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Estimating multidimensional development resilience

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ABSTRACT

Existing measures of resilience are typically based on a single well-being indicator. This is problematic in contexts where households face deprivations across multiple dimensions. We develop a multidimensional resilience measure, integrating probabilistic moment-based resilience measurement approaches with multidimensional poverty measurement methods. Applying these to household panel data from Ethiopia, we show that univariate and multidimensional resilience measures based on expenditure-based poverty, dietary diversity, and livestock asset holdings can yield varied inferences on the ranking of households as well as potential impact of development interventions. Univariate resilience measures constructed using consumption expenditure, dietary diversity and livestock asset holdings show distinct temporal and spatial distributional patterns. But while univariate measures are weakly correlated with one another and with different well-being metrics, multivariate measures exhibit much stronger rank correlations. When we contrast univariate measures of resilience to multidimensional measures of resilience, we find that the latter vary less over the study period; multidimensional resilience measures seem to capture more "persistent or structural" vulnerability and associated capacity of households. We also demonstrate the differences in these univariate and multivariate measures, including the potential of the composite multidimensional resilience measures for supporting targeting processes.

1. Introduction

Over the past two decades, governments and their development partners have undertaken significant investments in interventions that aim to improve the resilience of households or communities to shocks and stressors (Barrett et al., 2021).[1] Alongside this has been work that has sought to define and operationalize the notion of resilience. Over time, there has been increased understanding that resilience can be thought of as either: (1) the capacity to withstand exposure to negative stressors or shocks; (2) a return to equilibrium after a shock; or (3) a normative condition, the sustained capacity of an entity to avoid falling below some normative threshold standard of living (Barrett et al., 2021). The first strand of literature, which originates from ecology and psychology, defines resilience as a latent capacity (or vulnerability) of households, communities and systems to overcome stress or adversity (Rutter, 2012; Barrett et al., 2021).[2] This relates resilience with vulnerability (Pritchett et al., 2000; Chaudhuri et al., 2002; Chaudhuri, 2003; Ligon and Schechter, 2003; Günther and Harttgen, 2009; Hoddinott and Quisumbing, 2010; Hill and Porter, 2017; Gallardo, 2018). The second strand of literature conceptualizes resilience as the speed of recovery or adjustment to a pre-existing equilibrium following a shock (Perrings, 2006; Knippenberg and Hoddinott, 2017). The third and more recent conceptualization anchors resilience to normative well-being standards and hence defines resilience as the potential and likelihood of achieving a minimum standard of living or normative well-being (Barrett and Constas, 2014; Cissé and Barrett, 2018).

While work in the last decade has clarified the varied definitions of resilience, several significant methodological issues have arisen. First, the manner in which resilience is operationalized affects the assessment of the extent to which households are considered to be resilient; further, these different measures are often only weakly correlated (Upton et al., 2022). Second, resilience assessment has used various well-being

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[1] Major resilience-oriented funding initiatives have included the International Monetary Fund's Resilience and Sustainability Facility, the UK's Climate Adaptation and Resilience programme, and the US President's Emergency Plan for Adaptation and Resilience, among others.

[2] A widely used method that builds on this conceptualization is the Resilience Indicators for Measurement and Analysis (RIMA), developed by the Food and Agriculture Organization of the United Nations (FAO) (Alinovi et al., 2010; d'Errico et al., 2016; d'Errico and Di Giuseppe, 2018).

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indicators. Because a household's productive asset holdings determine its stochastic conditional income distribution over time, some studies define development resilience with respect to productive asset holdings, measured in terms of livestock or an asset index (Cissé and Barrett, 2018; Phadera et al., 2019; Scognamillo et al., 2023; Yao et al., 2023). Others anchor resilience measures to various food security or nutritional indicators (Upton et al., 2016; Knippenberg et al., 2019; Vaitla et al., 2020; Upton et al., 2022). Still others tie resilience measures directly to consumption expenditure and official poverty lines (Abay et al., 2022; Premand and Stoeffler, 2022; Upton et al., 2022).

The choice of measurement method and indicator(s) matters because resilience measures constructed based on different indicators may not generate similar orderings of households. These choices also affect evaluations of the effectiveness of interventions intended to improve development resilience. For example, Phadera et al. (2019) find that although a livestock transfer program in rural Zambia significantly improved short-term welfare outcomes, many households who received the treatment have a low likelihood of escaping expenditure-based poverty sustainably. Similarly, Sabates-Wheeler et al. (2021) concluded that while Ethiopia's Productive Safety Net Program has been successful in smoothing consumption shortfalls, it underperformed in building household assets and hence ultimate graduation out of poverty. Abay et al. (2022) show that building household resilience may require significant transfers and continuous participation in safety net programs as well as complementary income generating programs.

In this paper, we develop a novel method to address this second methodological issue, the choice of well-being indicators. Specifically, we develop a family of multidimensional resilience measures considering multiple dimensions of deprivation. An important feature of our approach is that they allow the researcher to make explicit the weight they give to different welfare indicators, and to assess how sensitive their measure of resilience is to variations in these weights. To do so, we draw on two existing methods: (1) the moment-based approach developed by Cissé and Barrett (2018); and (2) the literature on multidimensional poverty measurement (Alkire and Foster, 2011; Alkire and Santos, 2014).

We apply this novel method to five rounds of household panel data collected from rural Ethiopia. We show that when using the same data and resilience estimation method, univariate household resilience indicators based on different well-being indicators are only weakly correlated. When we combine multiple indicators into a multidimensional resilience indicator, the household-level rank correlation coefficients among different resilience estimators become appreciably greater, implying that inferences for the purposes of targeting or impact evaluation are more likely robust to reasonable variation in the well-being indicators employed to assess resilience.

We empirically demonstrate the differences in these univariate and multivariate measures, including the potential of the composite multidimensional resilience measures to support intervention targeting. While resilience measures based on consumption expenditure show the highest temporal variability, asset-based resilience measures exhibit limited temporal and spatial variation. Similarly, while community-level attributes and community-level fixed effects explain a large share of the variation in dietary resilience, such geographic factors explain only a limited portion of the variation in univariate and multivariate resilience associated with consumption and livestock-based resilience. These patterns suggest that while dietary resilience may be characterized by food environments and associated factors, those dimensions of resilience related to consumption and livestock mainly reflects household characteristics, not simply where households live. Productive assets play a pronounced role in explaining our multidimensional development resilience measures, which lends support to earlier literature that follow asset-based approaches to identify and target structural poverty (Sahn and Stifel, 2003; Carter and Barrett, 2006; Liverpool-Tasie and Winter-Nelson, 2011). This suggests that targeting building on asset-based measures may help build multidimensional resilience than those targeting approaches relying on transitory income or consumption expenditure. When we contrast univariate measures of resilience to multidimensional measures of resilience, we find that the latter vary less over the study period; hence these multidimensional resilience measures seem to capture more "persistent or structural" vulnerability and associated capacity of households. Consistent with the evolving literature on targeting poverty versus vulnerability (Barriga-Cabanillas et al., 2025), we show that the composite multidimensional measure of resilience can facilitate targeting of social protection programs that aim to build overall resilience of households. The multidimensional resilience measures outperform the univariate resilience measures, implying the value and potential of our multidimensional resilience measures to support the identification of vulnerable households for targeting interventions.

Our study contributes to two strands of evolving literature. The first contribution adds to the evolving debate on measuring resilience. Divergent resilience measurement approaches inhibit efforts to draw consistent and comparable lessons across contexts and domains (Constas et al., 2022). This study builds on prior comparative analyses of different univariate resilience measurement methods (Knippenberg et al., 2019; Constas et al., 2022; d'Errico and Båsund, 2022; Upton et al., 2022) by extending the analysis to multidimensional well-being indicators. Besides comparing the univariate and multidimensional measures of resilience, we also characterize the distribution of these measures and what explains the variation in these measures. Our second contribution relates to the evolving debate on targeting beyond current poverty to address vulnerability and build resilience, especially in contexts where vulnerability may be more pervasive than poverty. Our multivariate resilience measures capture both elements of normative well-being as well as vulnerability and hence the probability of avoiding falling below a minimum living standard. These multivariate measures perform slightly better at predicting safety net program participation than conventional poverty or univariate resilience measures.

The rest of the paper is structured as follows. Section 2 describes the data used for demonstrating and constructing multidimensional resilience measures. Section 3 outlines the empirical approach we used for constructing univariate and multidimensional resilience measures while 4 discusses the main results. Section 5 offers concluding remarks and potential avenues to extend this analysis.

2. Data

2.1. Data source and sample description

We use five rounds of household-level panel survey data fielded in four Highland regions of Ethiopia: Amhara, Oromia, Southern Nations, Nationalities, and Peoples (SNNP) and Tigray. The data were collected biennially in 2006, 2008, 2010, 2012 and 2014 as part of an ongoing evaluation of Ethiopia's Productive Safety Net Programme (PSNP). The PSNP was introduced in 2005 to respond to chronic and recurring food insecurity by providing regular transfers to food insecure households while also building community assets through labor-intensive public works (PWs) (Government of the Federal Democratic Republic of Ethiopia, 2004, 2010). Targeting used a mix of geographic and community-based targeting. The PSNP targeted historically food insecure woredas (districts). When the program began, woredas were selected on the basis of historical data on food aid allocations. Within woredas, local administrators selected the chronically food-insecure kebeles, assigning the woreda's "PSNP quota" among these areas. Within kebeles, task forces were created that identified households eligible for inclusion, specifically those with high levels of food insecurity and which had been recipients of past emergency food aid. Other household characteristics (assets; income from non-farming activities) were used to refine eligibility. Kebeles were given substantial discretion to modify this approach and to update their lists of eligible households;

for example, a household could be added to the program if suffered a significant asset loss and became food insecure as a result. Because each woreda was assigned a quota of households that could participate, not all eligible households were selected. About 80 percent of the PSNP beneficiaries were assigned to participate in labor-intensive PW projects, with the other 20 percent received direct support (DS) because they lacked labor needed for the PW and hence received unconditional transfers (Coll-Black et al., 2011; Berhane et al., 2013, 2014; Sabates-Wheeler et al., 2021). In addition to receiving transfers, some PSNP participants received technical support and agricultural input services along with access to credit services through the Household Asset Building Programme (HABP) (Berhane et al., 2014).

Within these regions, a sample of food-insecure woredas were selected in proportion to the overall number of chronically food-insecure woredas within that region and relative to the number of chronically food-insecure woredas in all four regions. Within each region, woredas were selected with probability proportional to size (PPS) based on the estimated chronically food insecure population. In total, 68 out of 190 woredas were selected. Restricting the sample to enumeration areas (EAs) where the PSNP was operating in 2006, two enumeration areas per woreda were chosen using PPS sampling for Amhara, Oromia, and SNNPR and three in Tigray. Using separate lists of PSNP beneficiary and non-beneficiary households, 15 PSNP beneficiary households and 10 non-beneficiary households were selected using simple random sampling (Gilligan et al., 2009; Berhane et al., 2014). For the purposes of this paper, households are included if: (a) they were surveyed in 2006; (b) they were surveyed in at least two consecutive rounds; and (c) have non-missing values for the outcome variables we consider (consumption expenditure, household dietary diversity Score, and tropical livestock unit) as well as other variables we used to construct resilience measures (i.e. household head characteristics, household economic status, etc.). Since our resilience measures require outcome variables in previous period, we used outcome variables in 2006 to construct resilience measures in 2008. We did not include households in Bale and Borena zone, as they are agro-pastoral zones whose economic structure is different from other zones. In the end our study sample is an unbalanced panel of 13,715 observations from 2,969 households over five survey rounds (2006, 2008, 2010, 2012, 2014).

Table 1 provides summary statistics of our study sample: (1) pooled from 2006 to 2014, and (2) for 2006 only. The distribution of the observable characteristics are comparable across the pooled sample and the baseline sample, except for some outcomes such as education and access to electricity, as expected, increase across rounds following the economic growth the country experienced.[3] The pooled sample shows that 76% of households are male-headed, farming is the primary occupation for 84% of households and mean household size is 5.3 members. Table 1 shows that 46 percent of year-household observations cover PSNP beneficiaries, while 36 percent of households benefited from the PW program, while another 9 percent received DS. On average, PSNP beneficiaries received 281 Birr per household member. Previous studies show that the attrition rates in these surveys are generally small and not systematically correlated with household characteristics, including PSNP participation (Berhane et al., 2013, 2014).

We employ three indicators to capture multiple dimensions of well-being and living standards. One is consumption expenditure, a widely used measure of well-being and living standards. The second measure captures access to healthy diets, household dietary diversity (HDDS), which is strongly correlated with both household caloric acquisition (Hoddinott and Yohannes, 2002) as well as access to micronutrients (Leroy et al., 2015). The third measure is livestock ownership. We chose livestock for two reasons. First, in Ethiopia livestock production and livestock assets are an important livelihood source. Rural households rely on livestock for generating income and for conducting as a farm input for manure, traction, and transport services. Second, livestock sales serve as major insurance against shocks in many parts of rural Ethiopia (Dercon and Christiaensen, 2011). Many rural households lack formal insurance and livestock is the most important liquid asset (Dercon and Christiaensen, 2011). This implies that households may face an important trade-off between satisfying current consumption objectives and maintaining their livestock assets to provide future income and thus consumption (McPeak, 2004). If households are satisfying their minimum consumption by depleting their livestock assets, they may not be sustainably resilient. Thus, holdings of livestock capture, in part, households' capacity to bear risk.

The last three rows in Table 1 report mean values for these indicators. We express all monetary values in Table 1 in 2014 constant prices.[4] Households spent 6423 Ethiopian Birr per adult-equivalent per year.[5] Mean Household Dietary Diversity Score (HDDS) is low, just 3.83 food groups. On average, households own 3.78 Tropical Livestock Units (TLU).

2.2. Selecting well-being indicators and normative thresholds

We follow the literature conceptualizing resilience as a normative condition (Barrett and Constas, 2014; Cissé and Barrett, 2018). This requires computing resilience as an individual's probability to achieve some minimal threshold which in turn requires us to identify a normative threshold for each indicator. Defining normative threshold for consumption and poverty-based measures of well-being is straightforward because we can assess these relative to Ethiopia's national poverty line. The poverty line for Ethiopia is estimated as the cost of food to satisfy the minimum daily caloric requirement as well as basic non-food items. The national poverty line for Ethiopia was 3781 Birr in 2011, equivalent to 4930.4 in 2014 prices (The World Bank, 2015).

Although the minimum threshold for household dietary diversity is not commonly defined, FAO and FHI360 (2016) offers some guidance using women's dietary diversity outcomes, setting five or more food groups as the minimum threshold for women's diet quality (micronutrient adequacy). We follow and apply this benchmark.[6] As shown in Fig. 1, HDDS, like logarithm of consumption expenditure, broadly resembles a normal distribution, with mean 3.8. The inverse hyperbolic sine of the TLU is least close to normal among these indicators, with a large share of households having no or very few livestock.

We build on two empirical and contextual patterns to define the minimum threshold for livestock holdings. First, rural households in Ethiopia – like many other African countries – typically use two oxen for ploughing land. And to maintain herd size, households need at least one male and one female. Considering the case of rural households in Zimbabwe, Hoddinott (2006) shows that households with one or two oxen (cows) were much less likely to sell than households with more than two of these animals, creating a natural, behavior-based TLU threshold. In a slightly different context, Balboni et al. (2022) identifies a similar livestock ownership threshold, above which households accumulate assets and grow out of poverty.

Second, we assess the relationship between livestock ownership and consumption expenditure via kernel-weighted local polynomial regression. Fig. 2 shows a nonlinear relationship between consumption and livestock assets: consumption is positively associated with livestock

[3] In Table A1 in the Appendix we report disaggregate statistics, across waves.

[4] At the latest survey round (2014), 1 USD was equivalent to 17 Ethiopian Birr. We computed USD values based on this rate.

[5] This conversion was applied for all welfare outcomes, PSNP transfers, value of productive assets, value of livestock as well as national poverty line. AEU is computed from household members' age and gender composition. Table A2 in the appendix shows the conversion weight table for the AEU.

[6] It should be noted, however, that the food groups used to construct HDDS are not identical to the groups used to construct the Minimum Dietary Diversity for Women (MDD-W).

Table 1
Summary Statistics.

	Pooled (2006–2014)			2006 Only		
	# of observations	Mean	SD	# of observations	Mean	SD
Male headed household	13 715	0.76	0.42	2819	0.79	0.41
Age of household head	13 715	47.73	14.86	2819	45.32	14.97
Household head no education	13 715	0.68	0.47	2819	0.76	0.43
Household head married	13 715	0.73	0.44	2819	0.73	0.44
Household size	13 715	5.34	2.21	2819	5.12	2.15
Main occupation farming	13 715	0.84	0.36	2819	0.86	0.35
Landholding per aeu (hectares)[+,@]	13 707	0.31	0.38	2819	0.34	0.34
Livestock asset value	13 715	12 345.84	15 591.59	2819	11 939.31	14 365.24
Production asset value per aeu[+,@]	13 356	193.41	783.15	2759	161.60	533.07
Household has electricity access	13 715	0.14	0.35	2819	0.05	0.21
Distance to the nearest town	13 715	14.74	10.90	2819	14.76	11.01
Total annual rainfall (mm)	13 715	990.31	309.47	2819	1035.95	295.26
PSNP beneficiaries	13 715	0.46	0.50	2819	0.51	0.50
PSNP direct support (DS) beneficiaries	13 715	0.10	0.29	2819	0.10	0.30
PSNP public work (PW) beneficiaries	13 715	0.36	0.48	2819	0.41	0.49
HABP beneficiaries	13 715	0.45	0.50	2819	0.29	0.45
PSNP and HABP beneficiaries	13 715	0.23	0.42	2819	0.17	0.37
PSNP benefit amount per capita (birr)[*,@]	6305	281.03	274.07	1444	253.45	232.22
Annual real consumption per aeu[@]	13 715	6441.53	7055.22	2819	4723.03	4109.77
Household Dietary Diversity Score (HDDS)	13 715	3.83	1.77	2819	3.37	1.44
Tropical Livestock Unit (TLU)	13 715	3.78	3.27	2819	3.79	3.24

[+] Small number of observations have missing values in 2006. These variables are used only from 2008 to 2014, therefore missing values in 2006 do not affect our analyses.
[@] All monetary variables are in Ethiopian birr, 2014 constant price. AEU stands for adult equivalent units.
[*] Including only PSNP beneficiaries. Non-beneficiaries have zero-value.

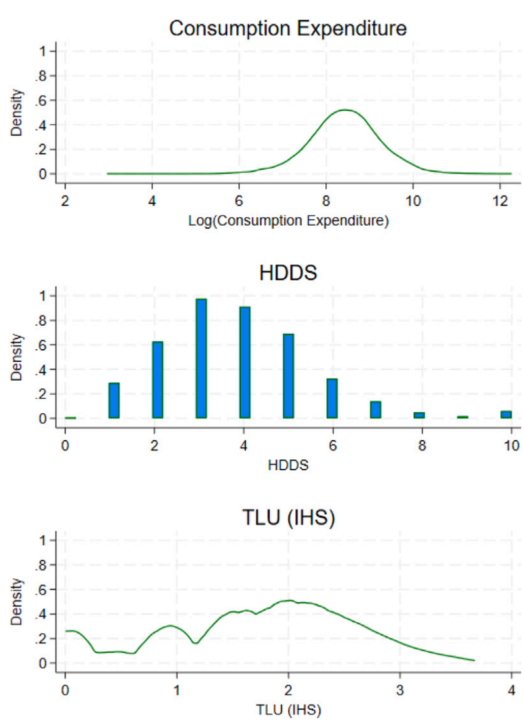

Fig. 1. Distribution of Well-being Indicators.

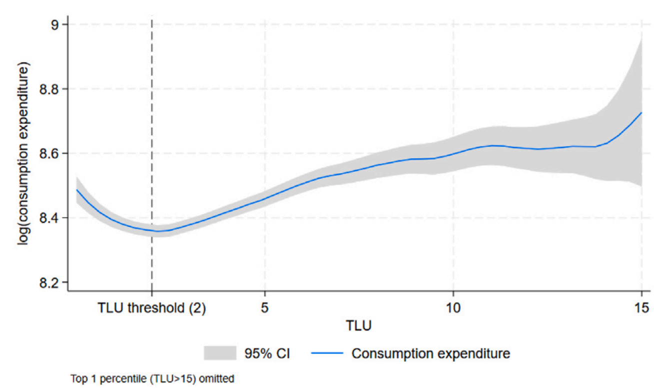

Fig. 2. Kernel-weighted local polynomial regression of consumption expenditure on TLU.

ownership but only after a minimum of two TLU. This confirms the contextual evidence that two oxen (or two cows) are needed to maintain minimum herd size in Ethiopia's highland regions, where households rely on mixed farming practices.[7] We replicate a few key analyses under different TLU thresholds in Appendix.[8]

Fig. 3 shows the temporal dynamics of our well-being indicators. The trend based on consumption expenditure and national poverty line show significant decline in poverty rate across time, although poverty rates are generally much higher than national averages because our sample comes from among the poorest areas of the country, those targeted for the PSNP. The share of households consuming below the minimum dietary diversity score also show some decline although not as much as the decline in poverty rates. The third line (based on the share of households owning < 2 TLU) show stable trend, with a marginal decline in livestock asset accumulation. These distinct trends suggest that statistical inferences on the temporal evolution of household resilience may depend on which measures of well-being are used as normative measures of well-being. Although all three outcomes are positively correlated with each other, the magnitude of these correlations differs; for example the correlation between household consumption expenditure and the HDDS is 0.34 while HDDS and TLU are more weakly correlated (0.18).

[7] Livestock ownership in pastoral communities and lowlands of Ethiopia exceeds that in the highland regions, as the drier conditions of the lowlands compels households to rely heavily on livestock production as source of livelihood. Thus, as shown by Lybbert et al. (2004) or Cissé and Barrett (2018), the threshold for these communities is likely to be higher than two TLU.

[8] Figure A2 replicates livestock resilience distribution in Fig. 4, and A3 replicate Fig. 6 under different TLU thresholds.

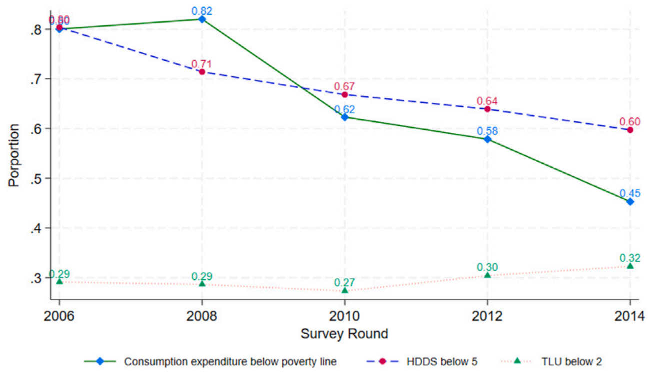

Fig. 3. Well-being indicators over time.

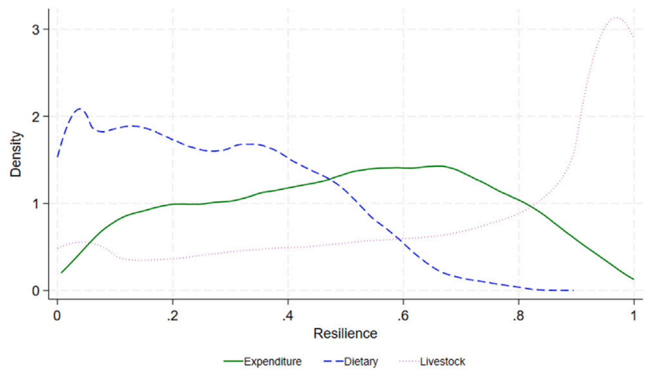

Fig. 4. Distribution of univariate resilience estimates.

3. Constructing resilience measures

3.1. Univariate resilience measures

We begin by constructing resilience measures based on the probabilistic moment-based approach (Cissé and Barrett, 2018) for each outcome. Note that estimation requires panel data, as resilience is fundamentally a dynamic concept (Barrett et al., 2021). Estimation involves three steps. First, we estimate expected outcomes (consumption expenditure, household dietary diversity score and tropical livestock units) of households i in district d in year t (W_{idt}) as a function of lagged well-being (W_{dit-1}), lagged outcomes squared (W^2_{dit-1}), a vector of household and community characteristics (X_{it}) including household demographics (age, gender, etc.), socioeconomic status (education, farm size, etc.), and average rainfall. We control for year and locality(district) fixed effects (γ_t and μ_d respectively.)

$$W_{idt} = \alpha_0 + \alpha_1 W_{idt-1} + \alpha_2 W^2_{idt-1} + \alpha_X X_{it} + \gamma_t + \mu_d + \mu_{idt} \tag{1}$$

Next, we model variation in the dispersion of each indicator (the second moment). We use the same specification as that shown in Eq. (1) to characterize the conditional variance of household well-being. Taking the residuals from the estimation of Eq. (1) and squaring them provides an estimate of the conditional variance of household welfare ($\sigma^2_{idt} = E[\mu^2_{idt}]$), given that $E[\mu_{idt}] = 0$, which we characterize using the following specification:

$$\sigma^2_{idt} = \hat{u}^2_{idt} = \beta_0 + \beta_1 W_{idt-1} + \beta_2 W^2_{idt-1} + \beta_X X_{it} + \delta_t + \lambda_d + \epsilon_{idt} \tag{2}$$

where we use the predicted value $\hat{\sigma}^2_{idt}$ as the conditional variance of household well-being.[9]

[9] Table A3 in the Appendix reports the regression estimates for the three well-being indicators.

Finally, we estimate households' resilience (τ_{idt}) as the conditional probability that a households' outcome in each period lies above a normative threshold $\underline{W}$:

$$\tau_{idt} = Pr(W_{it} \geq \underline{W} | X_{it}, W_{it-1}) = 1 - F_{W_{it}}(\underline{W}; \hat{W}_{idt}, \hat{\sigma}^2_{idt}) \tag{3}$$

where $F_{W_{it}}(\cdot)$ is household-time-specific conditional cumulative density function (CDF) of well-being. Assuming each outcome follows a normal distribution (see Fig. 1), we estimate $F_{W_{it}}(\underline{W}|\cdot) = \Phi(Z_{idt}|\cdot)$ where $\Phi(\cdot)$ is the CDF of the standard normal distribution and $Z_{idt} = \frac{\underline{W} - \hat{W}_{idt}}{\sqrt{\hat{\sigma}^2_{idt}}}$ is the normalized Z-score. As described above, we use the following thresholds: for consumption expenditure we use the national poverty line; for Household Dietary Diversity Score (HDDS) we use 5 food groups; and for livestock, we use 2 TLU.

We assess the robustness of the assumption used in the third step by replacing the normal distribution with a Gamma distribution. Specifically, we calibrate the Gamma distribution parameters using the method of moments such that $\left(\alpha = \frac{\hat{W}^2_{idt}}{\hat{\sigma}^2_{idt}}, \beta = \frac{\hat{\sigma}^2_{idt}}{\hat{W}_{idt}}\right)$, and construct the CDF $F_{W_{it}}(\cdot)$ with these parameters. Outcomes are similarly predicted under the two distributional assumptions (Appendix Figure A1), but the normal distribution generates a lower root mean squared error and the Gamma distribution generates extremely large predicted conditional means in TLU, thus we use normal distribution in this study. We test for spatial autocorrelation following using the methods found in Scognamillo et al. (2023). As we find only weak spatial autocorrelation, and because correcting for spatial autocorrelation does not substantively change our findings, we report results without this correction.

3.2. Multivariate resilience measures

Next, we construct multivariate resilience measures. Analogous to multidimensional poverty measurement, computing and aggregating different dimensions of resilience requires choice over how to aggregate the univariate measures. We follow Alkire and Foster (2011) by offering a family of multivariate measures. We present three approaches.

First, we construct weighted average resilience measures of each possible combination of the M univariate measures used. In our case, one can use $M = 2$ for any pair of consumption expenditures, HDDS, and TLU, or $M = 3$ for all three together. One can use weights specific to each univariate measure, w_m, if one dimension was assumed to be more important than others:

$$\tau_{ave,idt} = [\sum_{m=1}^{M} w_m \tau_{idt}{}^m]/M \tag{4}$$

We use equal weights, so that $w_m = \frac{1}{M}, \forall m$. This equally weighted average measure is intuitive, treating a probability point change in each measure as equally important.

Second, we construct *headcount ratio* – adjusted and unadjusted – of resilience following the multidimensional poverty literature (Alkire and Foster, 2011) as follows:

$$M_0(y,k) = H(y,k) \times A(y,k) \tag{5}$$

$y = (y_1, \ldots, y_d)$ is a vector of d univariate resilience measures and k is the number of univariate resilience measures below the threshold that determines households are classified "non-resilient". We use 0.5 as a cut-off for each univariate resilience measure. For instance, $k = 1$ implies that a household is defined as non-resilient if *any* of the univariate resilience in y is below cut-off, and $k = d$ implies that a household is defined as non-resilient only if *all* of the univariate resilience measures are below cut-off. $H(y,k)$ is the share of non-resilient households (or *unadjusted* headcount ratio), and $A(y,k)$ is the average number of univariate resilience measures below cut-off among non-resilient households (or intensity of non-resilience). These headcount ratios with different values of k are reported in Table 2.

Third, we construct bivariate and trivariate resilience measures using the concepts of union and intersection. We start with two well-being indicators (consumption expenditure & diet, expenditure & livestock, and diet & livestock), assuming they follow a bivariate normal distribution with some correlation coefficient, ρ. We use the Pearson's correlation coefficient $\hat{\rho}$ between two welfare outcomes in the data as our estimate of ρ. For each pair of the outcomes, we construct two different types of bivariate resilience measures as Eqs. (6) and (7) below.

$$\begin{aligned} \tau_{uni,it} &= Pr(W_{1it} \geq \underline{W_1} \text{ or } W_{2it} \geq \underline{W_2} | \cdot) \\ &= 1 - F_{W_{1it},W_{2it}}(\underline{W_1}, \underline{W_2}; \hat{W}_{1idt}, \hat{\sigma}^2_{1idt}, \hat{W}_{2idt}, \hat{\sigma}^2_{2idt}, \hat{\rho}_{12}) \end{aligned} \tag{6}$$

$$\begin{aligned} \tau_{int,it} &= Pr(W_{1it} \geq \underline{W_1}, W_{2it} \geq \underline{W_2} | \cdot) \\ &= 1 - F_{W_{1it}}(\underline{W_1}; \hat{W}_{1idt}, \hat{\sigma}^2_{1idt}) - F_{W_{2it}}(\underline{W_2}; \hat{W}_{2idt}, \hat{\sigma}^2_{2idt}) \\ &\quad + F_{W_{1it},W_{2it}}(\underline{W_1}, \underline{W_2}; \hat{W}_{1idt}, \hat{\sigma}^2_{1idt}, \hat{W}_{2idt}, \hat{\sigma}^2_{2idt}, \hat{\rho}_{12}) \end{aligned} \tag{7}$$

$\tau_{uni,idt}$ in Eq. (6) captures the conditional probability that either welfare outcome is above the normative threshold, while $\tau_{int,idt}$ in Eq. (7) captures the conditional probability that both welfare outcomes are above their thresholds. Similarly, we estimate the trivariate resilience measures using Eqs. (8) and (9).

$$\begin{aligned} \tau_{uni,it} &= Pr(W_{1it} \geq \underline{W_1} \text{ or } W_{2it} \geq \underline{W_2} \text{ or } W_{3it} \geq \underline{W_3} | \cdot) \\ &= 1 - F_{W_{1it},W_{2it},W_{3it}}(\underline{W_1}, \underline{W_2}, \underline{W_3}; \hat{W}_{1idt}, \hat{\sigma}^2_{1idt}, \hat{W}_{2idt}, \hat{\sigma}^2_{2idt}, \hat{W}_{3idt}, \hat{\sigma}^2_{3idt}, \hat{\rho}_{12}, \hat{\rho}_{13}, \hat{\rho}_{23}) \end{aligned} \tag{8}$$

$$\begin{aligned} \tau_{int,it} &= Pr(W_{1it} \geq \underline{W_1}, W_{2it} \geq \underline{W_2}, W_{3it} \geq \underline{W_3} | \cdot) \\ &= 1 - F_{W_{1it}}(\underline{W_1}; \hat{W}_{1idt}, \hat{\sigma}^2_{1idt}) - F_{W_{2it}}(\underline{W_2}; \hat{W}_{2idt}, \hat{\sigma}^2_{2idt}) - F_{W_{3it}}(\underline{W_3}; \hat{W}_{3idt}, \hat{\sigma}^2_{3idt}) \\ &\quad + F_{W_{1it},W_{2it}}(\underline{W_1}, \underline{W_2}; \cdot) + F_{W_{1it},W_{3it}}(\underline{W_1}, \underline{W_3}; \cdot) + F_{W_{2it},W_{3it}}(\underline{W_2}, \underline{W_3}; \cdot) \\ &\quad - F_{W_{1it},W_{2it},W_{3it}}(\underline{W_1}, \underline{W_2}, \underline{W_3}; \hat{W}_{1idt}, \hat{\sigma}^2_{1idt}, \hat{W}_{2idt}, \hat{\sigma}^2_{2idt}, \hat{W}_{3idt}, \hat{\sigma}^2_{3idt}, \hat{\rho}_{12}, \hat{\rho}_{13}, \hat{\rho}_{23}) \end{aligned} \tag{9}$$

One can understand the multidimensional measure as offering different options for weighting among imperfectly correlated well-being measures. The union and intersection measures are necessarily limiting constructs. Adopting the intersection measures imposes the strict normative standard that a household is only considered resilient if it meets the resilience criterion in each dimension. By contrast, the union measure is a relatively permissive measure, wherein a household is declared resilient if it appears resilient in just a single dimension. Under the intersection framework, no tradeoffs are permitted across indicators, so that considerably higher dietary resilience, for example, cannot compensate for modestly lower asset resilience. Indeed, as the number of imperfectly correlated measures grows, the intersection measure weakly falls while the union measure weakly increases, mechanically. The rate of change in each of those varies inversely with the correlation among the measures. As a result, the union and intersection measures somewhat mechanically generate skewed distributions when one combines multiple weakly correlated measures. The intersection and union measures are informative. We favor the average measure, $\tau_{ave,idt}$, as the best summary measure because it does not vary mechanically based on the multivariate correlation structure and the number of measures included and it can allow the analyst to weight different indicators to permit tradeoffs in different dimensions.

4. Estimation results

4.1. Univariate resilience estimates

Fig. 4 shows the distribution of three univariate resilience measures. The first is constructed using consumption expenditure; this is "expenditure resilience". The second measure builds on the dietary quality indicator HDDS and hence we label it as "dietary resilience" (Zaharia et al., 2021). The third captures households' livestock holdings, reflecting productive asset holdings and hence we label it "livestock resilience". Fig. 5 shows the spatial distribution of 2008–2014 average univariate resilience measures, aggregated at district (woreda) level. Consistent with the weak correlation across the welfare measures, we do not observe significant spatial overlap exhibiting high (low) level of resilience across the three measures (Fig. 5). For example, some woredas showing a high level of expenditure resilience are characterized by low dietary resilience.[10] Regions with low dietary resilience tend to have higher livestock and consumption expenditure resilience.

Table 2
Headcount Ratio.

	Unadjusted			Adjusted		
	(1) $k = 1$	(2) $k = 2$	(3) $k = 3$	(4) $k = 1$	(5) $k = 2$	(6) $k = 3$
2008	0.99	0.90	0.23	2.12	2.03	0.69
2010	0.94	0.55	0.12	1.61	1.22	0.36
2012	0.89	0.42	0.10	1.41	0.95	0.30
2014	0.86	0.34	0.06	1.26	0.73	0.18
Total	0.92	0.56	0.13	1.61	1.25	0.39

Table 3
Rank correlation among univariate resilience measures.

	Consumption expenditure	Dietary
Dietary	0.37	1.00
Livestock	0.10	0.15

Fig. 6 shows the temporal dynamics of the three univariate household resilience measures. Households' expenditure resilience has significantly improved across time, rising from an average of 0.24 (i.e., only a 24 percent likelihood of consumption expenditure above the poverty line) in 2008 to 0.66 in 2014. Similarly, households' dietary resilience shows modest improvements across time. However, households' livestock resilience remained unchanged over time.

Table 2 shows the unadjusted (column 1 to 3) and adjusted (column 4 to 6) headcount ratios for non-resilient households, i.e., the share who fall beneath a 0.5 probability threshold.[11] Column (1) shows that more than 92% of households are not resilient across at least one measure, with $k = 1$ (at least one resilience measure is below 0.5), and 13% of households are not resilient across all three resilience measures. Column (4) shows that non-resilient households with $k = 1$ are non-resilient with 1.61 measures on average.

4.2. Multidimensional resilience estimates

We first explore multidimensional resilience by characterizing correlations between univariate resilience measures. Table 3 reports the Spearman's rank correlations among the three univariate resilience measures. Although these measures are statistically correlated (all significant at 95%), the strength of the bivariate correlations is weak. For example, the correlation between the livestock-based resilience estimate and expenditure-based estimate is only 0.10.

Fig. 7 shows the distribution of multivariate resilience measures (average, union and intersection) of different combinations. These patterns vary depending on how we define multidimensional resilience. Note that, as expected, measures based on the union and intersection show two extremes while average resilience estimates fall between those two bounding measures.

Despite the visually obvious differences in the distributions generated by the different multivariate resilience measures, they generate consistent household orderings. As shown in Table 4, the average,

[10] Figure A4, A5 and A6 show temporal changes in each univariate resilience measures.

[11] The 0.5 probability is used for simplicity and researchers can define this threshold considering theoretical and contextual factors.

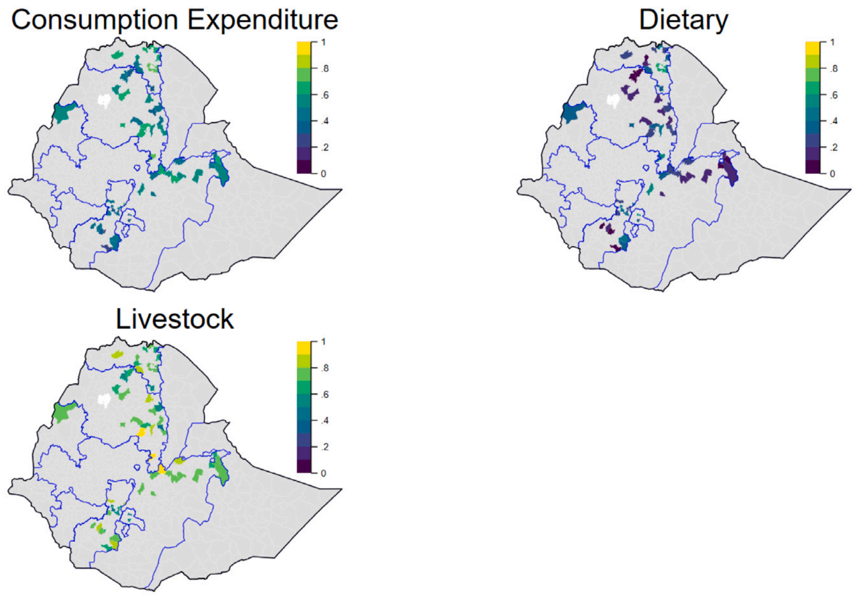

Fig. 5. Univariate resilience estimates, averaged by district (Woreda) - 2008 to 2014.

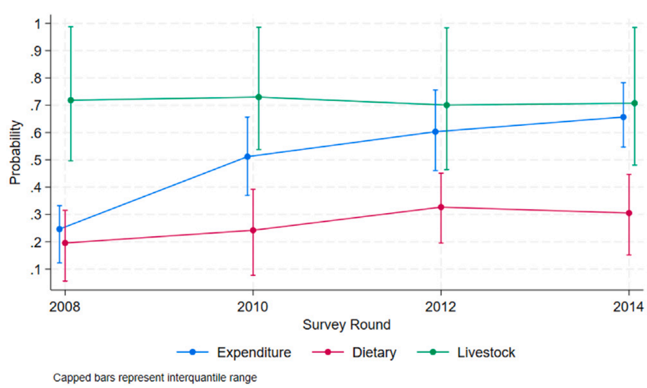

Fig. 6. Univariate resilience dynamics.

intersection and union multivariate resilience measures exhibit rank correlation coefficients ranging from 0.62–0.97, in contrast to the univariate measures whose correlations range from 0.10–0.37.

4.3. Characterizing the distribution of univariate and multidimensional resilience

While the rank correlations among univariate resilience measures (Table 3) suggest that these measures capture distinct dimensions of households' underlying latent resilience, what explains the distribution of these measures is not obvious. To address this, we use Shapley decompositions (Grömping, 2007; Israeli, 2007; Huettner and Sunder, 2012) to apportion the variation in these measures among groups of potential explanatory factors. For this purpose, we created four groups of characteristics: (i) household head demographic characteristics (age, gender, education, martial status and occupation), (ii) household characteristics (household size, access to electricity, distance to market, landholding, livestock and productive assets), (iii) location and community-level attributes (rainfall and village fixed effects), and (iv) temporal and survey year indicators (year fixed effects).[12]

Fig. 8 summarizes the results of this variance decomposition. Several results stand out. First, resilience measures based on consumption expenditure show the highest covariation over time; up to 34 percent of the variation in resilience can be explained by year dummies, mostly in expenditure resilience. This is consistent with previous studies demonstrating significant vulnerability as reflected by substantial transition into and out of poverty among rural households in Ethiopia (Hill and Porter, 2017). Recurrent covariate shocks, including drought and inflation, likely generate a common component to stochastic consumption expenditure (Dercon et al., 2005). The implication is that targeting based on a period-specific poverty measure can miss vulnerable or non-resilient populations, consistent with earlier findings that current consumption may not sufficiently capture chronic poverty levels in stochastic environments (Chaudhuri and Ravallion, 1994). This also implies that consumption-based resilience measures may capture the dynamic, transitory component of households' unobserved latent resilience and thus be effective when targeting interventions that aim to smooth consumption.

Second, community-level attributes (including village fixed effects) predict a large share of the variation in dietary resilience measures while explaining relatively smaller shares of the variation in consumption and livestock-based resilience measures. This likely reflects the important role of local markets as well as cultural norms and habits in shaping diets (Zaharia et al., 2021). This finding implies that geographic targeting can effectively build dietary resilience by accurately identifying and reaching non-resilient households within prioritized regions. However, if the objective is to build resilience beyond just diets, geographic targeting may not effectively serve communities and villages characterized by consumption and asset-based vulnerability.

Third, household attributes explain a plurality of the variation in consumption and livestock-based resilience measures. However, the household attributes have limited role in predicting dietary resilience. This finding suggests that asset-based approaches to poverty analysis (e.g., Attanasio and Székely, 2001; Sahn and Stifel, 2003; Carter and Barrett, 2006; Liverpool-Tasie and Winter-Nelson, 2011) may have broad reach in describing household resilience more broadly. However, household attribute-based targeting may not effectively serve to build dietary resilience as the link between assets and dietary resilience appears to be relatively weak.

[12] Table A4–A6 in the Appendix presents the regression outputs of univariate/multivariate resilience measures on these covariates.

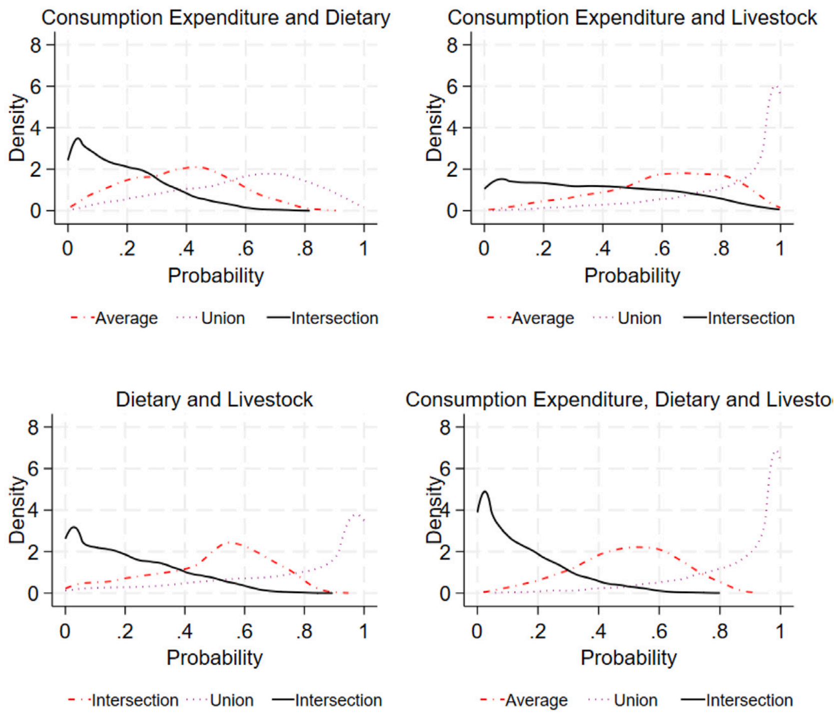

Fig. 7. Distribution of multivariate resilience estimates.

Table 4
Rank correlation among multivariate resilience measures.

	Consumption Expenditure & Dietary	Consumption Expenditure & Livestock	Dietary & Livestock
(a) Average			
Consumption Expenditure & Livestock	0.64	1.00	0.79
Dietary & Livestock	0.50	0.79	1.00
Consumption Expenditure & Dietary & Livestock	0.78	0.94	0.88
(b) Union			
Consumption Expenditure & Livestock	0.35	1.00	0.96
Dietary & Livestock	0.19	0.96	1.00
Consumption Expenditure & Dietary & Livestock	0.37	1.00	0.96
(c) Intersection			
Consumption Expenditure & Livestock	0.58	1.00	0.63
Dietary & Livestock	0.78	0.63	1.00
Consumption Expenditure & Dietary & Livestock	0.87	0.81	0.93

(a) Correlation across dimensions — multivariate

	Consumption Expenditure & Dietary		Consumption Expenditure & Livestock	
	Average	Union	Average	Union
Union	0.97	1.00	0.84	1.00
Intersection	0.94	0.84	0.97	0.72
	Dietary & Livestock		Consumption Expenditure & Dietary & Livestock	
	Average	Union	Average	Union
Union	0.87	1.00	0.80	1.00
Intersection	0.89	0.60	0.93	0.62

(b) Correlation within dimension — multivariate

Fourth, demographic characteristics of the household head – age and gender – explain very little household resilience under any measure. Indicator-based targeting that relies on household demographic features may be vulnerable to errors if the objective is to identify households that lack resilience.

Fifth, as we move from the univariate measures of resilience to multidimensional measures, we note that overall resilience becomes less dynamic and hence these composite measure are more likely to capture more persistent or structural vulnerability of households. Ownership and access to productive assets become more important in explaining the variation in the distribution of the multidimensional resilience measures while demographic characteristics of households such as gender, age and education of the household head decline in relative importance. Overall, these patterns imply that our understanding and inferences on the (temporal and spatial) distribution of household resilience will heavily depend on how one defines the normative measures that reflect well-being in the target population.

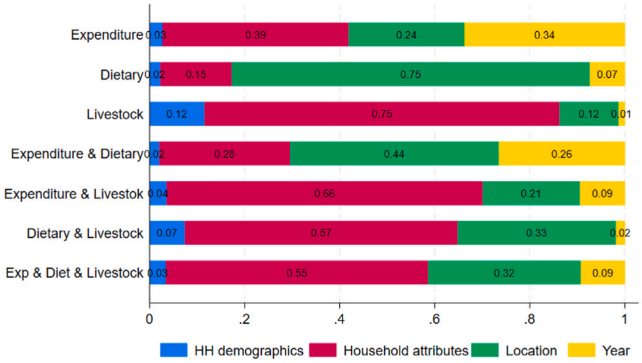

Fig. 8. Variance decomposition by explanatory factors.

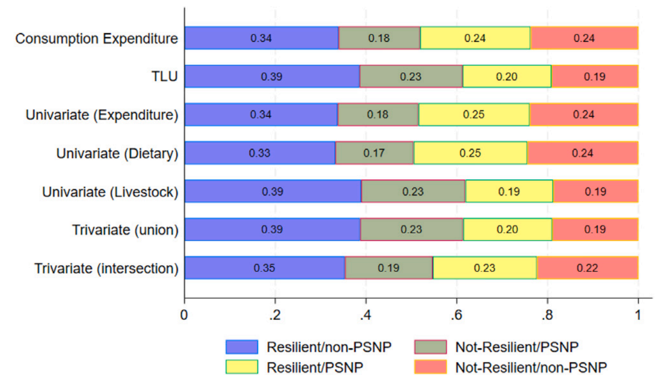

Fig. 9. Concordance between resilience measures and future PSNP participation.

The empirical patterns reflected in Fig. 8 have important implications for targeting of interventions intended to build resilience. The results in Fig. 8 highlight some of the important trade-offs associated with targeting methods and associated interventions aiming to address specific dimensions of household resilience. For example, the evidence that community-level attributes (including village fixed effects) explain only 12%–24% of the explainable variation in consumption and livestock-based resilience imply that resilience indexes constructed using consumption and livestock as normative well-being measures are more a characteristic of people than of places. This has important implications on the efficiency of universal geographic targeting, which is widely applied in many settings (Smythe and Blumenstock, 2022; Barriga-Cabanillas et al., 2025). For example, the first stage of the targeting in the PSNP in Ethiopia relies on geographic targeting and identification of historically food insecure districts (Gilligan et al., 2009; Berhane et al., 2014). On the other hand, the evidence that community-level attributes and fixed effects can predict up to 75% of the explainable variation in dietary resilience suggests that improving dietary resilience may require targeting and interventions that address beyond specific households, including food environments and markets. The fact that household demographics explain only 3%–12% of the explainable variation in resilience measures, likewise calls into question the usefulness of simple indicator targeting based on age or gender. The fact that households' productive assets and inputs have the greatest explanatory power in each of the resilience measures lends support to earlier literature that follow asset-based approaches to identify and target structural poverty (Attanasio and Székely, 2001; Sahn and Stifel, 2003; Carter and Barrett, 2006; Liverpool-Tasie and Winter-Nelson, 2011). Targeting based on asset holdings seems better able to address multidimensional resilience than approaches relying on transitory income or consumption expenditure, household demographics, or merely geography, although the relative gains are likely to vary with the specific objective of targeting.

Multidimensional resilience measures may be especially useful for programs that formally or in practice employ multiple criteria for qualifying participants or establishing program graduation. Operationalizing these multiple criteria can be challenging. Our composite measure of multidimensional resilience may help. For example, consider the targeting of the PSNP in Ethiopia over two stages. The first stage involved geographic targeting to identify historically food insecure districts (woredas). The second stage entailed community identification of beneficiary households in each of the included woredas based on a series of criteria thought to identify food insecure households, including those households with low household asset holdings (e.g., land, oxen) and limited income from alternative sources of employment. As described above, the household-level beneficiary selection was ultimately implemented through community-based targeting processes involving community meetings (Gilligan et al., 2009; Berhane et al., 2014; Abay et al., 2022).[13]

Although our method is not intended to evaluate PSNP targeting performance, we can assess whether our resilience metrics can predict future participation in the PSNP. For this purpose, we classify households as "resilient" and "non-resilient" following the share of Non-PSNP and PSNP households in each round. We then assess whether the resilience-based classification in the past round predicts future PSNP participation.

The matching analyses reported in Figs. 9 and 10 show some encouraging patterns and an important qualification. First, consistent with the targeting criteria of the PSNP, the livestock-based resilience measure correctly predicts future PSNP inclusion and exclusion 62% of the time; 39% of the population was classified as resilient by that measure and subsequently not in PSNP, while 23% was classified as non-resilient and subsequently participated in PSNP. The other two univariate measures accurately predict PSNP inclusion in only 52% of cases. This is intuitive given that livestock assets and related productive assets such as land are key targeting criteria for PSNP.

Second, the multidimensional union resilience measure outperforms the univariate resilience measures, implying the value and potential of our multidimensional resilience measures to support targeting and identification of vulnerable households. This corroborates recent shift from targeting poverty to targeting vulnerability (Barriga-Cabanillas et al., 2025).

Third, as shown in Fig. 10, the performance of the univariate and multidimensional resilience measures in predicting participation in the PSNP slightly improves across rounds, implying the value of additional rounds of data in measuring resilience.

The qualification, however, is that these differences are not large and we lack formal tests to ascertain whether these differences are statistically meaningful. Further, targeting based solely on TLUs has slightly stronger correspondence with actual PSNP participation patterns (consistent with the criteria used by the program) than that based on any of the resilience measures (Fig. 9), so it remains unclear whether any of these more complex measures improves on a simple asset measure.

5. Summary

The last decade has seen major progress in the conceptualization, measurement and operationalization of resilience in international development programming. To date, however, resilience measures have

[13] A recent community-based targeting experiment in Ethiopia shows that community leaders consider both asset ownership as well as productive capacity of households in their inclusion and exclusion criteria for social assistance (Abay et al., 2024).

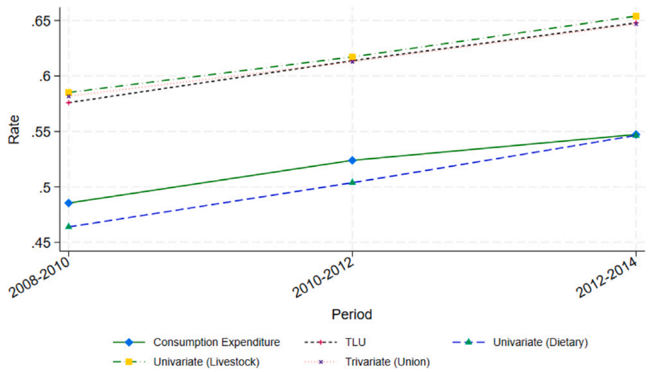

Fig. 10. Concordance between resilience measures and future PSNP participation over time.

considered just a single dimension of well-being, although the concept encompasses many dimensions of human well-being. As a result, for example, resilience indicators that rely on income-based indicators and poverty thresholds may ignore households' dietary resilience and the resilience of their productive livestock holdings that form the basis for future, sustained capacity to generate a non-poor income and access a healthy diet (Hoddinott, 2006). Much as unidimensional poverty measures may provide overly reductionist indicators of current well-being, thereby motivating the use of multidimensional poverty measures (Alkire and Foster, 2011; Alkire and Santos, 2014), so too might multidimensional resilience measures prove useful to analysts trying to target or evaluate interventions intended to build resilience among populations facing a range of imperfectly correlated deprivations.

Using five rounds of household panel data from Ethiopia, we first evaluate the implication of using alternative indicators of well-being for measuring household resilience using the probabilistic moment-based approach (Cissé and Barrett, 2018). We extend the existing univariate resilience measurement approach to capture multidimensional well-being indicators. We compute alternative aggregate resilience measures considering multiple dimensions and normative benchmarks (e.g., consumption expenditure-based poverty line, minimum dietary diversity, minimum livestock asset holding).

Our analyses highlight three important findings. First, we find that univariate resilience indicators constructed using alternative normative household well-being indicators (consumption expenditure, dietary diversity score, and livestock asset holdings) are weakly correlated. This implies that households that can be classified as "resilient" using one indicator and its associated normative threshold but not by another metric. Where Upton et al. (2022) showed that such variation occurs using different resilience measurement algorithms, we show that even using a single algorithm one gets such variation just by varying the underlying well-being indicator used. But where univariate measures are weakly correlated with one another, multivariate measures exhibit much stronger rank correlations. If one thinks of resilience as a latent household capacity to accommodate a wide range of stressors and shocks, no matter the indicator(s) one uses to track household well-being, then stability in households' rank ordering is highly desirable, and the gains from these – admittedly more complex – multivariate measures then seem meaningful.

Second, we find that univariate and multidimensional measures of resilience exhibit varying level of association with observable characteristics. In our data, location-specific characteristics common to all households explain large share of the variation in dietary resilience while relatively limited amounts of the observed variation in consumption and livestock resilience, while household demographic characteristics matter even less. Together, these raise questions about the potential differential implications of relying solely on geographic or age/gender-based household targeting for resilience-oriented interventions. This suggests that while geographic targeting may effectively build dietary resilience by accurately identifying and reaching non-resilient households within prioritized regions, geographic targeting may not effectively serve communities and villages characterized by consumption and asset-based vulnerability. By contrast, household access to or ownership of productive assets explains large share of the explainable variations in multivariate resilience measures. This suggests that asset-based approaches are perhaps reliable guides to targeting resilience-oriented interventions. This is consistent with the conceptual underpinning of resilience as stability in stochastic well-being dynamics where assets are the state variables that guide those dynamics (Barrett and Constas, 2014).

Third, multivariate resilience measures do a serviceable job of tracking actual community-based targeting in the case of Ethiopia's PSNP. In cases, like PSNP, where targeting explicitly aims to take a variety of household characteristics and capacities into consideration, these measures may prove a useful tool.

There are some important limitations to our analysis. We assume that the alternative welfare indicators are normally distributed (after appropriate transformations), which may not always be true. A natural extension of our approach will allow greater flexibility for heterogeneous distributions among included indicators. Furthermore, the alternative welfare indicators we used in this analysis may not be relevant for all contexts and livelihoods. Addressing these limitations represents a promising direction for future work.

CRediT authorship contribution statement

Seungmin Lee: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization, Data curation, Software, Validation, Writing – review & editing. **Kibrom A. Abay:** Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Formal analysis, Conceptualization, Data curation, Investigation, Visualization. **Christopher B. Barrett:** Writing – review & editing, Supervision, Investigation, Conceptualization, Formal analysis, Funding acquisition, Project administration, Resources, Writing – original draft. **John Hoddinott:** Writing – review & editing, Supervision, Formal analysis, Investigation, Resources, Writing – original draft.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2025.103583.

Data availability

Data will be made available on request.

References

Abay, K.A., Abay, M.H., Berhane, G., Chamberlin, J., 2022. Social protection and resilience: The case of the productive safety net program in Ethiopia. Food Policy 112, 102367.

Abay, K.A., Berhane, G., Gilligan, D.O., Tafere, K., Taffesse, A.S., 2024. Targeting Social Assistance in Fragile Settings: An Experiment on Community-Based Targeting. Intl Food Policy Res Inst.

Alinovi, L., Mane, E., Romano, D., 2010. Measuring household resilience to food insecurity: Application to Palestinian households. In: Agricultural Survey Methods. John Wiley & Sons, Ltd, pp. 341–368.

Alkire, S., Foster, J., 2011. Counting and multidimensional poverty measurement. J. Public Econ. 95 (7), 476–487.

Alkire, S., Santos, M.E., 2014. Measuring acute poverty in the developing world: Robustness and scope of the multidimensional poverty index. World Dev. 59, 251–274.

Attanasio, O.P., Székely, M., 2001. Portrait of the Poor: An Assets-Based Approach. Inter-American Development Bank.

Balboni, C., Bandiera, O., Burgess, R., Ghatak, M., Heil, A., 2022. Why do people stay poor? Q. J. Econ. 137 (2), 785–844.

Barrett, C.B., Constas, M.A., 2014. Toward a theory of resilience for international development applications. Proc. Natl. Acad. Sci. 111 (40), 14625–14630.

Barrett, C.B., Ghezzi-Kopel, K., Hoddinott, J., Homami, N., Tennant, E., Upton, J., Wu, T., 2021. A scoping review of the development resilience literature: Theory, methods and evidence. World Dev. 146, 105612.

Barriga-Cabanillas, O., Blumenstock, J.E., Lybbert, T.J., Putman, D.S., 2025. Probing the limits of mobile phone metadata for poverty prediction and impact evaluation. J. Dev. Econ. 174, 103462.

Berhane, G., Gilligan, D.O., Hoddinott, J., Kumar, N., Taffesse, A.S., 2014. Can social protection work in Africa? The impact of Ethiopia's productive safety net programme. Econ. Dev. Cult. Chang. 63 (1), 1–26.

Berhane, G., Hoddinott, J.F., Kumar, N., Taffesse, A.S., Diressie, M.T., Yohannes, Y., Sabates-Wheeler, R., Handino, M., Lind, J., Tefera, M., Sima, F., 2013. Evaluation of Ethiopia's Food Security Program: Documenting Progress in the Implementation of the Productive Safety Nets Programme and the Household Asset Building Programme. Technical Report, International Food Policy Research Institute.

Carter, M.R., Barrett, C.B., 2006. The economics of poverty traps and persistent poverty: An asset-based approach. J. Dev. Stud. 42 (2), 178–199.

Chaudhuri, S., 2003. Assessing Vulnerability to Poverty: Concepts, Empirical Methods and Illustrative Examples. Technical Report, Department of Economics, New York University.

Chaudhuri, S., Jalan, J., Suryahadi, A., 2002. Assessing household vulnerability to poverty from cross-sectional data: a methodology and estimates from Indonesia. Discussion Paper 0102–52, New York University.

Chaudhuri, S., Ravallion, M., 1994. How well do static indicators identify the chronically poor? J. Public Econ. 53 (3), 367–394.

Cissé, J.D., Barrett, C.B., 2018. Estimating development resilience: A conditional moments-based approach. J. Dev. Econ. 135, 272–284.

Coll-Black, S., Gilligan, D.O., Hoddinott, J., Kumar, N., Taffesse, A.S., Wiseman, W., 2011. Targeting Food Security Interventions When "Everyone Is Poor": The case of Ethiopia's Productive Safety Net Programme. Technical Report 24, International Food Policy Research Institute.

Constas, M.A., d'Errico, M., Pietrelli, R., 2022. Toward core indicators for resilience analysis: A framework to promote harmonized metrics and empirical coherence. Glob. Food Secur. 35, 100655.

Dercon, S., Christiaensen, L., 2011. Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. J. Dev. Econ. 96 (2), 159–173.

Dercon, S., Hoddinott, J., Woldehanna, T., 2005. Shocks and consumption in 15 Ethiopian villages, 1999–2004. J. Afr. Econ. 14 (4), 559–585.

d'Errico, M., Båsund, K.L., 2022. Subjective and objective measures of household resilience capacity in sub-Saharan Africa. Afr. J. Econ. Rev. 10 (5), 1–25, Number: 5.

d'Errico, M., Di Giuseppe, S., 2018. Resilience mobility in Uganda: A dynamic analysis. World Dev. 104, 78–96.

d'Errico, M., Garbero, A., Constas, M., 2016. Quantitative Analyses for Resilience Measurement. Guidance for Constructing Variables and Exploring Relationships Among Variables. Technical Report 7, Resilience Measurement Technical Working Group, Food Security Information Network, Rome.

FAO, FHI360, 2016. Minimum Dietary Diversity for Women: A Guide to Measurement. Technical Report.

Gallardo, M., 2018. Identifying vulnerability to poverty: A critical survey. J. Econ. Surv. 32 (4), 1074–1105.

Gilligan, D.O., Hoddinott, J., Taffesse, A.S., 2009. The impact of Ethiopia's productive safety net programme and its linkages. J. Dev. Stud. 45 (10), 1684–1706.

Government of the Federal Democratic Republic of Ethiopia, 2004. Productive Safety Net Programme: Programme Implementation Manual. Technical Report, Addis Ababa.

Government of the Federal Democratic Republic of Ethiopia, 2010. Productive Safety Net Programme: Programme Implementation Manual. Technical Report, Addis Ababa.

Grömping, U., 2007. Estimators of relative importance in linear regression based on variance decomposition. Amer. Statist. 61 (2), 139–147.

Günther, I., Harttgen, K., 2009. Estimating households vulnerability to idiosyncratic and covariate shocks: A novel method applied in madagascar. World Dev. 37 (7), 1222–1234.

Hill, R.V., Porter, C., 2017. Vulnerability to drought and food price shocks: Evidence from Ethiopia. World Dev. 96, 65–77.

Hoddinott, J., 2006. Shocks and their consequences across and within households in Rural Zimbabwe. J. Dev. Stud. 42 (2), 301–321.

Hoddinott, J., Quisumbing, A., 2010. Methods for microeconometric risk and vulnerability assessment. In: Fuentes-Nieva, R., Seck, P.A. (Eds.), Risk, Shocks, and Human Development: On the Brink, first ed. Palgrave Macmillan London, pp. 62–100.

Hoddinott, J., Yohannes, Y., 2002. Dietary Diversity as a Food Security Indicator. FCND Discussion Paper 136, International Food Policy Research Institute, p. 94.

Huettner, F., Sunder, M., 2012. Axiomatic arguments for decomposing goodness of fit according to Shapley and Owen values. Electron. J. Stat. 6, 1239–1250.

Israeli, O., 2007. A Shapley-based decomposition of the R-Square of a linear regression. J. Econ. Inequal. 5 (2), 199–212.

Knippenberg, E., Hoddinott, J.F., 2017. Shocks, social protection, and resilience: evidence from ethiopia. Technical Report 109, International Food Policy Research Institute, Addis Ababa, Ethiopia.

Knippenberg, E., Jensen, N., Constas, M., 2019. Quantifying household resilience with high frequency data: Temporal dynamics and methodological options. World Dev. 121, 1–15.

Leroy, J.L., Ruel, M., Frongillo, E.A., Harris, J., Ballard, T.J., 2015. Measuring the food access dimension of food security: A critical review and mapping of indicators. Food Nutr. Bull. 36 (2), 167–195, Publisher: SAGE Publications Inc.

Ligon, E., Schechter, L., 2003. Measuring vulnerability. Econ. J. 113 (486), C95–C102.

Liverpool-Tasie, L.S.O., Winter-Nelson, A., 2011. Asset versus consumption poverty and poverty dynamics in rural Ethiopia. Agricult. Econ. 42 (2), 221–233.

Lybbert, T.J., Barrett, C.B., Desta, S., Layne Coppock, D., 2004. Stochastic wealth dynamics and risk management among a poor population. Econ. J. 114 (498), 750–777.

McPeak, J., 2004. Contrasting income shocks with asset shocks: livestock sales in northern Kenya. Oxf. Econ. Pap. 56 (2), 263–284.

Perrings, C., 2006. Resilience and sustainable development. Environ. Dev. Econ. 11 (4), 417–427.

Phadera, L., Michelson, H., Winter-Nelson, A., Goldsmith, P., 2019. Do asset transfers build household resilience? J. Dev. Econ. 138, 205–227.

Premand, P., Stoeffler, Q., 2022. Cash transfers, climatic shocks and resilience in the Sahel. J. Environ. Econ. Manag. 116, 102744.

Pritchett, L., Suryahadi, A., Sumarto, S., 2000. Quantifying Vulnerability to Poverty: A Proposed Measure, Applied to Indonesia. World Bank Publications.

Rutter, M., 2012. Resilience as a dynamic concept. Dev. Psychopathol. 24 (2), 335–344.

Sabates-Wheeler, R., Lind, J., Hoddinott, J., Tefera Taye, M., 2021. Graduation after 10 years of Ethiopia's productive safety net programme: Surviving but still not thriving. Dev. Policy Rev. 39 (4), 511–531.

Sahn, D.E., Stifel, D., 2003. Exploring alternative measures of welfare in the absence of expenditure data. Rev. Income Wealth 49 (4), 463–489.

Scognamillo, A., Song, C., Ignaciuk, A., 2023. No man is an Island: A spatially explicit approach to measure development resilience. World Dev. 171, 106358.

Smythe, I.S., Blumenstock, J.E., 2022. Geographic microtargeting of social assistance with high-resolution poverty maps. Proc. Natl. Acad. Sci. 119 (32), e2120025119.

The World Bank, 2015. Ethiopia Poverty Assessment 2014. Technical Report.

Upton, J.B., Cissé, J.D., Barrett, C.B., 2016. Food security as resilience: reconciling definition and measurement. Agricult. Econ. 47 (S1), 135–147.

Upton, J., Constenla-Villoslada, S., Barrett, C.B., 2022. Caveat utilitor: A comparative assessment of resilience measurement approaches. J. Dev. Econ. 157, 102873.

Vaitla, B., Cissé, J.D., Upton, J., Tesfay, G., Abadi, N., Maxwell, D., 2020. How the choice of food security indicators affects the assessment of resilience—an example from northern Ethiopia. Food Secur. 12 (1), 137–150.

Yao, B., Shanoyan, A., Schwab, B., Amanor-Boadu, V., 2023. The role of mobile money in household resilience: Evidence from Kenya. World Dev. 165, 106198.

Zaharia, S., Masters, W.A., Ghosh, S., Shively, G.E., Gurung, S., Manohar, S., Thorne-Lyman, A.L., West, K.P., Appel, K.H., Liang, L., Shrestha, R., Bashaasha, B., Kabunga, N., Webb, P., 2021. Recovery without resilience? A novel way to measure nutritional resilience in Nepal, Bangladesh, and Uganda. Glob. Food Secur. 31, 100573.