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The dynamics of multidimensional food security in rural Ethiopia

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ABSTRACT

The aim of this study was to create a composite food security index that takes into account the four aspects of food security, which are availability, accessibility, usage, and stability, and to analyze how families' food security status changes over time. Principal Component Analysis (PCA) methods were used to create food security indices for each dimension of households. The results of the aggregate food security indices showed that in 2013, 2015, and 2018, 44%, 57%, and 45% of households, respectively, were food secure. Only 20% of households had consistent food security, while 67% had transitory food insecurity, meaning they had at least one instance of it during the study period. The remaining 13% of households were labeled as having chronic food insecurity because they experienced it continuously during the course of the research.

1. Introduction

Food insecurity is at the top of governments' agendas throughout the world, with an estimated 825 million people facing hunger, of whom the majority are located in Africa and Asia (Dessalegn, 2018; FAO, 2017; FAO, 2022). Ethiopia's urban and rural populations struggle with food insecurity, which ranges in severity from certain pastoral settlements to the rainy highland plateaus. Food insecurity affected 20.5% of Ethiopian households, with rural residents accounting for 22.7% and urban residents accounting for 13.9% (CSA and WFP, 2019), noting that the Ethiopian population is largely rural (78%; World Bank, 2023). Drought is a major source of food shortages in many parts of the country, as low moisture levels impact growing cycles for the agriculturally dependent rural population. The government has put in place a comprehensive intervention strategy to address the problem, which includes enhanced post-harvest management, promoting improved production through agricultural extension services, a large-scale safety net program, drought prevention through early warning systems and the adoption of pest-resistant crop varieties, and improving soil and water management (FAO, 2017).

Various economic, social, political, and environmental issues have an impact on food security, a concept that has many facets and a wide range of measures and metrics (Cochrane, 2021), with Mohamed (2017) identifying roughly 200 definitions and 450 indicators of food security. Additionally, the unit of assessment, methodology, and dimensions used in the literature on food security measures vary widely (Ansah et al., 2019). The term food security is a broad and flexible phrase with multiple strongly connected meanings due to its enormous complexity, as revealed by innumerable research and policy papers (Díaz-Bonilla, 2017; Lin, 2017; Mares, 2019; Petrescu-Mag et al., 2019; Miani et al., 2023). As a result, several academics highly advise incorporating more than one indication (Cafiero et al., 2018; Perez-Escamilla et al., 2017). However, due to the heterogeneous nature of the measurement units used to quantify food security indicators, absorbing all of them into a single dimension is particularly challenging. This idea has led to the development of composite indicators, which enhance the measurement of food security by combining two or more indicators.

A composite food security index enables the formulation of an index that is based on a variety of elements and can accurately incorporate many aspects of food security (Xie, 2019). Food security measurements based on composite indices have been introduced in prior empirical studies. Ibok et al. (2019), for example, established a potential food security index that can be compared to other traditional food security

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measures but does not account for all four components. Caccavale and Giuffrida (2020) also devised a composite measure for food security, but they used cross-sectional data, so it does not address the dynamic nature of food security. Von Grebmer et al. (2017) attempted to measure the multifaceted nature of food security using four indicators of malnutrition, child wasting, child stunting, and child mortality, however these are all largely connected to the dimension of food security utilization. Narayanan et al. (2019) also developed an index to examine women's nutritional empowerment, through which individuals get the ability to be well-nourished and healthy. These metrics have a focus on indicators at the national level, including income, poverty, malnutrition, food production, and macro-level statistics.

Upton et al. (2016) employed a comprehensive approach to evaluate food security by combining the Household Food Insecurity Access Scale (HFIAS), the Dietary Diversity Score (DDS), and the Coping Strategies Index (CSI) into a single estimation to exemplify how the indicators complement each other. Cafiero et al. (2018) employed eight-item household food security questionnaires to assess the accessibility dimension of food security. Vaitla et al. (2017) also developed latent variables from the association of four commonly-used measures of food security as a proxy measure of household food security. The results revealed that, in the face of rapidly shifting biophysical conditions, food security and nutritional sufficiency will be major contributors to the burden on world health in the next century. Taylor et al. (2019) employed the Food Insecurity Experience Scale (FIES), which defines food insecurity as having insufficient access to food, and the authors conclude by recommending the need for a more precise definition of food security as well as new quantitative methodologies for measuring food security. Earlier studies such as Caccavale and Giuffrida (2020), Iqbal et al. (2019), Narayanan et al. (2019), Von Grebmer et al. (2017), and Xie (2019) gave attention to food security measurements using one or two dimensions. Creating an evidence-informed policy based on evidence that is specific to particular dimensions is difficult. Moreover, earlier studies of food security in developing countries have been static, emphasizing a snapshot of data taken at a given point in time rather than looking at dynamic patterns of food security that require long-term data sets and on-going monitoring.

The novelty of this study lies in its approach to measuring food security in rural areas using a multidimensional composite index that captures the dynamic nature of food security over time. The study draws on data from a longitudinal survey conducted in four regions of Ethiopia between 2015 and 2018. The study also uses a factor analysis to incorporate the four dimensions of food security: availability, accessibility, utilization, and stability. We then construct a composite index based on these dimensions and use it to measure the level of food security in the study area. Accordingly, the contribution of the study is that it provides new empirical evidence on the prevalence, intensity, and dynamics of food insecurity in a rural area of Ethiopia. The study also identifies the dimension of food security that households had the most control over (utilization) and the types of food insecurity that were most prevalent (chronic and transitory). The study's longitudinal approach allows for a more nuanced understanding of how food security changes over time and provides insights into the factors that contribute to transitions between food security and food insecurity. Overall, the study's multidimensional composite index and longitudinal approach provide a novel and valuable contribution to the literature on food security in rural areas. The study's findings have important implications for policymakers and practitioners working to address food insecurity in Ethiopia and other similar contexts.

This study intends to bridge the gaps associated with earlier food security studies. Ultimately, the current study answers the following research questions: What was the level of food insecurity? Was there a link between the approach of food security measurements and the intensity of food security? Which dimension of food security did households have the most control over? What types of food insecurity are prevalent in rural areas? Were they chronic or transient conditions? Was a transition from food security to food insecurity seen within the study period? The following section outlines the methods used, which is followed by the Results and Discussion section, and we conclude the paper with policy recommendations.

2. Methods

2.1. Principal component analysis

Using Principal Component Analysis (PCA), a composite index is produced using a set of chosen indicator variables under each area of food security (Jiang et al., 2018; Qiuhong et al., 2018). PCA can break down several selected indicators into more components to gather more information on key indicators (Greco et al., 2019; Salvatore et al., 2019). PCA has been widely used in a number of studies to develop composite socioeconomic and food security indices (Artoni et al., 2018; Kumari et al., 2019; Libório et al., 2020; Rahman and Rahman, 2020). A composite food security index integrates several food security indicators from each dimension into a single index. The process of creating an index may be very subjective, especially when deciding how much weight to give to each component. The greatest variance-giving linear combination of index variables may be derived via PCA, and this lower number or index can be obtained instead (Jiang et al., 2018; Muema et al., 2018; Zeller et al., 2006). The derived food security index selected the best linear association among the food security indicator variables in each dimension (Lever et al., 2017). Each food security dimension contains n correlated indicator variables (x1, x2, x3 …, xn); PCA allows the development of discrete, independent components, each of which is a linearly weighted sum of the original variables.

Mathematically, PCA is specified in equation (1):

$$PC_{11} = \rho_{11}X_1 + \rho_{12}X_2 + \ldots\ldots\ldots\ldots\ldots + \rho_{1m}X_m \quad \text{Eq (1)}$$

$$PC_{nm} = \rho_{n1}X_1 + \rho_{n2}X_2 + \ldots\ \ldots\ldots\ldots\ldots + \rho_{nm}X_m$$

Where ρ_{mn} represents the weight for variable X in the nth and mth (n = 1, 2 … n and m = 1, 2 … m) principal component. Assuming that the sum of the squared weights equals one, as in $\rho_{i1}^2 + \rho_{i2}^2 + \rho_{i3}^2 + \ldots\ldots + \rho_{ij}^2 = 1.$, the first principle component explains the largest amount of variance in a data set. After that, each additional but minor reason for the change in the indicator variables follows. If the original variables have a greater degree of correlation, fewer factors are required to capture the shared information (Vyas and Kumaranayake, 2006).

Equation (2) can be used to calculate the households' food security score/index after the components have been identified.

$$FSI_i = \sum F_j \left(\frac{X_{ij} - \mu_j}{\sigma_j} \right) \quad \text{Eq (2)}$$

where FSI_i is the index of food security for households i, which assumes that data is distributed normally, with a median of 0 and a standard deviations of 1; F_j is the variable j's weight in the PCA model, is the X_{ij} variable's value for the jth household, and are the ith variable's mean and standard deviation, respectively, for all farm families.

It is crucial to develop an index that can be used to compare data across time because the study uses panel data. The three waves of survey data were integrated, and PCA was run on the resulting three-period data set, as per Chung et al. (2021). Equation (2) was frequently applied to multiply the actual values of the indicator variables from each survey round with the calculated weights, producing an index that is consistent over time. As a consequence, the weighted z-scores from each time period are added to the actual values of the variables to produce the index of food security for farm households.

There are two primary aggregation methods for creating combined indices in the literature, and each method has pros and cons. The simplest approach is additive aggregation, which involves ranking households according to each indicator and summing the results (Greco et al., 2019). The complete compensable character of aggregation, which allows the good performance of other indicators to make up for the inferior performance of other indicators, makes this technique unattractive. Despite the calculation being a little more challenging than basic aggregate, geometric aggregation solves the whole compensability issue. In order to produce the overall food security indices for this study, the scores for each dimension were combined using the geometric mean. According to Anand and Sen (1997), power ways of order that are bigger than one are particularly helpful in creating composite indices of food security measurements that give the four aspects equal weight. The United Nations Development Program (UNDP, 2016) and other researchers have used this approach to calculate the Human Development Index (HDI) and the Human Poverty Index (HPI) (Antony and Rao, 2007; Greco et al., 2019; Napoli et al., 2011). As a result, the four aspects of food security are aggregated in this study using Sen's recommendation (Anand and Sen, 1997) of power three, which is the aggregated food security index described in equation (3) below:

$$\text{Food Security}_{\text{index}} = \frac{1}{4}\left[\left(\text{Ava}_i^3 + \text{Acc}_i^3 + \text{Uti}_i^3 + \text{Sta}_i^3\right)^{\frac{1}{3}}\right] \qquad \text{Eq (3)}$$

Ava_i = Availability, Acc_i = Associability, Uti_i = Utilization, and Sta_i = Stability

Through research into a wealth of food security literature (Ansah et al., 2019; Reincke et al., 2018; Vaitla et al., 2017; Weatherspoon et al., 2019), each food security dimension's essential indicator variables have been selected because they are strongly connected to it. The PCA analysis should include more than two indicator variables, while it is possible to do the analysis with just two variables provided there is a correlation of at least 0.70 between the variables (Lasisi and Attoh-Okine, 2018). In general, the research design and data sets dictate the minimal indicator variable requirements.

By using PCA, it is possible to identify the most significant dimensions of food security from the FIES data set and use these dimensions to develop composite indicators of food security. The variability of measuring units and the difficulty of merging many indicators into a single dimension are some of the difficulties that can be solved when utilizing multiple indicators to estimate food security. The utilization of PCA can assist in identifying the key dimensions of food security that are most applicable to a specific population or context. In addition, this analysis can facilitate the development of composite indicators that accurately reflect these dimensions. Several studies have used PCA to analyze and interpret data on food security. For example, Ansah et al. (2019) used PCA to identify the most significant dimensions of food security among households in Ghana, and Cafiero et al. (2018) used PCA to develop a composite indicator of food security based on eight-item household food security questionnaires. Similarly, Petrescu-Mag et al. (2019) used PCA to develop a composite indicator of food security in Romania, and Xie (2019) used PCA to identify the most significant dimensions of food security among Chinese households. Overall, the advantage of using PCA in the context of food security is that it can help to identify the most significant dimensions of food security from a set of multidimensional indicators and develop composite indicators that reflect these dimensions. This can assist to overcome some of the difficulties involved in utilizing numerous indicators to quantify food security and can be especially helpful when working with complicated data sets that contain a lot of variables.

There are four indicator variables for each of the study's four food security pillars: availability, access, stability, and usage. According to the dataset, Perez-Escamilla et al. (2017), Babych and Kovalenko (2018), and Babych and Kovalenko (2018), the indicator variables were chosen and sixteen factors were used to develop total food security indices for farm families (as shown in Table 1).

[1] Ethiopian Socioeconomic Survey.

Table 1
Description and measurement units of selected food security indicators under each dimension.

Dimensions	Variables	Definition of Variables	Units
Availability	Land_size	Size of cultivated land in the agricultural growing season	Ha
	Production[a]	The total amount of cereal production in the agricultural growing season	kg[b]
	Crop_stored	Amount of crop stored for future consumption	kg
	Food_gift	Amount of crop obtained as a gift from others	kg
Accessibility	Income	Households' yearly real income[c] per adult equivalence (sum of farm and non-farm income)	Birr
	FPI	The regional food price index (PFI)	%
	Market_dist	Households' distance from the nearest market	Km
	Food_exp	Amount of money spent to buy miscellaneous food items per adult equivalence	Birr
Utilization	Num_crops	Number of crops produced in the agricultural growing season	Number
	Diet_diversity[d]	Number of food groups consumed in seven days	Number
	Livestock	Number of edible livestock	TLU
	Water_hygiene	If a household has a access to clean water	1 = Yes 0 = No
Stability	Shock_freq	Number of health shocks occurred to the household heads per year	Number
	Income_sources	Main sources of income for HHs	Number
	Num_months	Number of months in which the Households do not have enough food	Number
	Asset_value	Value of physical farm and household assets	Birr

[a] Quantity of cereal production in tiff equivalent of wheat, barley, sorghum, maize, and millet.
[b] Name of Ethiopian Currency (Currently 1USD = 27.6 Eth Birr).
[c] CPI-deflated real prices are used in computing the value of crop output.
[d] DDS: Dietary Diversity Score is often used as a proxy measure of the nutritional quality of household's diet. An adult household member can have a food group of 0–12 while a child may have 0–8 food group. Each food group contains more than one food item. Hence, when a household lays on more food groups that implies a household consumes more variety of foods.
Source: From ESS[1] 2013–2018

2.2. Data source

The measurement used in this study is based on agricultural production panel data, at the household plot level, which were collected in 2012/2013, 2014/2015, and 2017/2018. The World Bank's Integrated Surveys on Agriculture (LSMS-ISA) and the Central Statistics Agency of Ethiopia (CSAE) worked together to gather the data. This study includes four Ethiopian regional states: Amhara, Oromia, SNNP, and Tigray (although Somali is more populous than Tigray, the livelihood type is more diverse and a specific index is required to integrate pastoralist livelihoods, a task for future research; the data reflects SNNP before the creation of Sidama and South West regional states, which occurred in 2019 and 2021 respectively). The numbers of households interviewed were 3969 (2013), 5262 (2015), and 4594 (2018). A panel of 1412 farm homes was chosen in each wave, resulting in a total of 4236 observations. The five principal food crops that make up this sample of farming families, (teff, wheat, barley, maize, and sorghum), were grown on around three-fourths of all the cultivated land. Table 2 shows the study's sample size by area and year.

[2] Ethiopian Socioeconomic Survey.

Table 2
Sample size by region and year.

Regions/Years	2013	2015	2018	Total
Tigray	252	252	252	756
Amhara	448	448	448	1344
Oromia	318	318	318	954
SNNP	394	394	394	1182
Total	1412	1412	1412	4236

Source: From ESS[2] 2013–2018

2.3. Method of analysis

2.3.1. Descriptive statistics

Each food security dimension's variables are summarized using descriptive statistics, which also includes measurements of central trends, dispersions, charts, tables, and t-tests. Yearly variations during the research period are analyzed using a mean difference test.

2.3.2. Steps of multidimensional food security index estimation

The food security index for farm households is calculated in this study using a number of PCA procedures. About 1% of all observations had at least one covariate with missing values. In order to employ the PCA, it is assumed that there would be some connection between some of the food security measures. For each aspect of food security, a correlation test was run between the variables (Appendix A). It may be possible for each major component to more effectively account for variance if food security metrics have higher correlations. The association coefficients for each aspect of food security were significant enough to use the PCA.

The raw data sets can be used for the PCA estimate if the indicator variables are computed in the same units. However, this method favors variables that have more variance over those with less variance. The primary index variables (raw data) were adjusted using a median of zero and a standard deviation of one before PCA estimation since the index variables used to calculate the food security index had varied units of measurement.

The PCA estimate findings were confirmed using an intermediate step that validated the component matrix and variable coefficient weights. The number of variables in the analysis is equal to the number of recovered PCA components. On the other hand, Kaiser's rule or the page layout line were used to compute the number of components that needed to be kept. The estimate results show that each food security dimension's initial component has an eigenvalue greater than one, supporting the component retention. The first principal component, which explained the most variation and had an eigenvalue greater than one, was used as a measure of household economic status by Adjimoti and Kwadzo (2018) and Houweling et al. (2003). Here, the same methodology is used, and each food security dimension's first primary component is the food security index for farm households.

3. Results and Discussion

3.1. Descriptive statistics' food security indicator variables

Table 3 displays the descriptive information for the food security indicators that were employed to calibrate each food security dimension. Even though several of the indicator variables had constant development between 2013 and 2018, their means did not reveal a clear trend. For instance, factors that are crucial to food security such as income, food spending, and diet variety all increased steadily. From 7158 Birr in 2013 to 8824 Birr in 2018, the average real income of agricultural households per adult equivalent grew. In real terms, household income increased by nearly 18% in 2018 compared to 2013. This conclusion supports the findings of Nyasha et al. (2017) and attests to a significant increase in income during the research period. Over the same time period, the average food expenditure of farm households per adult equivalent increased from 1726 Birr to 2353 Birr. This figure is consistent with the findings of Wolle et al. (2020), who calculated the average food consumption expenditures per family at 2237 Birr. Similarly, from 107% in 2013 to 134% in 2018[3], the average food price index (FPI) grew. In the seven days before to the survey, farm households' average dietary diversity increased from roughly 8 types of food groups in 2013 to 9 types of food groups in 2018. According to this, families likely ate a wider variety of foods in 2018 than they did during prior survey periods. This finding aligns with Usman and Callo-Concha (2021) findings which revealed that households in 2019 consumed far more dietary variety than in prior periods (this does not necessarily indicated strengthened food security or nutritional intake, see: Cochrane and Cafer, 2018). Similarly, farm household access to clean drinking water increased from 73% in 2013 to 86% in 2018. When it comes to clean drinking water, the situation is different. The proportion of families with access to safe drinking water remains low, falling short of both national and sustainable development objectives. Despite the fact that Bogale et al. (2020) observed a national increase in clean drinking water, Andualem et al. (2021) discovered that only a minuscule fraction of the population had access to improved drinking water.

The average size of a household's farm, however, shrank from 1.25 ha in 2013 to 1.21 ha in 2018. Holden and Tilahun (2020) found that between 1998 and 2016, the average farm size decreased from 1.15 to 0.90 ha. This is owing to the fact that, as a result of population growth, farmland has been fragmented and average farm sizes have shrunk dramatically. The average grain yield climbed from 628 kg per hectare in 2013 to 716 kg per hectare in 2015, but it subsequently fell to 695 kg per hectare in 2018. Similar to the other food security indicators, the mean value of the remaining ones (crops that were stored, food that was given as presents, crops that were harvested, livestock, sources of income, the number of months where there was not enough food, and asset value) increased between 2013 and 2015 but decreased in 2018. Heads of households suffered health shocks around once in 2013, and this number fell to 0.62 in 2015. Health shocks are not evenly distributed across persons. However, in 2018 the shock frequency once more increased to 1.10. In 2013, 2015, and 2018, respectively, 50%, 36%, and 58% of the heads of household encountered health shocks. Part of the explanation for rise in 2018 is that a major shock occurred in the Fall/Winter season of 2015 and again in 2016, due to consecutive failed rains, pushing nearing ten million people into emergency situations (eroding their assets and thereby generally worsening the economic situation for households). The average distance between farm homes and the nearest market during the duration of the study was 47.8 km, suggesting that households may have sold and bought items in the same actual market sites.

The results of the *t*-test revealed that, with the possible exception of the parameters of land size, marketplace distance, amount of planted crops, number of months without enough food, and asset values, there were substantial differences in the values of the variables between 2013 and 2018.

3.2. Result of PCA of each food security dimension

The suitability of the data for PCA is assessed using the Kaiser-Meyer-Olkin (KMO) sample adequacy test. The results of the values shown in Table 4, for each element of food security, show that the study's data set is suitable for PCA. KMO will take values between 0 and 1. Even though values greater than 0.5 are regarded to be sufficient for PCA application, smaller values demonstrate that the variables have less in common for the PCA estimate (Kaiser, 1974). A high KMO score, then, denotes that the major components may account for a comparatively bigger share of the variation. All food security dimensions had a KMO value more than 0.5, which denotes a moderate level of correlation between the selected variables in each domain. Hence, using estimation of PCA to calculate the index of food security for farm households is appropriate.

The first main aspect of each food security pillar (availability, accessibility, use, and stability) is shown in Table 4. The first major

[3] 2010 = 100 (2010 was taken as a base year).

Table 3
Descriptive statistics of food security indicators.

Variables	2013		2015		2018		Full Sample		*t*-test
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	
	Availability								
Land size	1.25	0.88	1.22	0.95	1.21	1.01	1.23	0.95	0.31
Production	627.6	379.4	715.6	404.1	694.6	383.5	679.3	390.8	0.00***
Crop stored	312.3	353.8	385.9	359.5	228.6	229.8	308.9	326.3	0.00***
Food gift	23.8	79.9	146.7	128.4	141.0	123.4	103.9	126.1	0.00***
	Accessibility								
Income	7158.4	4186.7	8589.8	4680.2	8823.9	3863.5	8190.7	4319.0	0.00***
Food expenditure	1726.1	404.4	2173.5	547.1	2352.7	532.6	2084.1	564.0	0.00***
Food Price Index	1.08	0.074	1.21	0.027	1.35	0.052	1.21	0.12	0.00***
Market distance	47.8	20.3	47.8	20.3	47.8	20.3	47.8	20.3	1.00
	Utilization								
Diet diversity	7.85	2.24	7.99	2.25	8.63	2.21	8.16	2.26	0.00***
Number of crops	3.57	1.67	3.69	1.59	3.55	1.59	3.60	1.62	0.70
Water hygiene	0.73	0.44	0.78	0.41	0.86	0.35	0.79	0.41	0.00***
livestock	4.57	3.31	4.59	3.52	2.39	2.45	3.85	3.29	0.00***
	Stability								
Shock frequency	1.05[a] (50%)[b]	1.23	0.62 (36%)	0.96	1.03 (58%)	1.10	0.90 (48%)	1.12	0.68
Income sources	1.85	0.76	2.01	0.78	1.74	0.72	1.87	0.76	0.00***
Number of months	0.89	1.65	1.13	1.80	0.86	1.80	0.96	1.75	0.63
Asset value	4755.5	3046.4	5418.2	3680.8	4803.0	3435.1	4992.2	3410.1	0.69

***indicates 1 % level of significance.
[a] On average, how many times the sample household heads faced health shock in each year.
[b] The proportion of household heads who faced health problem.
Source: Study findings from ESS survey (2013, 2015 and 2018)

Table 4
CA estimation result of food security dimensions.

Variables	Component Loadings
Availability	
Land size	0.50
Production	0.55
Crop stored	0.44
Food gift	0.51
The proportion of variations explained	0.53
The eigenvalue of the first component	2.14
Kaiser-Meyer-Olkin measure of sampling adequacy (KMO):	0.73
Accessibility	
Income	0.54
Food expenditure	0.63
Food Price Index	0.40
Market distance	−0.38
The proportion of variations explained	0.53
The eigenvalue of the first component	2.12
Kaiser-Meyer-Olkin measure of sampling adequacy (KMO):	0.56
Utilization	
Diet diversity	0.60
Number of crops	0.53
Livestock	0.38
Water hygiene	0.46
The proportion of variations explained	0.51
The eigenvalue of the first component	2.03
Kaiser-Meyer-Olkin measure of sampling adequacy (KMO):	0.64
Stability	
Shock frequency	−0.51
Income sources	0.55
Number of months	−0.38
Asset value	0.53
The proportion of variations explained	0.55
The eigenvalue of the first component	2.19
Kaiser-Meyer-Olkin measure of sampling adequacy (KMO):	0.62

Source: Study's findings from ESS survey (2013, 2015 and 2018)

components account for 48, 53, 51, and 55% of the total variance of the dimension indicators, respectively. The proportions of each indicator variable in the index produced are shown by the size of the component's loading coefficients. The availability dimension variables for land size, crop storage, productivity, and food gift have positive component loading coefficients larger than 0.4, indicating a substantial correlation between these factors and the indices produced. The impact of the factors on the degrees of food security in families theoretically showed the predicted sign. Higher food security indices are related to variables with positive component loading coefficients; in contrast, poorer food security indices are related to variables with negative component loading coefficients. For farm households, land is the most precious asset and a crucial element in boosting agricultural output and, consequently, food security. Therefore, a positive correlation between the land size variable and the resulting index of food security is anticipated. For the utilization dimension indicators, the component's loads coefficients were positive and greater than 0.38. Market distance has a negative coefficient, indicating that the further a household is from the market center, the less food security they have, although other access variables have several beneficial aspects that contribute to the food security index. This aligns with other research in rural Ethiopian agricultural households, as in Cochrane and Thornton (2021). Unexpectedly, the loading of the FPI variable had a positive sign. This may be because the majority of smallholder farmers produced food crops, therefore they relied more on production than on purchasing food crops for consumption. Small-scale farmers often take a mixed approach to saving and selling their harvests, depending on other variables included in this study, such as land size (e.g., availability of surplus) and market access. When there are numerous net food crop sellers or producers, increasing food prices improve food security by increasing farmers' income (Dimova, 2015; Martin and Glauber, 2020). The amount of revenue sources and the variables impacting the real value of assets have a positive component load, whereas stability factors like shock frequency and the number of monthly homes without adequate food have a negative component load.

The household food security index in this study is built by changing the component's loads coefficients for all of the indicator's variables. The range of values for the estimated index suggest that household food security ranges from 0 to 1. Higher index values indicate greater food security; the indices have a median of 0 and a standard deviation of 1

Table 5
Households' average food security index in each dimension.

Variable	Mean	Minimum	Maximum
Availability	0.57	0.11	0.97
Accessibility	0.48	0.02	0.98
Utilization	0.70	0.03	0.99
Stability	0.54	0.02	0.97

Source: Study findings from ESS survey (2013, 2015 and 2018)

(Caccavale and Giuffrida, 2020; McKenzie, 2005). The index values have to stay inside the range of 0 and 1 because of the normalization.[4] For the availability, accessibility, usage, and stability dimensions, farm families' average indices were 0.57, 0.48, 0.70, and 0.54 respectively. Table 5 shows the average food security indices for households in each dimension.

3.3. Classification of households' food security status

The arbitrary nature of choosing a threshold point is the fundamental difficulty in analyzing families' food security status over time. Setting a cut-off point necessitates classifying the sample into "food secure" and "food-insecure" categories. The PCA literature describes random and data-driven segregation algorithms that divide indices into several groups and are based on the premise that indices are evenly distributed. According to arbitrary cuts, which are frequently employed, the wealthiest 20% of families are classified as "vulnerable to food insecurity," the lowest 40% of households are classified as "food insecure," and the remaining 40% are classified as "food insecure" (Manaloor et al., 2021; Santos et al., 2019). Andrews (2021) and Apampa (2021) employed this approach using a data segregation mechanism to divide households into food-secure and food-insecure groups with the index's mean values as a cut-off point. However, an arbitrary cut-off food insecurity index would affect the status or rankings of households' food security (De Waal, 2017), and may incorrectly classify households based on percentage groupings. The data-driven approach, on the other hand, provides insight into the food security status of households since the evaluation of the overall food security pattern is based on the actual food security of household's (Lentz et al., 2019). A data-driven approach is considered important from various points of view because it can be used to assist in the development of indicator-based indices and is based on the actual household condition. Homes classed as usually food insecure were those with indices below the mean, while those classified as moderately secure were those with indices above the mean. This relative categorization enables analysis of changes in households' degrees of food security over time.

As shown in Fig. 1, 52%, 56%, and 53% of families were food-secure in 2013, 2015, and 2018, respectively, whereas 48%, 44%, and 47% of homes were food-insecure. In terms of accessibility, 51% of households were food-secure in 2013, 54% in 2015, and 53% in 2018, respectively, while 58%, 46%, and 47% were food-insecure. According to the stability component, in 2013, 2015, and 2018, 54%, 64%, and 55% of families were food secure, whereas 46%, 36%, and 50% of households were food insecure. Between 2013 and 2015, the percentages of food-secure households increased in terms of availability, accessibility, and stability. Between 2015 and 2018, the proportion of food-secure families decreased in terms of availability, accessibility, and stability. As earlier noted, this might be related to a climatic condition that occurred during the 2015/16 agricultural seasons, which had a direct impact on crop output. In terms of use, in 2013, 2015, and 2018, 55%, 57%, and 59% of families were food secure, respectively.

Each component of food security for households is shown in Fig. 1. In order to create effective policies, it is also critical to understand the dimension(s) in which families experienced food security or insecurity. Families may experience food insecurity in just one of the four aspects (availability, accessibility, usage, and stability), or they may experience food insecurity in all four dimensions. According to Table 6, the proportion of families experiencing food insecurity across the four categories considerably decreased from 12% in 2013 to 3% in 2018. For households that were food security in all dimensions, there was an increase from 4% in 2013 to 16% in 2018. The percentage of households with access to enough food improved dramatically across all parameters. Additionally, in 2013, 2015, and 2018, respectively, 84%, 75%, and 81% of farm households experienced food insecurity in at least one dimension.

Additionally, to create overall food security indices for each farm household, the indices of each dimension of food security were combined utlising power mean of equation. Table 7 reveals that in 2013, 2015, and 2018, respectively, 44%, 57%, and 46% of families were food secure, compared to 56%, 43%, and 54% who were food insecure. In order to combine the four aspects of food security—availability, accessibility, use, and stability—the accompanying dynamic analysis was carried out (discussed in the following sub-section).

3.4. Dynamics of households' food security status

The percentage of families that moved from one cluster to another over the survey periods was investigated using an economic transition matrix created for the study. The transition matrix, which was built using quantiles of the total food security indices, depicts the migration of families into and out of a certain category between 2013 and 2018. The transition matrix's ijth entry, which shows the proportion of households that switched from group i to group j, contains this information. The percentage of families that continued to report the same five food security indicators is shown by the values on the main diagonal. Table 8 shows the cumulative percentage of all quantiles in 2018, whereas the cumulative percentages of all quantiles in 2013 is displayed in the last column. The relative stability of food security situations amongst households based on quantiles, shown in Table 8, aligns with other studies (Cochrane, 2017; Krishna, 2010), wherein the percentage of households transitioning between categories of food secure and insecure (or vice versa) are few, compared to the stable majority of households. The data-driven approach, discussed below (Tables 9 and 10), however finds greater levels of movement between categories than the quantile approach indicates.

Table 9 shows that in 2013 and 2015, 63% and 58% of households, respectively, were food-secure, while the remaining 37% and 42% remained food-insecure. According to the study, the proportion of households that were food secure decreased between 2013 and 2015. The most important point to make in this case is that not all households that were food secure in 2013 were still so in 2015. Food security's position and state have altered. For instance, 17% of families experiencing food insecurity remained so in 2015 (immobile), whereas 20% of such households saw a change from food insecurity to food security status in 2015 (mobile). In contrast, 38% of homes in the food security group in both 2013 and 2015 remained food secure, whereas 25% of households in the food security group in 2013 were transferred to the food insecurity group in 2015. In general, the move towards more food insecurity, rather than overcoming food insecurity, indicates that more families were in the food insecurity category between 2013 and 2015. The use of actual data, as opposed to quantiles, identifies new findings, showing a much more dynamic environment when it comes to food security status, with nearly half of households changing status within a short time period.

Table 10 depicts the change in household' food security status from 2015 to 2018. Households that were food secure made up just 43% of the population in 2018, down from 58% in 2015. But from 42% in 2015 to 57% in 2018, the proportion of households experiencing food insecurity increased. El Nino's combined effects on failed rainstorms and droughts led to a considerable rise in food insecurity (Cochrane, 2021; Oxfam, 2016). Additionally, Table 10 depicts how household food security changed between 2015 and 2018. During this time period, 29% of families experiencing food insecurity remained so (immobile), whereas

[4] $\frac{X-X_{min}}{X_{max}-X_{min}}$ Normalization is a ratio of the actual value of a variable minus the minimum value a viable to the maximum value of a variable minus the minimum value of a variable.

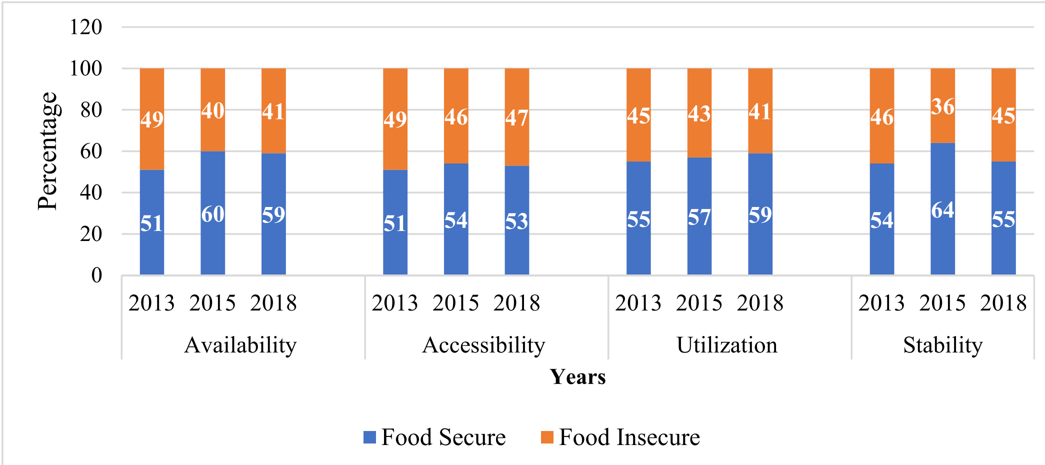

Fig. 1. Food security status by dimension and year.
Source: Study findings from ESS survey (2013, 2015 and 2018)

Table 6
Households' food security status in terms of dimensions.

Food security status by dimension	2013	2015	2018	T-test (Diff between 2018 and 2013)
Food-insecure in all dimensions	12	7	3	0.00***
Food-insecure in at least one dimension	84	75	81	0.08**
Food-secure in all dimensions	4	18	16	0.00***

*, **, and *** indicate statistically significant at 10, 5, and 1 % level, respectively.
Source: Study findings from ESS survey (2013, 2015 and 2018)

Table 7
Households' food security status using the aggregate indices.

Overall food security status	2013	2015	2018
Food-secure	44	57	45
Food-insecure	56	43	55

*, **, and *** indicate statistically significant at 10, 5, and 1% level, respectively.
Source: Study findings from ESS survey (2013, 2015 and 2018)

13% made the transition from food security to insecurity. However, 28% of households in the food-secure category became food insecure, while 30% remained in the same category. More families are migrating into the food insecurity category as a percentage than into the food security category as a percentage. The triggers that explain the commencement and departure of food insecurity were investigated by Jacknowitz et al. (2015), who find that transitioning into and out of food security is often associated with changes in income, the experience of maternal depression, the availability of adults in the family (e.g., productive labor), and poor health. In line with Krishna (2010), for the Ethiopian case Cochrane (2017, 2021) finds the factors include death in the family, a major health

Table 9
Economic transition matrix 2013–2015.

2015				
2013		Food-insecure (%)	Food-secure (%)	Total
	Food-insecure	17	20	**37**
	Food-secure	25	38	**63**
	Total	**42**	**58**	**100**

Source: Study findings from ESS survey (2013, 2015 and 2018)

Table 10
Transition matrix between 2015 and 2018.

2018				
2015		Food-insecure (%)	Food-secure (%)	Total
	Food-insecure	29	13	**42**
	Food-secure	28	30	**58**
	Total	**57**	**43**	**100**

Source: Study findings from ESS survey (2013, 2015 and 2018)

crisis, and indebtedness, each of which are influenced by broader institutional factors.

Using a "spells" method that considers how long a household was food insecure, families were classified as "chronically" and "transitorily" food insecure. Therefore, households with at least one spell of food security were classified as transitorily food insecure, while households with three or more spells of persistent food insecurity were classified as chronically food insecure. Table 11 displays the evolution of household food security over the course of the three survey waves. Out of the total sample, 20% of houses experienced food security during the course of the three survey periods, whereas 13% of homes had persistent (chronic) food insecurity for the whole survey period. The remaining 67% of families were transitorily food insecure, which means they became food insecure at least once throughout the three years of the study. This study

Table 8
Transition matrix for quantiles of food security scores between 2013 and 2018.

2018 Food Security Quantiles Values are in %							
2013 Food Security Quantiles Values are in %	**Quantiles**	**1**	**2**	**3**	**4**	**5**	**Total (2013)**
	1	22	20	20	20	18	**100**
	2	23	21	21	19	16	**100**
	3	22	20	19	18	21	**100**
	4	18	19	20	21	22	**100**
	5	15	19	20	22	23	**100**
	Total (2018)	**100**	**100**	**100**	**100**	**100**	**100**

Source: Study findings from ESS survey (2013, 2015 and 2018)

Table 11
Changes of households' food security status throughout 2013, 2015, and 2018.

	Movement (2013 → 2015 → 2018)	Food secure	Food Insecure	Freq.	% (%)	Cum.%
Food-secure	FS[a] → FS → FS	3 spells	0 spells	284	20	20
Chronically food-insecure	FI → FI → FI	0 spell	3 spells	179	13	13
Transitorily food-insecure	FS → FS → FI[b]	2 spells	1 spell	252	19	67
	FS → FI → FI	1 spell	2 spells	235	17	
	FS → FI → FS	2 spells	1 spell	120	8	
	FI → FS → FI	1 spell	2 spells	134	9	
	FI → FS → FS	2 spells	1 spell	142	10	
	FI → FI → FS	1 spell	2 spells	66	4	
				1412	**100**	**100**

[a] Food-secure.
[b] Food-insecure.
Source: Study findings from ESS survey (2013, 2015 and 2018)

finding, however, contradicts Gebre et al. (2021), whose empirical findings from southern Ethiopia find that 35% and 24% of families, respectively, experienced chronic and transitory food insecurity. Sileshi et al. (2019), analyzing eastern Ethiopia, found that roughly 24% of households had chronic food insecurity and 12% faced transitory food insecurity, which is lower than that of our study finding. This divergence is most likely explained because these two studies collect data from specific regions, and capture geographically-specific data, whereas this study includes four regions and covers the majority of the population (and includes diverse geographic settings, albeit all within regions that predominantly rely on agricultural as the main livelihood).

4. Conclusion and policy implications

Motivated by the multidimensional nature of food security and its dynamic nature, this study employed LSMS-ISA data to address the following unanswered questions: What was the level of food insecurity? Was there a link between the method used to measure food security and the level of food security? This study's major goal was to find out how common food insecurity is in rural regions and to pinpoint the causes in relation to different dimensions of food security. The study also attempted to understand the dynamics of food security in these regions, including the processes that result in food insecurity and the strategies used by households to overcome it. According to the survey results, more than half of all households were food secure in all aspects. In terms of availability, accessibility, and utilization, the number of food-secure households has grown over time. However, the stability component shows that between 2015 and 2018, fewer households were food secure. The percentage of farm households that were food secure increased from 4% in 2013 to 16% in 2018 in these four categories. The percentage of households experiencing food insecurity in the four categories decreased from 12% to 3% over a five-year period. However, during this time period, the majority of farm households experienced food insecurity on at least one metric, in other words temporary food insecurity, which means they did so for at least one occasion, while a small minority experienced chronic food insecurity.

- ➢ The high proportion of food-insecure households, which is higher than the average of previous food security studies, suggests that this study considers a wide range of food security indicator variables and dimensions. As a result, this study suggests that the proportion of food-secure households has been underestimated. Strategies based on multiple food security components might well be beneficial in revealing the depth of the food security problem, and accordingly interventions require multi-sectoral components to address the different domains of food security.
- ➢ Policies that promote food availability, accessibility, utilization, and stability will surely assist in improving food security. As a result, more effort should be made to ensure that all aspects of food security are protected.
- ➢ The predominantly transitory nature of food insecurity highlights that it would be more difficult to justify a targeted approach because the target would keep shifting. The chronic nature of food insecurity has implications for targeting of policy interventions, but it would be challenging to push the food security status. The latter suggests that the well-targeted Productive Safety Net Program can serve the needs of the chronically food insecure, while a different approach (as opposed to scaling the safety net) will be required to address transitory food insecurity.

5. Limitation and suggestion for further research

Earlier food security studies were static in nature, focusing on food security at a single point in time, and employing only one or two food security factors. This study contributes to the methodology for measuring household food security over a three-year period by developing a multidimensional food security index. However, there are a few issues that should be looked into further. Future research could build on this work by attempting to validate the indices by integrating other food security indicators, such as consumption and anthropometric outcomes, under each dimension. Given the heterogeneous nature of rural Ethiopia, and the impacts of interventions and shocks accordingly, regional disaggregation in future research will assist in offering specific recommendations.

Author contributions

M.A.; performed the study and developed the main text. **H.A.**; contributed to the first draft manuscript and enriched it up to the final version. L.C.; contributed to the manuscript in its finalization stages.

Code availability

Not applicable.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Data availability

Data will be made available on request.

Acknowledgment

Not applicable.

Abbreviation

CSA Central Statistics Agency

ERSS Ethiopian Rural Socio-Economic Survey
ESS Ethiopian Socioeconomic Survey
FAO Food and Agricultural Organization
GDP Gross Domestic Product
HDI Human Development Index
HPI Human Poverty Index
IFAD International Fund for Agriculture Development
IFPRI International Food Policy Research Institute
LSMS-ISA Living Standard Measurement Survey- Integrated Surveys on Agriculture
PCA Principal Component Analysis
SNNP Southern Nation, Nationality and People
UNDP United Nation Development Program
WFP World Food Program

Appendices 1.

Appendix A. Principal Component Estimation of Each Food Security Dimension

```
*Availability*
corr land_size production crop_stored food_gift
(obs=4,236)
             | land_s~e produc~n crop_s~d food_g~t
-------------+------------------------------------
 land_size   | 1.0000
 production  | 0.4418 1.0000
 crop_stored | 0.3297 0.3397 1.0000
 food_gift   | 0.3503 0.4991 0.2992 1.0000
pca land_size production crop_stored food_gift
Principal components/correlation  Number of obs=4,236 (total observation 1412*3)
                Number of comp.=4
                    Trace=4
 Rotation: (unrotated = principal)     Rho=1.0000
--------------------------------------------------------------------------
 Component| Eigenvalue Difference Proportion Cumulative
-------------+------------------------------------------------------------
  Comp1 |  2.13838  1.40217    0.5346  0.5346
  Comp2 |  .736213  .0917968   0.1841  0.7186
  Comp3 |  .644416  .163426    0.1611  0.8798
  Comp4 |  .48099   .    0.1202  1.0000
--------------------------------------------------------------------------
 Principal components (eigenvectors)
-------------------------------------------------------------------
 Variable | Comp1  Comp2  Comp3  Comp4 | Unexplained
-------------+--------------------------------------+-------------
 land_size | 0.4968 0.0380 -0.8189  0.2849 |   0
 production | 0.5475 -0.2924 0.0463 -0.7827 |   0
 crop_stored| 0.4410 0.8419 0.3109  0.0124 |   0
 food_gift | 0.5089 -0.4520 0.4802  0.5533 |   0
-------------------------------------------------------------------
. loadingplot
. scoreplot
. estat loading
Principal component loadings (unrotated)
 component normalization: sum of squares(column) = 1
------------------------------------------------------
           | Comp1  Comp2  Comp3  Comp4
-------------+----------------------------------------
 land_size | .4968 .03797 -.8189  .2849
 production | .5475 -.2924 .04631 -.7827
 crop_stored|  .441  .8419  .3109 .01235
 food_gift | .5089  -.452  .4802  .5533
------------------------------------------------------
. predict pcAva,score
(3 components skipped)
Scoring coefficients
 sum of squares(column-loading) = 1
------------------------------------------------------
 Variable | Comp1  Comp2  Comp3  Comp4
-------------+----------------------------------------
 land_size | 0.4968 0.0380 -0.8189 0.2849
 production | 0.5475 -0.2924 0.0463 -0.7827
 crop_stored | 0.4410 0.8419 0.3109 0.0124
 food_gift | 0.5089 -0.4520 0.4802 0.5533
------------------------------------------------------

. estat kmo
```

```
Kaiser-Meyer-Olkin measure of sampling adequacy
 -----------------------
  Variable |  kmo
 -------------+---------
  land_size | 0.7550
  production | 0.6883
  crop_stored| 0.7986
  food_gift | 0.7191
 -------------+---------
   Overall | 0.7300
 -----------------------
. *Acessablity*
. corr income food_exp FPI market_dis
(obs=4,236)
      | income food_exp  FPI market~t
-------------+------------------------------------
  income  | 1.0000
 food_exp | 0.6357 1.0000
   FPI  | 0.2338 0.5002 1.0000
 market_dist | -0.3004 -0.4065 -0.0374 1.0000

. pca income food_exp FPI market_dis
Principal components/correlation      Number of obs =4,236
                  Number of comp. =4
                     Trace   =4
 Rotation: (unrotated = principal)         Rho =1.0000
 --------------------------------------------------------------------------
  Component | Eigenvalue Difference Proportion Cumulative
 -------------+------------------------------------------------------------
   Comp1 |  2.12303  1.15001    0.5308  0.5308
   Comp2 |  .973016  .334953    0.2433  0.7740
   Comp3 |  .638063  .372169    0.1595  0.9335
   Comp4 |  .265894   .            0.0665  1.0000
 --------------------------------------------------------------------------
 Principal components (eigenvectors)
 ---------------------------------------------------------------------
  Variable |  Comp1  Comp2  Comp3  Comp4  | Unexplained
 -------------+---------------------------------------+-------------
   income | 0.5424 -0.1210 0.6905 -0.4630 |    0
  food_exp | 0.6270  0.0698 0.0393  0.7749 |    0
    FPI  | 0.4050  0.7105 -0.4413 -0.3693 |    0
  market_dist|-0.3856  0.6897 0.5717  0.2208 |    0
 ---------------------------------------------------------------------
. loadingplot
. scoreplot
. estat loading
Principal component loadings (unrotated)
 component normalization: sum of squares(column) = 1
 -----------------------------------------------------
           | Comp1  Comp2  Comp3  Comp4
 -------------+----------------------------------------
   income         | .5424  -.121  .6905  -.463
  food_exp       |  .627  .0698 .03933  .7749
    FPI  |  .405  .7105 -.4413 -.3693
  market_dist| -.3856 .6897  .5717  .2208
 -----------------------------------------------------
. predict pcAcc,score
(3 components skipped)
Scoring coefficients
 sum of squares(column-loading) = 1
 -----------------------------------------------------
  Variable | Comp1  Comp2  Comp3  Comp4
```

. (*continued*).

```
Rotation: (unrotated = principal)   Rho    =  1.0000
--------------------------------------------------------------------------
 Component | Eigenvalue Difference   Proportion Cumulative
-------------+------------------------------------------------------------
  Comp1 |  2.0025  1.05723    0.5006  0.5006
  Comp2 |  .945267  .29301    0.2363  0.7369
  Comp3 |  .652257  .252277    0.1631  0.9000
  Comp4 |  .399979   .     0.1000  1.0000
--------------------------------------------------------------------------
Principal components (eigenvectors)
--------------------------------------------------------------------
 Variable        | Comp1  Comp2  Comp3  Comp4 | Unexplained
-------------+----------------------------------------+-------------
 diet_div        | 0.6031 -0.1631 -0.1017 -0.7742 |   0
 num_crops | 0.5421 0.1661 -0.6726  0.4756 |   0
103507  livestock | 0.3524 0.7849      0.5079  0.0425 |   0
water_hygi~e| 0.4672 -0.5742 0.5286  0.4155 |    0
--------------------------------------------------------------------
. loadingplot
. scoreplot
. estat loading
Principal component loadings (unrotated)
 component normalization: sum of squares(column) = 1
------------------------------------------------------
             | Comp1  Comp2  Comp3  Comp4
-------------+----------------------------------------
 diet_div          | .6031 -.1631 -.1017 -.7742
 num_crops | .5421  .1661 -.6726  .4756
 livestock | .3524  .7849  .5079 .04247
water_hygi~e | .4672 -.5742  .5286  .4155
------------------------------------------------------
```

. (*continued*).

```
. predict pcUti,score
(3 components skipped)
Scoring coefficients
 sum of squares(column-loading) = 1
 -----------------------------------------------------
  Variable | Comp1  Comp2  Comp3  Comp4
 -------------+---------------------------------------
  diet_div | 0.6031 -0.1631 -0.1017 -0.7742
  num_crops | 0.5421 0.1661 -0.6726 0.4756
  livestock | 0.3524 0.7849 0.5079 0.0425
 water_hygi~e | 0.4672 -0.5742 0.5286 0.4155
 -----------------------------------------------------
. estat kmo

Kaiser-Meyer-Olkin measure of sampling adequacy
 -----------------------
  Variable |  kmo
 -------------+---------
  diet_div | 0.5987
  num_crops | 0.6584
  livestock | 0.7339
 water_hygi~e| 0.6284
 -------------+---------
   Overall | 0.6341
 -----------------------
. *Stability*
. corr shock_freq income_sources num_months asset_value
(obs=4,236)

       | shock_~q income~s num_mo~s asset_~e
-------------+-----------------------------------
 shock_freq | 1.0000
income_sou~s | -0.4978 1.0000
 num_months | 0.3890 -0.1910 1.0000
 asset_value | -0.3580 0.6167 -0.2705 1.0000
. pca shock_freq income_sources num_months asset_value
Principal components/correlation     Number of obs =  4,236
           Number of comp. =   4
           Trace   =   4
 Rotation: (unrotated = principal)   Rho    =  1.0000
 --------------------------------------------------------------------------
  Component | Eigenvalue Difference   Proportion Cumulative
 -------------+------------------------------------------------------------
   Comp1 |  2.18633  1.29643    0.5466  0.5466
   Comp2 |  .889895  .29401    0.2225  0.7691
   Comp3 |  .595886  .267994    0.1490  0.9180
   Comp4 |  .327891   .    0.0820  1.0000
 --------------------------------------------------------------------------
Principal components (eigenvectors)
 -------------------------------------------------------------------
  Variable  | Comp1  Comp2  Comp3  Comp4 | Unexplained
 -------------+--------------------------------------+-------------
  shock_freq | -0.5171 0.2278  0.7381 0.3687 |   0
 income_sou~s | 0.5539 0.4204 -0.0974 0.7120 |   0
  num_months | -0.3798 0.8023 -0.3975 -0.2326 |   0
  asset_value | 0.5306 0.3574  0.5364 -0.5504 |   0
 -------------------------------------------------------------------
. loadingplot
. scoreplot
. estat loading
Principal component loadings (unrotated)
```

. (*continued*).

```
component normalization: sum of squares(column) = 1

----------------------------------------------------
    | Comp1  Comp2  Comp3  Comp4
-------------+--------------------------------------
 shock_freq | -.5171  .2278  .7381  .3687
income_sou~s | .5539  .4204 -.09736  .712
 num_months | -.3798  .8023 -.3975 -.2326
 asset_value | .5306  .3574  .5364 -.5504
----------------------------------------------------
. predict pcSta ,score
(3 components skipped)
Scoring coefficients
 sum of squares(column-loading) = 1
----------------------------------------------------
 Variable | Comp1  Comp2  Comp3  Comp4
-------------+--------------------------------------
 shock_freq | -0.5171 0.2278 0.7381 0.3687
income_sou~s | 0.5539 0.4204 -0.0974 0.7120
 num_months | -0.3798 0.8023 -0.3975 -0.2326
 asset_value | 0.5306 0.3574 0.5364 -0.5504
----------------------------------------------------
. estat kmo
Kaiser-Meyer-Olkin measure of sampling adequacy
----------------------
 Variable |  kmo
-------------+---------
 shock_freq | 0.6658
income_sou~s | 0.5901
 num_months | 0.6219
 asset_value | 0.6350
-------------+---------
  Overall | 0.6253
----------------------
. sum pcSta,meanonly
. gen npcSta= (pcSta- r(min)) / (r(max) - r(min))
. **Overall food security indecies****
. gen FSI=(0.25*(npcAva^3+npcAcc^3+ npcUti^3+ npcSta^3))^0.333
. sum pcAva pcAcc pcUti pcSta npcAva npcAcc npcUti npcSta
 Variable |  Obs  Mean Std. Dev.  Min  Max
------------+-------------------------------------------------------
 pcAva |  4,236 5.56e-10  1.46232 -5.887403 4.478063
 pcAcc |  4,236 9.17e-10 1.457061 -4.332113 4.617533
 pcUti |  4,236 -2.95e-10 1.415096 -6.037987 2.447181
 pcSta |  4,236 1.46e-09 1.478624 -4.925025 4.19441
 npcAva |  4,236 .5679825 .1410762   0   1
------------+-------------------------------------------------------
 npcAcc |  4,236 .4840541 .1628066   0   1
 npcUti |  4,236 .7115931 .1667729   0   1
 npcSta |  4,236 .5400581 .1621398   0   1
```

. (*continued*).

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