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Persistence in Food Insecurity and Poverty in Ethiopia

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Abstract:

Using three rounds of data from the Ethiopia Socioeconomic Survey (ESS), we estimate a series of dynamic random effect probit models accounting for unobserved heterogeneity and the initial conditions problem using four measures of food insecurity and poverty. The descriptive analysis suggest higher levels of downward mobility and lower rates of exit for the food insecurity measures relative to food poverty and general poverty. There also appear to be lower levels of persistence in the subjective measure of food insecurity although for all measures close to the majority of the sample experience at least one period of food insecurity, food or general poverty. The estimation results provide some evidence of persistence or state dependence exists for subjective food insecurity, food and relative poverty measures. There is also evidence of cross effects so that being subjectively food insecure in the past increases the probability of being food poor and relatively poor in the current period.

Keywords: Food insecurity; Poverty; State dependence; Ethiopia; farm households

JEL codes I32, Q12, C23

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Introduction

Food insecurity and poverty are key components of the Sustainable Development Goals, with the evidence on current levels of food insecurity and malnutrition underlining the difficulty in achieving the 2030 targets (FAO et al., 2017). Both food insecurity and poverty are understood to be complex phenomena encompassing multiple dimensions (Barrett, 2010; Alkire and Santos, 2014). As a result a wide variety of measures of food insecurity and poverty are applied to capture different elements (Lele et al 2016). Research has also explored the relationships between different measures (Hoddinott and Yohannes, 2002; Maxwell et al., 2014).

An important component on the literature on poverty, both within developed and developing countries, has trying to identify the extent to which the experience of poverty is transitory or persistent (Bigsten and Shimeles, 2008; Bane and Ellwood, 1986). In contrast, as highlighted by Hendriks, (2015) there has been relatively little research "on the stability dimension of food security" (p.611, para 6) although recent work in this area is emerging (Maxwell et al., 2014; D'Souza and Jolliffe, 2016).

Similar to the research on unemployment persistence it is important to understand whether persistence in food insecurity is due to (unobserved or observed) characteristics of households or whether there is state dependence. That is, does being food insecure in one period has "scarring effects" increasing the probability of food insecurity in the next (Arumplamlam et al, 2000)? The multi-dimensional nature of food insecurity and poverty suggests cross-effects might also exist. For example, if a household is judged to be currently food insecure in one dimension, does increase the household's future probability of being food insecure or poor in another dimension?

The aim of this paper is to explore the extent of food insecurity and poverty persistence and the evidence for cross-scarring effects where being food insecure (or poor) in one dimension) affects another. Using three rounds of data from the Ethiopia Socioeconomic Survey (ESS), we estimate a series of dynamic random effect probit models which account for unobserved heterogeneity and the initial conditions problem (Wooldridge, 2005). The structure of the paper is as follows. In section 2 we introduce the data, discuss the definitions of food security and poverty used, and then provide of basic description of the data. Section 3 provides a description of the econometric methodology applied and how the identification of the persistence or state dependence effect can be distinguished from the impact of structural household characteristics and temporary shocks. Section 4 reports the estimation results and section 5 concludes.

Definitions and Data

The data used below is drawn from rounds 1 (2011-12), 2 (2103-14) and 3 (2015-16) of the Ethiopia Socioeconomic Survey (ESS) collected by the Central Statistical Agency of Ethiopia as part of the World Bank's Living Standards Measurement Integrated Programme (LSMS). The survey is a panel with households recruited in Round 1 revisited in Rounds 2 and 3. In Round 1 the sample was concentrated on Rural and Small town areas in Ethiopia. In Round 3 the sample was enhanced to include a greater number of urban households and including Addis Ababa. The data collected contains information on household characteristics, consumption, and (for farm households) crop and livestock production. In addition, community level information is collected plus various climate and other variables associated with the area in which the households resides have been added to the available data. From the data collected, LSMS programme constructs and makes available a number of consumption aggregates, including household food and total consumption (Central Statistical Agency et al, 2017). From the available data a panel of farm households has been constructed.

The literature on food security emphasises*: availability, access and utilization* as distinct and important elements. These are seen as hierarchical in nature, food availability "is necessary but not sufficient for access, and access is necessary but not sufficient for utilization" Hendriks (2015, page 611, para 7). Here we capture some of these different elements in the following measures. First, a measure based on the Household's dietary diversity score (HDDS) (FAO 2010). Drawing on questions on the household's food consumption over the last week, the HDDS score measures the number of food groups (out of a maximum of 12) consumed by the households over the last week. While dietary diversity is recognized as having a positive impact on nutrition there has been no agreed cut-off which define food insecurity using the measure (Ruel, 2003). Here, we define the food insecurity indicator as any household which reports consuming 4 or less food groups. This defines households who fall in the lowest 25% of HDDS dietary diversity measure as food insecure. The second measure is based on Household Food Insecurity Access Scale (HFIAS). This scale draws on a number of questions capturing more subjective measures of food insecurity

(Coates et al J, 2007). Here we use the HFIAS scale to define food insecure household as a household which is defined as having either mildly, moderately or severely limited access to food. The last measure focusses on food poverty and the household's ability to access sufficient nutrition. Using the available data on annual food consumption per adult equivalent in the household we define household food poverty using the Ethiopian Government Food poverty threshold of 1985 BIRR per adult equivalent (adjusted for food inflation). This threshold is based on the cost of 2,200 kcal per day for food consumption for each adult plus an element for essential non-food items. (Ministry of Finance and Economic Development, 2012).

Finally, to allow an exploration of the relationship between food insecurity measures and wider poverty we apply a general poverty threshold to define households in general poverty. Here we use a relative threshold where a household is defined as poor in any period if its annual household expenditure per adult equivalent falls in one of the lowest three deciles. Ravillion (1998) argues strongly that poverty lines should be defined using absolute rather than relative thresholds. However, relative thresholds have been in used in a range of developing country contexts including in Ethiopia (Bigsten and Shimeles, 2008) as they provide useful information on the relative mobility of households controlling for general changes in the economic situation of households.

In addition to the food insecurity and poverty measures used, the analysis below considers the impact of a number of key variables which frame food availability and access for the household which may change for households over the period. These variables can be considered of two types. First, variables such as land holding and total livestock units which are correlated with the wealth or resources available household in any period. The second are variables which capture the main types of shocks such as climate and health which impact on the household's ability to produce food. As is discussed in the next section other types of household characteristics e.g. distance to markets, which do not typically change for individual households in the short periods will be captured though the econometric modelling via unobserved heterogeneity.

Table 1: Key Variables

Variable	Mean	SD
Food Insecure(Dietary Diversity)	0.22	0.42
Food Insecure (HFIAS)	0.23	0.42
Food Poverty	0.34	0.47
Relative Poverty	0.31	0.46
Household Size (Adult Equivalents)	4.43	1.80
Number of days Head of Household Sick	2.30	7.97
Landholding (Hectares)	1.38	7.74
Total Livestock Units	2.08	3.28
Enhanced Vegetation Index	44.83	14.82
N	3100	3100

Pooled Data Round 1-3 Ethiopia Socioeconomic Survey.

Table 1 reports the descriptive statistics for the sample used in estimation in the paper. Overall, the incidence of food poverty and general poverty is higher in the sample than food insecurity as measured by the dietary or HFIAS index. In addition to the variables which capture household wealth, the number of sick days for the head of household and Enhanced Vegetation Index are included to capture the impact of health and climatic shocks. The Enhanced Vegetation Index is based on Satellite imaging of the earth and quantifies the density of plant growth (at the sub-regional level) and has been successfully used as a drought indicator (Atkinson et al 2011).

Table 2 provides a number of descriptive measures capturing the dynamics of the food insecurity and poverty measures. First consider Rows 1 and 3 which indicate the extent of movements between the states across any two consecutive rounds of the data. For example in row 1 using the dietary diversity measure, 15.7% of the households who were food secure in one round were defined as food insecure by the next.. Row 3 provides the mobility out of food insecurity so that 62.5% of those defined as food insecure in one round were food secure by the next. Comparing across the measures there are clear differences between the food insecurity measure and the food and general poverty measure, with higher levels of mobility into the lower category and lower rates of exit. For example, relative to the dietary diversity measure, 26.4% of households who were food secure in one round were defined as insecure in the next while 47.2% of those defined as food poor in one period where not in the next.

Table 2: Period to Period Transitions and Persistence of Food Insecurity and Poverty Measures

Percentage		Food Insecure (Dietary Diversity)	Food Insecure (HFIAS)	Food Poverty	Relative Poverty
Below Threshold t+1|Above t		15.7	19.91	26.46	22.42
N		(2166)	(2406)	(2230)	(2150)
Above Threshold t+1|Below t		62.53	65.56	47.24	51.05
N		(934)	(694)	(870)	(950)
Rounds Below Threshold					
	0	47.45	50.88	41.37	43.4
	1	30.63	31.87	34.07	30.99
	2	15.05	14.44	17.25	17.78
	3	6.87	2.82	7.31	7.83
N		(1136)	(1136)	(1136)	(1136)

The second section of Table 2 provides a simple indication of the extent of food insecurity and poverty persistence as captured by these measures, reporting the number of rounds any households spent below the defined thresholds. For example, for the dietary diversity measure, 6.9 % of households were defined as being food insecure in all rounds, whereas 47.5% were never defined as being food insecure. One notable difference here is the apparent low levels of very low levels of persistence (2.8%) in the HFIAS measure relative to the other measures. However, the proportion of households experiencing at least one period remains high across all measure ranging from 49% to 56%.

Empirical Specification

As there are only three rounds of data available, an analysis of a spells of time spent by household food insecurity or poverty is not possible. Rather we specify and estimate simpler discrete dynamic models to capture the persistence/state dependence and any cross effects between the measures

$$y_{it}^{k} = \alpha + \beta_1 y_{it-1}^{dd} + \beta_1 y_{it-1}^{hfias} + \beta_2 y_{it-1}^{pov} + \delta z_{it} + \mu_i + e_{it}, \quad k = dd, hfias, pov \qquad (1)$$

Where $y_{it}^{k} = 0,1$ is one of binary measure of food security or poverty (=1 if food insecure/ poor 0 if not), $y_{it}^{dd}, y_{it}^{hfias}, y_{it}^{pov}$ are the two food insecurity measures and *either* the food *or* general poverty measures.[1] The β_k captures both the standard persistence/state dependence effect of the lagged dependent variable plus the cross effect of the lagged value of one value on the current value of the dependent variable. The variables specified in the z_{it} vector allow for the impact of effects which change over time, i.e. wealth, weather and health shocks. All remaining time invariant characteristics are assumed to be captured by the μ_i unobserved heterogeneity terms, while e_{it} accounts for other time varying but unobserved shocks. The standard discrete dynamic approach to capturing state dependence is nested in equation (1) when no cross-effects are specified.

As is well known in estimating model (1) there is an initial conditions problem as the lagged dependent variable will be correlated with the unobserved heterogeneity. The inclusion of the other lagged variables also induces this problem if it is assumed that the unobserved heteroegnity terms are correlated across the different equations. Without adjustment, this would cause the persistence estimates to be overestimated. To adjust can use the procedure suggested by Wooldridge (2005), projecting the unobserved heterogeneity term on the initial values of the lagged values plus the household averages of the time varying regressors.

$$\mu_i = \varphi_1 y_{i0}^{dd} + \varphi_2 y_{i0}^{hfias} + \varphi_3 y_{i0}^{pov} + \lambda \bar{z}_i + \eta_i \qquad (2)$$

Subsituting (2) into (1) generates an equation which can be estimated using standard procedures for Random effects Probit models, i.e.

$$y_{it} = \alpha + \beta y_{it-1} + \delta z_{it} + \varphi y_{i0} + \lambda \bar{z}_i + \eta_i + e_{it} \qquad (3)$$

Results

A number of specifications consistent with equation 3 are estimated. First, in Table 3, we report the results of standard discrete dynamic estimations, which exclude the lagged cross-effects of one food insecurity or poverty measure. Table 4 then reports on the estimations which allow for such effects. Finally Table 5 clarifies the economic importance of the Table 4 results by providing information on the marginal impact of being in food insecurity or poverty in one round on the probability of being food insecurity or poverty in the next round.

[1] Due to the high degree of correlation between the food poverty and general poverty measure we do not include both in the estimations.

Table 3 Dynamics of Food Insecurity & Poverty: No Interaction between the Food Insecurity & Poverty measures

Variable	**Food Insecure (Dietary Diversity)**	**Food Insecure (HFIAS)**	**Food Poverty**	**Relative Poverty**
Food Insecure(Dietary Diversity) (*t-1)*	-0.1621			
	(1.0)			
Food Insecure (HFIAS) (*t-1*)		0.2373		
		(2.9)		
Food Poverty *(t-1)*			0.4286	
			(3.4)	
Relative Poverty *(t-1)*				0.1955
				(1.5)
Household Size (Adult Equivalents)	-0.1586	0.0893	0.3329	0.3734
	(3.0)	(2.2)	(7.4)	(7.4)
Number of days Head of Household Sick	0.0058	0.0052	0.001	-0.0028
	(1.2)	(1.4)	(0.3)	(0.7)
Landholding	0.0217	-0.0001	-0.1148	-0.0487
	(0.8)	(0.001)	(4.2)	(0.9)
Total Livestock Units	-0.0545	0.0053	-0.0069	-0.0153
	(2.8)	(0.4)	(0.5)	(1.1)
Enhanced Vegetation Index	-0.0039	-0.0126	-0.0102	-0.0145
	(0.6)	(2.6)	(2.1)	(2.7)
Food Insecure(Dietary Diversity) (*t=0)*	0.99			
	(5.6)			
Food Insecure (HFIAS) (t=0)		0.2906		
		(3.7)		
Food Poverty (t=0)			0.2521	
			(1.9)	
Relative Poverty (t=0)				0.5668
				(3.9)
Log Likelihood	-1500.9	-1613.8	-1771.8	-1679.4
rho	0.3739	0.0001	0.0305	0.2016
p-value	<0.01	0.49	0.38	0.02

Absolute t value in brackets under each coefficient. Following the approach suggested by Wooldridge (2005) to account for the initial conditions problem the estimations include the initial value of the lagged dependent variable (reported above) and also (not reported) within Household means for Household Size, Days Household Head Sick, Landholding, Total Livestock unit and Enhanced Vegetation Index, a constant and a dummy variable for round 3. Full estimation results are available on request from the authors

Under each coefficient in Table 3 the absolute value of the t statistic for the significance of the coefficient is reported. Also at the bottom of the Table 3 the value of log likelihood for each estimation plus the value of ρ. As expected all the Wald tests undertaken suggest that the set of explanatory variables used explain a significant proportion of the variance of the explanatory variables (at 1% significance). The value ρ represents the proportion of the variance unexplained by the regressors but accounted for by variation in the unobserved heterogeneity between individuals $\rho = \frac{\sigma_{\mu}^{2}}{\sigma_{\mu}^{2} + \sigma_{e}^{2}}$ The p-value reported below is associated with the Chi squared test the significance of this coefficient and hence formally indicates whether taking account of unobserved heterogeneity is important. In a number of cases the coefficient is insignificant (most strikingly for the food insecurity measure based on HFIAS measure). The unobserved heterogeneity is controlling for all factors which affect the probability that the household is food insecure or poor but are unchanging over time and so a priori we would expect it to be important and statistically significant.[2] An alternative explanation is that the short nature of the panel means that the Wooldridge adjustment is less able to distinguish state dependence from unobserved heterogeneity than the alternative methods for dealing with the initial conditions problem (Heckman, 1981). The values of the y_{i0} are also reported in Table 3. The coefficients on these variables are all statistically significant (at 5%) suggesting that the no adjustment for the initial conditions would lead to bias.[3]

The results of the coefficients on the lagged dependent variables suggest that state dependence is potentially important in 2 out of 4 of the measures, with the values for both the HFIAS based measure and for food poverty are statistically significant at 1%. The values of the other coefficients are also generally in line with expectations. Although rarely statistically significant, when they are the impact of the variables correlated with wealth (land holding and Total Livestock Units) is negative on the probability of being food insecure or poor. Generally as expected, the impact of the Enhanced Vegetation Index is negative, i.e. better growing seasons are associated with a lower probability of being food insecure or poor. However, the number of days in which the Head of Household has been sick does not appear to play a significant role. The impact of household size is less consistent. Although it is

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[2] The nature of questions underlying the HFIAS food insecurity measure may imply that the unobserved heterogeneity might be less important for this measure than for the other cases.

[3] The values for $\overline{z}$ were also included in each for brevity are not reported.

always statistically significant, increasing effective household has an apparent negative impact on the dietary diversity measure of food insecurity but positively affects the other measures.

Table 4 reports the results for the specifications which allow for cross measure effects. That is for each estimation we include both the lagged dependent variable but also the lagged variables of the other food insecurity measure plus either the food poverty or the general poverty measure. These results therefore provide an indication as to whether any of the food insecurity or poverty measures affect the future probability of all types of food insecurity or poverty. As for Table 3, the overall estimation and the estimated coefficients are generally well specified, although the ρ estimates again suggest that either unobserved heterogeneity is unimportant for the HFIAS and food poverty measure or that the Wooldridge procedure may be unable to effectively distinguish between state dependence and unobserved heterogeneity in these cases. However, the significance of the included initial values does suggest that the initial values problem does need to be accounted for in the estimations.

The estimated coefficients on the lagged values of Food Insecurity (Dietary Diversity), Food Insecurity (HFIAS), Food Poverty and Relative Poverty provide the initial evidence of the importance of cross effects. For the dietary diversity measure, only relative food poverty lagged seems to play any statistically significant role. However, for the HFIAS food insecurity measure there is (as for Table 3) evidence of direct state dependence form the lagged value of the HFAS based measure but also some evidence which suggest that both previous experience of food poverty and general relative poverty in the previous round increase the probability that a household is food insecure in the current round. For food poverty, both food poverty lagged and the being food insecure as measured by the HFIAS food insecurity measure increases the probability of current food poverty. Similarly for relative general poverty, lagged general poverty plus the lagged HFIAS measure increases the probability of current relative poverty. Here there is also some weak evidence that the lagged dietary diversity measure helps predict current relative poverty.

Table 4 Dynamics of Food Insecurity & Poverty: No Interaction between the Food Insecurity & Poverty measures

Variable	Food Insecure (Dietary Diversity)		Food Insecure (HFIAS)		Relative Poverty	Food Poverty
Food Insecure(Dietary Diversity) (*t-1)*	-0.1817	-0.1807	0.0437	0.0416	0.1283	0.0667
	(1.1)	(1.1)	(0.5)	(0.5)	(1.5)	(.8)
Food Insecure (HFIAS) (t-1)	0.0299	0.0434	0.2115	0.2138	0.359	0.2019
	(0.3)	(0.4)	(2.6)	(2.6)	(4.0)	(2.5)
Food Poverty (t-1)		0.0884		0.1272		0.4383
		(0.9)		(1.8)		(5.6)
Relative Poverty (t-1)	0.1878		0.1239		0.2302	
	(1.9)		(1.5)		(1.7)	
Household Size (Adult Equivalents)	-0.1484	-0.1511	0.0934	0.0955	0.3598	0.3252
	(2.8)	(2.9)	(2.2)	(2.3)	(7.4)	(8.)
Number of days Head of Household Sick	0.006	0.0063	0.0051	0.0053	-0.002	0.0014
	(1.3)	(1.4)	(1.4)	(1.5)	(.5)	(.4)
Landholding	0.0181	0.0192	-0.0002	-0.0005	-0.0455	-0.1017
	(.7)	(.7)	(.)	(.1)	(.9)	(3.9)
Total Livestock Units	-0.0555	-0.0541	0.0022	0.0025	-0.0154	-0.0069
	(2.9)	(2.8)	(.2)	(.2)	(1.1)	(.5)
Enhanced Vegetation Index	-0.0036	-0.0034	-0.012	-0.0118	-0.0136	-0.0093
	(.6)	(.6)	(2.4)	(2.4)	(2.6)	(1.9)
Food Insecure(Dietary Diversity) (*t=0)*	0.8782	0.9344	0.1267	0.1269	0.1543	0.1479
	(5.2)	(5.4)	(1.6)	(1.7)	(1.8)	(2.)
Food Insecure (HFIAS) (t=0)	0.03	0.0318	0.3101	0.3117	-0.1832	-0.0804
	(0.3)	(0.3)	(3.9)	(4.0)	(2.)	(1.)
Food Poverty (t=0)		0.2509				0.1867
		(2.2)				(2.4)
Relative Poverty (t=0)	0.3231		0.0578	0.0754	0.4425	
	(3.)		(.7)	(1.1)	(3.1)	
Log Likelihood	-0.6398	-0.5582	-11.1128	-10.8507	-1.8158	-9.1588
rho	0.3453	0.364	0.0001	0.0001	0.1399	0.0001

Absolute t value in brackets under each coefficient. Following the approach suggested by Wooldridge (2005) to account for the initial conditions problem the estimations include the initial value of the lagged dependent variable (reported above) and also (not reported) within Household means for Household Size, Days Household Head Sick, Landholding, Total Livestock unit and Enhanced Vegetation Index, a constant and a dummy variable for round 3. Full estimation results are available on request from the authors

In order to provide an indication of the economic significance of the cross-effects reported in Table 4, the marginal effect on the current probability of being the various food insecurity or poverty measures of being in a particular state in the previous period is reported in Table 5. Considering the lagged coefficients in Table 4 which are statistically significant with the Table 5 results does suggest that "scarring" effects of the various aspects of food poverty may be significant. For example, being subjectively food insecure in the past (by the HFIAS measure) increases the probability of being food poor and relatively poor. Specifically column 2 indicates the impact of being food insecure using the HFIAS measure in the previous round is to increase the current probability of being food insecure in terms of Dietary diversity by 1%, food insecure by HFIAS measure by 6.5%, of food poor by 6.7% and relative poor by 10.6%. Similarly, being relatively poor in the past increases the probability of food insecurity. In contrast, there seems less evidence of persistence in the dietary diversity food insecurity measure.

Table 5 Marginal Effects: Lagged Impact of Food Insecurity & Poverty on Current Food insecurity Poverty Probability

		Lagged values		
	Food Insecure (Dietary Diversity)	**Food Insecure (HFIAS)**	**Food Poverty**	**Relative Poverty**
Prob(Food Insecure (Dietary Diversity))	-0.038	0.010	0.019	0.042
Prob(Food Insecure (HFIAS))	0.012	0.065	0.038	0.037
Prob(Food Poverty)	0.022	0.067	0.151	
Prob(Relative Poverty)	0.037	0.106		0.068

Summary and Conclusions

This paper has explored the extent of food insecurity and poverty persistence and the evidence for cross-scarring effects where being food insecure (or poor) in one dimension of food insecurity or poverty affects another. Using three rounds of data from the Ethiopia Socioeconomic Survey (ESS), we estimated a series of dynamic random effect probit models accounting for unobserved heterogeneity and the initial conditions problem. Four measures of food insecurity and poverty are used base on dietary diversity, subjective questions on food insecurity, food poverty and relative general poverty.

The descriptive analysis suggest that there are higher levels of downward mobility and lower rates of exit for the food insecurity measures based on dietary diversity and subjective food insecurity relative to the food poverty and general poverty measures. There also appear to be lower levels of persistence in the subjective measure of food insecurity with only 2.8% of the sample food insecure in all periods, relative to 6% to 7% for the other measures. However, for all measures the majority or very close to the majority of the sample experience at least one period of food insecurity, food or general poverty in the three rounds.

The estimation results suggest, after controlling for unobserved heterogeneity and time varying shocks, that persistence or state dependence is associated with subjective food insecurity, food poverty while there is some evidence of this also for relative poverty. In addition there is some evidence of cross effects. For example being subjectively food insecure in the past increases the probability of being food poor and relatively poor in the current round. Similarly, being food poor in the past increases the probability of current subjective food poverty. In contrast, there seems much less evidence of strong persistence or cross effects associated with the dietary diversity food insecurity measure.

One caveat to these results is that estimation technique used to control for the initial conditions problem due to Woodridge does appear to have some difficulty in some cases in identifying both state dependence and unobserved heterogeneity. Future work will explore the robustness of the results using other techniques to separate the two effects.

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