0.4999	0.000	1.0000
Head's years of schooling	2.3456	4.8424	0.000	21.0000
Rural	0.2404	0.4274	0.000	1.0000
Nomadic	0.1180	0.3226	0.000	1.0000
Internally displaced (IDP)	0.1184	0.3231	0.000	1.0000
Agricultural land ownership	0.0875	0.2826	0.000	1.0000
a. Descriptive Statistics—12-Indicator Comparison Index (c_{12})				
	Mean	SD	Min	Max
Comparison score c_{12} (12 indicators, 5 dimensions)	0.4471	0.1863	0.000	1.0000
MPI poor: $c_{12} \geq 1/3$	0.7422	0.4375	0.000	1.0000
MPI severely poor: $c_{12} \geq 1/2$	0.4440	0.4969	0.000	1.0000
MPI vulnerable: $0.20 \leq c_{12} < 1/3$	0.1588	0.3655	0.000	1.0000
b. Alkire–Foster Headline Measures ($k = 1/3$, primary specification)				
Index	Value	95% CI Lower	95% CI Upper	
MPI (M_0)	0.423	0.414	0.432	
Incidence (H), %	74.1	72.7	75.5	
Intensity (A), %	57.1	56.5	57.7	

Table 2. Cont.

c. Alkire–Foster Headline Measures at k = 0.35 (SNBS national MPI comparison)						
Index	Value	95% CI Lower	95% CI Upper			
MPI (M ₀)	0.406	0.397	0.416			
Incidence (H), %	69.1	67.6	70.6			
Intensity (A), %	58.8	58.3	59.4			
d. Alkire–Foster Headline Measures, 12-Indicator Comparison Index (c12)						
Index	Value	95% CI Lower	95% CI Upper			
MPI (M ₀)	0.395	0.386	0.403			
Incidence (H), %	74.2	72.8	75.6			
Intensity (A), %	53.2	52.7	53.7			
e. Alkire–Foster Headline Measures by Settlement Type, with 95% Confidence Intervals						
Settlement/Index	Value	CI Lower	CI Upper			
Urban—MPI (M ₀)	0.366	0.354	0.377			
Incidence (H), %	67.5	65.7	69.4			
Intensity (A), %	54.1	53.4	54.9			
Rural—MPI (M ₀)	0.458	0.440	0.476			
Incidence (H), %	79.5	76.7	82.3			
Intensity (A), %	57.6	56.6	58.6			
Nomadic—MPI (M ₀)	0.665	0.651	0.678			
Incidence (H), %	98.8	97.9	99.8			
Intensity (A), %	67.2	66.0	68.4			
f. Alkire–Foster Headline Measures by Region, with 95% Confidence Intervals						
Region	M ₀	M ₀ 95% CI	H, %	H 95% CI	A, %	A 95% CI
Bakool	0.690	[0.671, 0.708]	97.9	[96.6, 99.2]	70.4	[68.8, 72.1]
Gedo	0.568	[0.537, 0.599]	88.2	[84.3, 92.0]	64.4	[62.3, 66.5]
Lower Juba	0.553	[0.529, 0.577]	91.6	[88.8, 94.5]	60.4	[58.5, 62.2]
Bay	0.550	[0.516, 0.585]	90.1	[85.5, 94.8]	61.1	[58.6, 63.5]
Hiraan	0.532	[0.508, 0.556]	90.2	[87.2, 93.2]	59.0	[57.2, 60.8]
Middle Shabelle	0.526	[0.497, 0.554]	88.5	[84.9, 92.1]	59.4	[57.5, 61.3]
Mudug	0.514	[0.484, 0.543]	84.7	[80.9, 88.4]	60.7	[58.9, 62.5]
Galgaduud	0.475	[0.445, 0.506]	83.6	[79.7, 87.5]	56.9	[54.7, 59.0]
Sanaag	0.471	[0.427, 0.515]	78.7	[73.6, 83.8]	59.9	[56.8, 62.9]
Sool	0.432	[0.390, 0.474]	73.7	[68.6, 78.8]	58.6	[55.5, 61.6]
Bari	0.397	[0.356, 0.439]	65.9	[60.2, 71.5]	60.3	[57.8, 62.9]
Nugaal	0.377	[0.344, 0.411]	68.4	[62.9, 73.9]	55.1	[52.9, 57.4]
Togdheer	0.376	[0.345, 0.407]	70.9	[65.5, 76.3]	53.1	[51.1, 55.1]
Banadir	0.362	[0.338, 0.386]	70.2	[66.0, 74.4]	51.6	[50.0, 53.1]
Lower Shabelle	0.303	[0.269, 0.336]	61.2	[55.2, 67.1]	49.5	[47.5, 51.5]
Waqooyi Galbeed	0.297	[0.262, 0.331]	57.4	[51.3, 63.6]	51.6	[49.3, 53.9]
Awdal	0.286	[0.250, 0.322]	52.7	[46.4, 58.9]	54.3	[51.8, 56.8]

Notes: N = 7212 households; all population-weighted statistics (wgt_pop). c = AF deprivation score in [0, 1]; MPI poor = 1 if $c \geq 1/3$. Index: 11 indicators, 4 equally weighted dimensions; uniform deprivation cutoffs applied to all households (standard AF). Shocks and unemployment are excluded from the index and enter the model as regressors instead. (a) c12 uses the original 12-indicator, 5-dimension structure (unemployment included as a deprivation indicator, weight 1/10, under an “Inclusion” dimension)—the exact structure used before unemployment was moved to the regressor side. Indicator-level prevalences and covariate means shown in Table 2 above are shared inputs to both indices and are not repeated here. Shown separately from Table 2 so the two index structures are never read as a single, merged set of statistics. (e) Notes: 95% CIs computed via svy: mean with subpop () (not a plain “if” restriction, which understates the SE for a subgroup mean estimated from a complex survey design). N = 7212 households; population weighted. (f) Notes: 95% CIs computed via svy: mean with subpop (); same caveat as Table 2e. N = 7212 households; population weighted. Regions ranked descending by M₀.

Table 3 presents clear differences in multidimensional poverty by settlement type under the primary index. The mean deprivation score increases from 0.427 in urban areas

to 0.504 in rural areas and 0.668 among nomadic households, with the MPI headcount rate reaching 98.9% in the latter group (Table 3a reports the corresponding figures under the 12-indicator comparison index: 0.416, 0.464, and 0.580, with a headcount rate of 98.0% among nomadic households the same qualitative pattern, with the primary index reading somewhat higher throughout, consistent with the national-level gap documented in Table 2b,d). Covariate shock prevalence is higher outside urban areas, at 89.8% among nomadic households compared to 65.0% in urban areas. Remittance receipt is lower among nomadic households (11.3%) compared to urban (21.4%) and rural (21.5%) households. Educational attainment declines across settlement types, from 2.9 years among urban household heads to 1.8 years in rural areas and 0.3 years among nomadic households.

Table 3. Multidimensional Poverty by Household Settlement.

	Urban Mean	Urban SD	Rural Mean	Rural SD	Nomadic Mean	Nomadic SD
Deprivation score c (11 indicators)	0.4274	0.2097	0.5044	0.1964	0.6675	0.1298
MPI poor: $c \geq 1/3$	0.6753	0.4683	0.7953	0.4036	0.9885	0.1067
Covariate shock	0.6498	0.4771	0.7265	0.4458	0.8983	0.3024
Idiosyncratic shock	0.0794	0.2704	0.0414	0.1992	0.0283	0.1659
Remittances received	0.2136	0.4099	0.2147	0.4107	0.1130	0.3168
Household size	8.1501	2.9660	7.2364	2.6412	7.0804	2.5759
Head's years of schooling	2.9065	5.3653	1.8294	4.0505	0.3475	1.5999
Internally displaced (IDP)	0.1342	0.3409	0.0630	0.2431	0.1454	0.3526
a. Multidimensional Poverty by Household Settlement—12-Indicator Comparison Index (c12)						
	Urban Mean	Urban SD	Rural Mean	Rural SD	Nomadic Mean	Nomadic SD
Comparison score c12 (12 indicators)	0.4162	0.1906	0.4642	0.1729	0.5804	0.1094
MPI poor: $c12 \geq 1/3$	0.6840	0.4650	0.7805	0.4140	0.9803	0.1390

Notes: All statistics are population-weighted (wgt_pop). c = AF deprivation score in [0, 1]; MPI poor = 1 if $c \geq 1/3$. (a) Notes: Same sample and settlement definitions as Table 3.

Two points are worth noting from Table 2b–d. First, the primary index's M_0 (0.423, 95% CI [0.414, 0.432]) and the 12-indicator comparison index's M_0 (0.395, 95% CI [0.386, 0.403]) do not overlap; the primary index's lower bound (0.414) sits above the comparison index's upper bound (0.403), a gap of 0.011. This is a statistically confirmed difference, not merely a description of the two structures: removing unemployment from the index is associated with a significantly higher M_0 estimate. The mechanism is intensity, not incidence is essentially unchanged (74.1% versus 74.2%, CIs overlap substantially), while intensity is significantly higher under the 11-indicator structure (57.1%, CI [56.5, 57.7]) than under the 12-indicator structure (53.2%, CI [52.7, 53.7]), consistent with a low-prevalence indicator (10.2% of households) having previously diluted the average deprivation share among the poor toward zero. Second, at the Somalia National Bureau of Statistics (SNBS) report's own published cutoff of $k = 0.35$, this paper's recomputed estimates ($M_0 = 0.406$, $H = 69.1\%$, $A = 58.8\%$) are all higher than the officially published figures ($M_0 = 0.363$, $H = 67.0\%$, $A = 54.3\%$). This gap is consistent with the uniform-cutoff methodology adopted here (The Alkire–Foster Framework Section): the SNBS report applies settlement-specific exemptions, particularly for nomadic households that are associated with lower measured deprivation for that subgroup, so the higher national estimate here is consistent with removing those exemptions to preserve subgroup decomposability. This is offered as methodological reconciliation rather than a claim that either figure is incorrect. Third, the robustness index c_{alt} —the alternative 3-dimension structure described in The Alkire–Foster Framework Section, which never included unemployment as an indicator—is unaffected by this restructuring: $H = 0.728$, $A = 0.585$, and $M_0 = 0.426$, unchanged from the previous run. Notably,

c12's point estimates ($H = 0.742$, $A = 0.532$, $M_0 = 0.395$) reproduce the very first index computed for this paper before any of the subsequent revisions, which is a useful internal consistency check on the reconstruction.

As shown in Table 2f, the precision of the regional estimates also varies considerably. For example, Bakool's 95% confidence interval for (M_0), [0.671, 0.708], has a width of 0.037, whereas Sanaag's interval, [0.427, 0.515], has a width of 0.088. Thus, Bakool's confidence interval is only about 42% as wide as Sanaag's, meaning that Sanaag's interval is approximately 2.38 times wider than Bakool's. This indicates substantially greater statistical uncertainty around the Sanaag estimate. Such differences in interval width reflect differences in the estimated standard errors, which may arise from variation in regional sample sizes, within-region variability, and the survey design. Accordingly, the regional ranking in Table 2f should be interpreted primarily as a comparison of estimated poverty levels, while differences in the precision of these estimates should also be considered.

4.2. Empirical Findings and Discussion

Table 4 reports results from fractional probit, OLS, and binary probit models, while Table 5 presents the corresponding average marginal effects. Across models in Table 4, coefficient signs and statistical significance are largely consistent, indicating robustness to functional form choice.

Table 4. Multidimensional deprivation across the models.

	(1) Frac. Probit	(2) OLS	(3) Probit (mpi_poor)	(4) Frac. Probit (c_alt)	(5) Frac. Probit (c12)	(6) Frac. Probit (c_purged)	(7) Frac. Probit (c_purged_educ)
Covariate shock	0.0661 *** (0.0173)	0.0248 *** (0.0064)	0.1386 ** (0.0580)	0.0618 *** (0.0192)	0.0512 *** (0.0158)	0.0527 *** (0.0171)	0.0485 ** (0.0189)
Idiosyncratic shock	0.0142 (0.0275)	0.0053 (0.0103)	0.0363 (0.1004)	0.0539 * (0.0308)	0.0199 (0.0250)	0.0198 (0.0271)	0.0108 (0.0306)
Remittances received	−0.1088 *** (0.0191)	−0.0406 *** (0.0071)	−0.3193 *** (0.0618)	−0.0871 *** (0.0210)	−0.0930 *** (0.0175)	−0.0987 *** (0.0191)	−0.1074 *** (0.0206)
Household size	0.0113 *** (0.0031)	0.0042 *** (0.0012)	0.0317 *** (0.0111)	0.0096 *** (0.0033)	0.0105 *** (0.0028)	−0.0011 (0.0031)	0.0334 *** (0.0035)
Dependency ratio	0.0130 (0.0182)	0.0054 (0.0067)	0.1762 ** (0.0782)	−0.0036 (0.0207)	0.0147 (0.0163)	0.0035 (0.0188)	−0.0904 *** (0.0207)
Female share of members	0.0228 (0.0391)	0.0071 (0.0145)	0.0553 (0.1444)	0.0367 (0.0438)	−0.0007 (0.0350)	0.0283 (0.0385)	0.0076 (0.0431)
Head age	−0.0031 *** (0.0007)	−0.0012 *** (0.0002)	−0.0100 *** (0.0026)	−0.0007 (0.0007)	−0.0028 *** (0.0006)	−0.0027 *** (0.0007)	−0.0019 ** (0.0007)
Head age squared	−0.0001 ** (0.0001)	−0.0000 ** (0.0000)	−0.0000 (0.0002)	−0.0001 ** (0.0001)	−0.0001 * (0.0000)	−0.0001 ** (0.0001)	−0.0002 *** (0.0001)
Female-headed household	−0.0883 *** (0.0164)	−0.0331 *** (0.0062)	−0.1890 *** (0.0597)	−0.0649 *** (0.0181)	−0.0739 *** (0.0148)	−0.0825 *** (0.0162)	−0.0466 *** (0.0178)
Head's years of schooling	−0.0405 *** (0.0017)	−0.0145 *** (0.0006)	−0.0899 *** (0.0060)	−0.0442 *** (0.0020)	−0.0353 *** (0.0015)	−0.0395 *** (0.0016)	−0.0293 *** (0.0018)
Rural	0.1957 *** (0.0175)	0.0738 *** (0.0067)	0.3674 *** (0.0650)	0.2151 *** (0.0195)	0.1256 *** (0.0158)	0.1729 *** (0.0172)	0.1645 *** (0.0190)
Nomadic	0.5306 *** (0.0227)	0.2021 *** (0.0083)	1.7092 *** (0.1881)	0.5702 *** (0.0256)	0.3467 *** (0.0192)	0.4739 *** (0.0225)	0.4991 *** (0.0247)
Internally displaced (IDP)	0.3720 *** (0.0229)	0.1421 *** (0.0085)	0.9104 *** (0.1580)	0.3696 *** (0.0255)	0.3357 *** (0.0206)	0.3564 *** (0.0225)	0.3461 *** (0.0251)

Table 4. Cont.

	(1) Frac. Probit	(2) OLS	(3) Probit (mpi_poor)	(4) Frac. Probit (c_alt)	(5) Frac. Probit (c12)	(6) Frac. Probit (c_purged)	(7) Frac. Probit (c_purged_educ)
Agricultural land ownership	−0.0033 (0.0244)	−0.0011 (0.0091)	0.1341 (0.1162)	0.0211 (0.0285)	−0.0137 (0.0216)	0.0021 (0.0244)	−0.0050 (0.0275)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6883	6883	6883	6883	6883	6883	6883

Notes: Dependent variable: AF deprivation score c in $[0, 1]$ (11 indicators, 4 dimensions, uniform cutoffs for all households, Shocks and unemployment excluded). Survey weights applied. Taylor-linearised SEs in parentheses. Region FE included; coefficients omitted. Col. (4): robustness index c_alt (3-dimension structure with the broadened health-access indicator; see The Alkire–Foster Framework Section). Col. (5): comparison index $c12$ (12 indicators, 5 dimensions, unemployment included as a deprivation indicator; see Table 2a), using the same regressors as col. (1) reproduces the coefficients from the very first specification used in this project, before the index was restructured, which is a useful internal consistency check. Col. (6): mechanical-overlap robustness check, c_purged (overcrowding indicator dropped from the index, its weight redistributed across Living Standards’ remaining indicators; see Section 3.3.3), same regressors as col. (1); tests whether household size’s coefficient reflects the deterministic link between $hsize$ and the overcrowding indicator rather than an independent association. Col. (7): second mechanical-overlap robustness check, c_purged_educ (schooling indicator dropped from the index, attendance absorbing Education’s full 1/4 weight alone; see Section 3.3.3), same regressors as col. (1); tests the analogous concern for household head’s years of schooling, which is closely related to the schooling indicator. Base location: urban. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

As shown in Table 5, exposure to covariate shocks is associated with a statistically significant 2.6 percentage point higher deprivation score. By contrast, the coefficient on idiosyncratic shocks is small and not statistically distinguishable from zero in this baseline, pooled specification (Table 4 col. 1: 0.0142, $p > 0.10$; Table 5 AME: 0.0057, $p > 0.10$). This association becomes marginally significant only under the alternative three-dimension index structure (c_alt , Table 4 col. 4: 0.0539, $p < 0.10$), suggesting the idiosyncratic-shock association is sensitive to how the deprivation index is constructed and should be interpreted cautiously rather than treated as a robust baseline finding. This pattern is broadly consistent with the literature on risk and vulnerability in developing countries, in which household-specific shocks are typically harder to detect in aggregate cross-sectional data than community-wide shocks, even where informal risk-sharing is limited (Dercon, 2004; Heltberg & Lund, 2009).

Remittances are theorized to relax household budget constraints and support resilience to adverse shocks. As shown in Table 5, remittance receipt is consistently associated with a lower deprivation score, on the order of 4.3 percentage points in the primary fractional probit specification. This association is stable across all model specifications in Tables 4 and 5 and is consistent with the broader literature on remittances as an informal consumption-smoothing mechanism (Acosta et al., 2008). In the Somali context, this pattern may be consistent with remittances helping households sustain investment in areas such as children’s education, although this specific channel is not directly tested in the present analysis and should be treated as a plausible interpretation rather than a demonstrated mechanism.

Household head’s years of schooling is associated with a lower deprivation score, on the order of 1.6 percentage points per additional year (Table 5), broadly in line with the human capital literature (Becker, 1992; Harmon et al., 2003; Krueger & Lindahl, 2001; Sianesi & Reenen, 2003). As noted in Section 3.3.3, this association should be read alongside the partial mechanical overlap between the schooling indicator embedded in the deprivation index and this regressor.

Table 5. Average Marginal Effects.

	(1) Frac. Probit AME	(2) Probit AME (mpi_poor)
Covariate shock	0.0263 *** (0.0069)	0.0351 ** (0.0147)
Idiosyncratic shock	0.0057 (0.0109)	0.0092 (0.0255)
Remittances received	−0.0433 *** (0.0076)	−0.0809 *** (0.0157)
Household size	0.0045 *** (0.0012)	0.0080 *** (0.0028)
Dependency ratio	0.0052 (0.0073)	0.0446 ** (0.0199)
Female share of members	0.0091 (0.0155)	0.0140 (0.0366)
Head age	−0.0012 *** (0.0003)	−0.0025 *** (0.0007)
Head age squared	−0.0000 ** (0.0000)	−0.0000 (0.0000)
Female-headed household	−0.0352 *** (0.0065)	−0.0479 *** (0.0152)
Head’s years of schooling	−0.0161 *** (0.0007)	−0.0228 *** (0.0017)
Rural	0.0779 *** (0.0070)	0.0931 *** (0.0162)
Nomadic	0.2113 *** (0.0090)	0.4331 *** (0.0419)
Internally displaced (IDP)	0.1481 *** (0.0091)	0.2307 *** (0.0372)
Agricultural land ownership	−0.0013 (0.0097)	0.0340 (0.0295)
Region FE	Yes	Yes
Observations	6883	6883

Notes: Marginal effects at sample means; discrete first difference for binaries. Region FE included; coefficients omitted. Survey weights applied. SEs are Taylor-linearised. *** $p < 0.01$, ** $p < 0.05$.

Household size is positively correlated with the deprivation score in the primary specification, but the mechanical-overlap check in Section 3.3.3 shows this association is essentially entirely an artifact of the overcrowding indicator embedded in the index: household size’s coefficient collapses to statistically indistinguishable from zero (from 0.0113, $p < 0.01$, to −0.0011, $p = 0.730$) once that indicator is removed. Unlike household head’s schooling above, this is not merely a caveat on interpretation household size shows no remaining association with deprivation once the mechanical channel is closed and should not be read as evidence of a resource-dilution effect independent of the index’s own construction.

The results also show pronounced spatial variation. Rural households show significantly higher deprivation scores than urban households, and the gap is even larger for nomadic households. This pattern aligns with the rural poverty literature (Haider et al., 2018) and research on pastoralist marginalization in East Africa, which highlights structural constraints such as limited mobility, weak market integration, and inadequate access to public services (Lind et al., 2020; Little et al., 2014). The especially large coefficient for

nomadic households is consistent with severe multidimensional deprivation among mobile livelihoods in fragile and conflict-affected contexts.

Female-headed households are associated with lower deprivation scores. Although this differs from much of the cross-country gender-poverty literature, it is consistent with the Somali context, where decades of conflict have reshaped household roles: [Ingiriis and Hoehne \(2013\)](#) note that prolonged conflict, state collapse, and widespread male unemployment led many women to become primary income earners and household heads, while some men became economically inactive. This pattern is consistent with female headship in Somalia reflecting resilience and economic adaptation rather than vulnerability alone, though the cross-sectional design here cannot establish the direction of this relationship.

Finally, the results show a non-linear association between household head's age and the deprivation score, with predicted deprivation rising until approximately age 48 and declining thereafter. This pattern is broadly consistent with lifecycle welfare models ([Deaton & Paxson, 1993](#)), which describe how household welfare tends to evolve with age as income, consumption, and asset holdings change over the life course.

Column (6) directly addresses the potential mechanical overlap between household size and the multidimensional deprivation index discussed in Section 3.3.3. When the overcrowding indicator is excluded from the index, the estimated coefficient on household size declines from 0.0113 ($p < 0.01$) to -0.0011 and becomes statistically insignificant ($p = 0.730$). The reversal in both magnitude and sign indicates that the positive association between household size and multidimensional deprivation observed in columns (1)–(5) is largely attributable to the mechanical role of household size in the construction of the overcrowding indicator, rather than to an independent association with the remaining dimensions of deprivation.

Importantly, excluding the overcrowding indicator does not materially alter the study's central findings. The estimated effects of covariate shocks, remittances, and idiosyncratic shocks remain stable in terms of both direction and statistical significance. The coefficient on covariate shocks changes from 0.0661 to 0.0527, while the coefficient on remittances changes from -0.1088 to -0.0987 ; both remain statistically significant at the 1% level. Similarly, the coefficient on idiosyncratic shocks changes only from 0.0142 to 0.0198 and remains statistically insignificant in both specifications. Overall, these changes represent relatively modest differences in magnitude, ranging from approximately 9% to 20%.

Column (7) addresses the analogous concern for household head's years of schooling raised in Section 3.3.3. When the schooling indicator is excluded from the index, leaving attendance as Education's sole indicator, carrying the dimension's full 1/4 weight alone, the estimated coefficient on `head_educ_years` declines from -0.0405 ($p < 0.01$) to -0.0293 , a 27.7% reduction, but remains highly statistically significant ($p < 0.001$) in both specifications. This is a materially different result from column (6): rather than collapsing to zero, roughly three-quarters of the coefficient's magnitude survives the indicator's removal, consistent with a partial, correlational overlap; `dep_schooling` reflects any household member aged 15 or older, not specifically the head, rather than the near-total mechanical relationship found for household size.

The coefficients this paper's central claims depend on are similarly stable under this second check. The coefficient on covariate shocks changes from 0.0661 to 0.0485 (both significant at conventional levels), the coefficient on remittances changes only from -0.1088 to -0.1074 (essentially unchanged), and the coefficient on idiosyncratic shocks changes from 0.0142 to 0.0108 and remains statistically insignificant in both specifications. As with column (6), the changes in these three coefficients are modest and do not alter their sign or significance pattern.

4.3. Are Remittances Associated with Reduced Shock Sensitivity?

To assess whether remittance receipt is associated with a weaker relationship between shock exposure and multidimensional deprivation, this section examines the interaction model specified in Equation (10).

Table 6 reports the shock $\times$ remittance interaction model (renamed from “Mediation effect of remittance”, since no formal causal mediation analysis was conducted). The interaction between idiosyncratic shocks and remittances is negative and statistically significant ($\beta = -0.1498$, $p < 0.05$), indicating that this raw coefficient is smaller among remittance recipients. Because this coefficient sits on the fractional-probit index scale rather than the deprivation score itself, the conditional average marginal effect (AME) of each shock by remittance status computed via the delta method as specified in Section 3.4.2 is the methodologically correct quantity to report, and is used throughout the rest of this section.

Table 6. Shock $\times$ Remittance Interaction Results.

	(1) Frac. Probit	(2) OLS	(3) Probit (mpi_poor)
Covariate shock	0.0554 *** (0.0193)	0.0212 *** (0.0073)	0.1181 * (0.0669)
Idiosyncratic shock	0.0541 * (0.0321)	0.0208 * (0.0121)	0.1148 (0.1302)
Remittances received = 1	−0.1302 *** (0.0342)	−0.0468 *** (0.0123)	−0.3512 *** (0.1016)
Covariate shock $\times$ Remittances	0.0493 (0.0397)	0.0160 (0.0144)	0.0785 (0.1235)
Idiosyncratic shock $\times$ Remittances	−0.1498 ** (0.0603)	−0.0582 *** (0.0223)	−0.2327 (0.2048)
Household size	0.0115 *** (0.0031)	0.0042 *** (0.0012)	0.0319 *** (0.0111)
Dependency ratio	0.0129 (0.0182)	0.0054 (0.0067)	0.1780 ** (0.0782)
Female share of members	0.0269 (0.0392)	0.0086 (0.0146)	0.0629 (0.1450)
Head age	−0.0031 *** (0.0007)	−0.0012 *** (0.0002)	−0.0101 *** (0.0026)
Head age squared	−0.0001 ** (0.0001)	−0.0000 ** (0.0000)	−0.0000 (0.0002)
Female-headed household	−0.0885 *** (0.0164)	−0.0331 *** (0.0062)	−0.1897 *** (0.0597)
Head’s years of schooling	−0.0405 *** (0.0017)	−0.0145 *** (0.0006)	−0.0899 *** (0.0060)
Rural	0.1963 *** (0.0175)	0.0740 *** (0.0067)	0.3685 *** (0.0649)
Nomadic	0.5327 *** (0.0226)	0.2029 *** (0.0083)	1.7138 *** (0.1877)
Internally displaced (IDP)	0.3722 *** (0.0228)	0.1422 *** (0.0085)	0.9107 *** (0.1575)
Agricultural land ownership	−0.0033 (0.0244)	−0.0011 (0.0091)	0.1359 (0.1162)
Region FE	Yes	Yes	Yes
Observations	6883	6883	6883

a. Conditional Average Marginal Effects on c, by Remittance Status				
Shock Type	Remittance Status	AME (pp)	95% CI	p-Value
Covariate shock	Non-recipient	+2.21 **	[0.70, 3.72]	0.004
Covariate shock	Recipient	+4.13 **	[1.38, 6.89]	0.003
Idiosyncratic shock	Non-recipient	+2.15	[−0.35, 4.66]	0.092
Idiosyncratic shock	Recipient	−3.78	[−7.76, 0.20]	0.063

Table 6. Cont.

b. Conditional Average Marginal Effects on mpi_poor, by Remittance Status				
Shock Type	Remittance Status	AME (pp)	95% CI	p-Value
Covariate shock	Non-recipient	+2.81	[−0.30, 5.92]	0.077
Covariate shock	Recipient	+6.11	[−0.39, 12.61]	0.065
Idiosyncratic shock	Non-recipient	+2.73	[−3.34, 8.81]	0.378
Idiosyncratic shock	Recipient	−3.66	[−13.37, 6.04]	0.459
c. Formal Test of the Interaction Contrast (Difference in Conditional AMEs)				
Shock Type	Difference (Recipient – Non-Recipient)	SE	95% CI	p-Value
Covariate shock	0.0192	0.0157	[−0.0116, 0.0501]	0.221
Idiosyncratic shock	−0.0593**	0.0239	[−0.1061, −0.0125]	0.013

Notes: Dependent variables: cols (1)–(2) AF deprivation score c in $[0, 1]$; col (3) MPI poor ($c \geq 1/3$). Interaction terms use factor-variable syntax so reported coefficients are directly usable with margins. Region FE included. Survey weights applied. SEs are Taylor-linearised. (a) Notes: Conditional average marginal effect of each shock type on the deprivation score c , evaluated at sample means, by remittance status (delta-method SEs, Model 4a). $N = 6883$. (b) Notes: Conditional average marginal effect of each shock type on mpi_poor ($c \geq 1/3$), evaluated at sample means, by remittance status (delta-method SEs, Model 4c). $N = 6883$. (c) Notes: Formal test of $[E(c | \text{shock} = 1, R = 1) - E(c | \text{shock} = 0, R = 1)] - [E(c | \text{shock} = 1, R = 0) - E(c | \text{shock} = 0, R = 0)]$ for each shock type, using the joint variance–covariance matrix of both conditional AMEs from a single margins call (not a naive subtraction of Table 6a’s two rows, which are correlated and would understate or overstate the true SE if combined independently). Model 4a, $N = 6883$. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

To further interpret the interaction effects, Table 6a reports the conditional average marginal effects of shock exposure on multidimensional deprivation by remittance status. The results reveal an important distinction between idiosyncratic and covariate shocks. For idiosyncratic shocks, the estimated effect is positive among non-recipients (+2.2 percentage points, $p = 0.092$) but negative among remittance recipients (−3.8 percentage points, $p = 0.063$). Consistent with the statistically significant interaction term, and now confirmed directly rather than inferred: the formal test of the difference between these two conditional effects $[E(c | \text{shock} = 1, R = 1) - E(c | \text{shock} = 0, R = 1)] - [E(c | \text{shock} = 1, R = 0) - E(c | \text{shock} = 0, R = 0)]$, with its own delta-method standard error gives −0.0593 (SE = 0.0239, 95% CI [−0.1061, −0.0125], $p = 0.013$). The difference itself, not merely each side of it, is statistically significant: remittances are associated with a significantly smaller marginal effect of idiosyncratic shocks on the deprivation score, moderating this relationship (Table 6c).

In contrast, covariate shocks are positively associated with deprivation for both non-recipients (+2.2 percentage points, $p = 0.004$) and recipients (+4.1 percentage points, $p = 0.003$). However, because the corresponding interaction term is not statistically significant, the difference between these conditional effects does not provide evidence that remittances significantly moderate the association with covariate shocks. The same formal contrast test applied to covariate shocks confirms this directly: the estimated difference is 0.0192 (SE = 0.0157, 95% CI [−0.0116, 0.0501], $p = 0.221$), not statistically distinguishable from zero (Table 6c). Overall, the results suggest that the buffering role of remittances is more evident for idiosyncratic shocks than for shocks that affect households more broadly.

As a robustness check, the same conditional AMEs are computed with mpi_poor ($c \geq 1/3$) in place of the continuous score c , using the binary probit interaction model (Model 4c, Table 6b). For idiosyncratic shocks, the sign reversal repeats +2.7 percentage points among non-recipients versus −3.7 percentage points among recipients, but neither estimate is statistically significant on this coarser, binary outcome ($p = 0.378$ and $p = 0.459$, respectively), which is unsurprising given the binary outcome’s lower statistical power relative to the continuous score. For covariate shocks, the same pattern as on c repeats:

both non-recipients (+2.8 percentage points, $p = 0.077$) and recipients (+6.1 percentage points, $p = 0.065$) show a positive, marginally significant association, with no evidence of a moderating role for remittances. Both robustness results are consistent with the primary findings on c: the idiosyncratic-shock reversal is directionally stable across outcome measures even where power is limited, and covariate shocks show no buffering under either specification.

In the Somali context, where formal insurance and public social protection remain limited, this pattern is consistent with remittances serving as a private coping mechanism for household-specific shocks, although the cross-sectional design does not permit causal interpretation.

Whether this buffering pattern varies across settlement types or specific subgroups is examined in Table 7.

Table 7. Fractional Probit by Settlement Type.

	(1) Urban	(2) Rural	(3) Nomadic
Household size	0.0096 ** (0.0039)	0.0137 ** (0.0058)	0.0230 *** (0.0082)
Dependency ratio	0.0279 (0.0222)	0.0131 (0.0393)	−0.1072 *** (0.0347)
Female-headed household	−0.0872 *** (0.0213)	−0.0694 ** (0.0325)	−0.0560 (0.0352)
Head's years of schooling	−0.0389 *** (0.0019)	−0.0414 *** (0.0033)	−0.0446 *** (0.0092)
Internally displaced (IDP)	0.4710 *** (0.0280)	0.2354 *** (0.0522)	—
Covariate shock	0.0561 ** (0.0236)	0.0176 (0.0396)	0.0772 ** (0.0379)
Remittances received = 1	−0.1479 *** (0.0382)	−0.0082 (0.0751)	−0.0975 (0.1297)
Covariate shock × Remittances	0.0564 (0.0470)	−0.0556 (0.0826)	0.0771 (0.1337)
Idiosyncratic shock	0.0406 (0.0358)	0.1206 (0.0740)	0.1148 (0.0917)
Idiosyncratic shock × Remittances	−0.0993 (0.0699)	−0.4162 *** (0.1184)	−0.0493 (0.1110)
Observations	4130	1844	909

Notes: Dependent variable: AF deprivation score c in $[0, 1]$. Specification includes shock × remittance interactions (as in Table 6). The Observations row reports the true urban/rural/nomadic subpopulation size ($4130 + 1844 + 909 = 6883$, exactly matching the analytical sample), obtained by combining $e(\text{sample})$ with each settlement condition after estimation—not $svy's\ e(N)$ for $subpop()$ estimation, which instead reports the full survey design retained for variance estimation ($6998/7148/7161$) and is not the number of households in each settlement. The full survey sample is 7212 households; the analytical (regression) sample after listwise deletion is 6883 households (Table 2 note). Location dummies excluded within each subgroup (zero within-group variation). IDP excluded from the nomadic subgroup (near-zero within-group variation). Region FE included; coefficients omitted. *** $p < 0.01$, ** $p < 0.05$.

Table 7 indicates substantial heterogeneity across settlement types. The significant idiosyncratic shock × remittance interaction is concentrated among rural households ($−0.4162$, $p < 0.01$), while the corresponding interactions for urban ($−0.0993$) and nomadic ($−0.0493$) households are statistically insignificant. The main effect of remittances is significant only among urban households ($−0.1479$, $p < 0.01$). Covariate shocks are positively associated with deprivation among urban and nomadic households, but no significant re-

mittance interaction is observed in any subgroup. Thus, the buffering association identified in the pooled model appears to be driven primarily by rural households rather than being uniform across settlement types.

Table 8 provides a diagnostic assessment of multicollinearity. All VIF values are below 1.5, indicating no evidence of problematic multicollinearity among the explanatory variables. This diagnostic is distinct from the mechanical-overlap concern discussed in Section 3.3.3. While VIF assesses correlation among regressors, the *c_purged* specification examines the potential overlap between regressors and the construction of the dependent variable. The latter robustness check shows that the household-size coefficient becomes statistically insignificant once the overcrowding indicator is removed, supporting the interpretation that its baseline association is largely mechanical.

Table 8. Multicollinearity Diagnostics: Variance Inflation Factors.

Variable	R ²	VIF	Tolerance
Head age	0.319	1.468	0.681
Head age squared	0.259	1.349	0.741
Nomadic	0.209	1.265	0.791
Female-headed household	0.206	1.260	0.794
Rural	0.201	1.252	0.799
Agricultural land ownership	0.189	1.233	0.811
Head's years of schooling	0.170	1.205	0.830
Household size	0.166	1.198	0.834
Covariate shock	0.162	1.193	0.838
Dependency ratio	0.161	1.191	0.839
Remittances received	0.119	1.135	0.881
Internally displaced (IDP)	0.081	1.089	0.919
Female share of members	0.062	1.066	0.938
Idiosyncratic shock	0.034	1.036	0.966

5. Conclusions

This study examined the association between covariate and idiosyncratic shocks and multidimensional poverty in Somalia, with particular attention to whether remittance receipt moderates these relationships differently across shock types. The findings show that the relationship between shocks, remittances, and deprivation depends importantly on the nature of the risk households face. Covariate shocks are consistently associated with higher multidimensional deprivation, but there is no evidence that remittance receipt significantly moderates this association. By contrast, although idiosyncratic shocks do not exhibit a statistically significant average association with deprivation in the baseline specification, their relationship with poverty differs substantially by remittance status: the conditional association is positive among non-recipient households and negative among remittance-recipient households.

This pattern suggests that the insignificant average association for idiosyncratic shocks masks important heterogeneity in households' capacity to cope with household-specific risks. The subgroup results further indicate that this buffering pattern is concentrated among rural households rather than being uniform across the population. Remittance receipt is also independently associated with lower multidimensional deprivation, although this association should not be interpreted as evidence of a causal poverty-reducing effect.

5.1. Policy Implications

These results carry a specific policy implication rather than a general one: private remittance transfers and public social protection are not substitutes, because they appear to cover different risk types. Remittances are associated with lower deprivation among households facing idiosyncratic shocks, so measures that reduce the cost and friction of

transfers lower transaction fees, broader mobile-money access, stronger financial inclusion for diaspora-linked households may support this channel where it already operates, and this association is strongest for rural households specifically, suggesting geographic targeting matters. Covariate shocks show no comparable remittance-buffering association, which points toward a different implication: policy responses to droughts, floods, and price shocks that affect entire communities likely need to rely on public and humanitarian mechanisms (social protection, contingency financing, early-response systems) rather than assuming diaspora transfers will scale with community-wide need. We present these as implications suggested by the associations reported here and by the supporting literature, not as effects this study has demonstrated to follow from any specific policy intervention.

5.2. Future Research Directions

Four limitations of this study point directly to future research needs rather than to caveats alone. First, remittance receipt is treated as exogenous on the assumption that it reflects pre-existing migration networks; this assumption cannot be tested with cross-sectional data, and future work with panel data or a credible instrument (e.g., historical migration-network shocks) could identify the association more causally. Second, the covariate/idiosyncratic shock classification here follows event type rather than measured co-movement across households, because community- or enumeration-area-level exposure rates are not available in this survey; future data collection that captures shock incidence at the community level would allow this classification to be verified empirically rather than assumed. Third, the remittance variable used here is a binary receipt indicator without transfer amounts or frequency, which limits any test of whether transfers respond dynamically to shocks; panel data capturing transfer values over time would allow that transnational-insurance mechanism to be tested directly rather than inferred. Fourth, this study's index reflects one reasonable set of dimensions, indicators, and cutoffs among several defensible alternatives; future work applying this framework to other fragile, remittance-dependent settings would clarify how sensitive these findings are to context as well as to index construction.

5.3. Recommendations

For researchers: prioritize panel or quasi-experimental data collection in remittance-dependent, shock-prone settings, since the associational findings here cannot support causal policy design on their own. For statistical agencies fielding surveys like the SIHBS: consider adding community-level shock indicators and remittance amount/frequency questions in future survey rounds, since both were binding data constraints on this analysis. For policymakers: treat remittance-facilitation measures and public social protection as complementary instruments targeted at different risk types, rather than as alternative ways to achieve the same protective goal, and prioritize rural households specifically when designing interventions premised on remittances' idiosyncratic-shock buffering role, given that this association was not detected in urban or nomadic subgroups.

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Abbreviations

The following abbreviations are used in this manuscript:

AF	Alkire–Foster (methodology)
AME	Average Marginal Effect
FIES	Food Insecurity Experience Scale
GDP	Gross Domestic Product
IDP	Internally Displaced Person
MPI	Multidimensional Poverty Index
OLS	Ordinary Least Squares
OPHI	Oxford Poverty and Human Development Initiative
SE	Standard Error
SIHBS	Somalia Integrated Household Budget Survey
SNBS	Somalia National Bureau of Statistics
UNDP	United Nations Development Programme
FE	Fixed Effects (region FE in the tables)

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