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IFPRI Discussion Paper 00971

May 2010

Asset Versus Consumption Poverty and Poverty Dynamics in the Presence of Multiple Equilibria in Rural Ethiopia

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FINANCIAL CONTRIBUTORS AND PARTNERS

IFPRI's research, capacity strengthening, and communications work is made possible by its financial contributors and partners. IFPRI receives its principal funding from governments, private foundations, and international and regional organizations, most of which are members of the Consultative Group on International Agricultural Research (CGIAR). IFPRI gratefully acknowledges the generous unrestricted funding from Australia, Canada, China, Denmark, Finland, France, Germany, India, Ireland, Italy, Japan, the Netherlands, Norway, the Philippines, South Africa, Sweden, Switzerland, the United Kingdom, the United States, and the World Bank.

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ABSTRACT

Effective poverty reduction programs require careful measurement of poverty status. Several studies have shown conceptually that assets reflecting productive capacity form a more robust basis for identifying the poor than do flow variables such as expenditures or income.[1] Nonetheless, little work has empirically compared poverty measurements based on assets and expenditures. This paper uses panel data from Ethiopia to generate an asset-based poverty classification scheme. Regression results are used to estimate an asset index and classify households into categories of structural poverty. Asset index dynamics are also explored to test for the existence of multiple asset index equilibria; evidence of potential poverty traps. Results provide evidence of multiple equilibria in the study sample as a whole as well as convergence at different levels over space, depending on commercialization opportunities and agroecological factors. The asset-based poverty classifications consistently predict future poverty status more accurately than do income-based measures, confirming that the asset-based measure could be used to more carefully target poverty interventions in rural areas and to more accurately assess the impact of those interventions.

Keywords: asset poverty, poverty dynamics, rural Ethiopia

[1] See Carter and Barret (2006); Adato, Carter, and May (2006); Lybbert et al. (2004); Sahn and Stifel (2003); Sahn and Stifel (2000); Carter and May (1999); and Mogues (2006) for theoretical discussion and application of the theory of asset poverty.

1. INTRODUCTION

Given their limited resources, governments in Africa must make difficult choices when developing policies to combat poverty. For example, policies could emphasize alleviating conditions for the poorest of the poor or assisting marginally poor households to become consistently nonpoor. Policies to reduce the proportion of people living in extreme poverty might not reduce the number of people living below the poverty line, while interventions that provide safety nets for households living close to the poverty line might not support the society's poorest (UNDP 2006). Whatever the specific objectives of a poverty reduction approach, policymakers must distinguish among households in different degrees or forms of poverty in order to devise informed interventions. Identifying the nature of the poverty that a household is experiencing can be particularly difficult in rural populations that depend on highly variable incomes from agricultural production in an informal economy. In such a setting it may be difficult to distinguish those households that are consistently poor or nonpoor from those that are transitionally in one status or the other due to passing weather or market conditions.

Most poverty classification in developing countries has been based on the comparison of household per capita consumption expenditures against an income or expenditures poverty line. With the increasing availability of panel data, more nuanced measures of poverty can be derived to enable finer distinctions among the poor. Panel data allow the distinction between those experiencing transitory income poverty and those who remain in persistent income poverty (Carter and May 2001; Carter and Barrett 2006). In addition to providing information on the persistence of conditions, panel data allow for the estimation and validation of poverty measures based on assets rather than consumption expenditures alone. Asset-poverty measures highlight the structural nature of poverty by focusing on the productive capacity of a household. They make it possible to identify households whose incomes are unlikely to rise above the poverty level without external assistance; those who are vulnerable, with assets that suggest that their incomes could easily cross the poverty line (in either direction); and those who are nonpoor and can be expected to maintain nonpoor expenditures independently. Asset measures can further reveal whether households moving into or out of income poverty are transitioning due to a structural (and therefore enduring) change in their resource base or a temporary change in conditions (Carter and Barrett 2006).

Time series data on assets can be used to estimate the patterns of growth in assets over time to reveal the existence of poverty traps. If asset dynamics reveal locally increasing returns to scale, then bifurcated growth paths can emerge in which households with assets below a critical threshold cannot grow themselves out of poverty, while households with assets above this level can (Carter and Barrett 2006). Based on households' initial asset bases and asset dynamics, the so-called Micawber threshold permits a distinction between deep-rooted, persistent structural poverty and transitory poverty that passes naturally with time due to systemic growth processes. The threshold makes it possible to identify those households that will most likely never grow out of poverty (or to a higher possible equilibrium) without external assistance (and are thus in a poverty trap), those who are vulnerable (these could be poor or nonpoor, given their current asset stock) and headed downward toward a poverty trap (or lower-level equilibrium), and those who are nonpoor and can be expected to maintain a nonpoor status on their own, ceteris paribus.

Asset-based poverty measures hold considerable value as tools for assessing the poverty impacts of policy, but difficult methodological issues are involved in accurately mapping between assets and income. In particular, efforts to estimate the asset base required to generate income above the poverty line are complicated by the multiplicity of assets held by households (many of which have no market price), the potential for complementarities among some of these assets, and the likelihood that many factors affecting these assets' productivity are unobserved. These issues may be especially pertinent in rural settings where environmental conditions will affect the return on physical assets and where the interactions among specific assets may be substantial.

This paper uses panel data from rural Ethiopia to estimate the relationship between assets and consumption expenditures and consequently to generate an asset index. It then computes static and dynamic asset poverty lines that can be used to classify households by both their current expenditures and their capacity to independently maintain or raise expenditures, based on their assets. This analysis also uses the asset index generated to test empirically for the existence of an asset threshold (Micawber threshold) around which household accumulation trajectories split, thus indicating the existence of multiple equilibria of asset bundles and possibly a poverty trap (Carter and Barrett 2006). Both parametric and nonparametric estimations reveal the presence of bifurcated asset index dynamics and multiple equilibria of asset bundles in rural Ethiopia. The lower-level equilibrium is slightly above the static asset poverty line and the higher equilibrium at about two times the asset poverty line.

A key contribution of this paper is to test the validity of the asset-based poverty classifications relative to an expenditures-based classification. Results indicate that the asset-based classifications identify households that are likely to be in expenditures poverty in the future more accurately than do current expenditures. Results also confirm that many households classified as nonpoor based on current expenditures lack the assets to maintain that level of consumption. The findings of this study imply that the asset-based measure could be used to more carefully describe rural poverty, target government interventions, and assess the impact of those interventions.

2. POVERTY MEASUREMENT AND POVERTY STATUS CLASSIFICATION

The concept of poverty has been broadened over the years to incorporate aspects of human well-being besides income, such as education, infrastructure and other public services, property rights, political freedom, and the prevalence of widespread corruption (UN 2005). Be that as it may, poverty measurement is still typically based on some income or expenditures poverty line, constituting a threshold below which one is considered to be in poverty. As Cutler (1984) describes, the poverty line represents "a collection of minimum needs amounts," and poverty classification using national poverty lines reflects existing prices and perceptions of minimum needs in particular countries.[2]

With reference to a poverty line, income-based measures of poverty classify as "poor" those households whose per capita consumption expenditures over a period were below the poverty line. Based on flow variables and informant recall, these indicators are more prone to measurement error than are indicators based on visible assets such as land or livestock (Wooldridge 2002). Moreover, expenditures-based measures of well-being cannot distinguish between consumption supported by erosion of assets and consumption based on production. Various studies have shown income-based measures to indicate high levels of transitory poverty and underestimate chronic poverty (Baulch and Hoddinott 2000; Hulme and Shepherd 2003). Although transitory poverty measured by expenditures could indicate the vulnerability of households to various shocks, it also complicates efforts to attribute poverty reduction in specific households to interventions.

One problem with expenditures-based poverty measurement is that expenditures in many households will rise above or fall below the poverty line through time regardless of policy interventions. Such movement is especially likely among agricultural households in developing countries with poorly functioning or nonexistent formal credit and insurance markets and households whose income is largely based on weather conditions, crop yields, and commodity prices. Changes in consumption expenditures could also reflect accumulation or loss of productive assets. By combining households that are likely to be transitorily in poverty with those whose poverty is structural, income-based classification can give an imprecise and potentially misleading impression of poverty dynamics and policy impacts. Moreover, in rural areas with limited financial services, households may increase consumption expenditures at the expense of their productive assets, or they may defer consumption to make investments. In either case, current consumption expenditures alone could misrepresent more fundamental well-being.

Asset-based approaches use the expected returns on a household's physical and human assets to categorize households into poverty classes. The static asset poverty line in this study is generated using regression analysis to determine the minimum assets required to sustain consumption at the expenditure poverty line. Households whose assets imply that their income will be below the poverty line are in asset poverty, while those whose assets are expected to yield incomes above the poverty line are asset nonpoor. In any given year, exogenous factors may give an asset-poor household the ability to consume above the poverty line. Due to lack of productive assets, such a household is unlikely to sustain this consumption and thus can be expected to remain poor. Likewise, a household with many assets may experience a year of low consumption, but the asset-based approach would continue to classify the household as asset nonpoor because it has the apparent capacity to increase consumption without external assistance.

Estimation of the asset poverty line is complicated by the potentially nonlinear relationship between assets and income and by asset multiplicity and complementarities (meaning the fact that households have diverse assets whose returns depend on the availability of other assets). Most current research using this asset-based approach to poverty measurement adopts either a one-dimensional asset measurement justified by the predominance of one asset in a region (say, livestock) or uses factor analysis (or a similar procedure) to generate an asset index. For example, Mogues (2006) and Lybbert et al. (2004) use herd dynamics to test for poverty traps and/or explore poverty dynamics in largely pastoralist populations. Others, such as Little, Barrett, and Carter (2006), use a poverty measure based on tropical livestock units (TLUs) in their study of poverty in Ethiopia, claiming that livestock correlate with many

[2] The United Nations established the international poverty line indicating extreme poverty at $1.08 per day, in 1993 purchasing power parity terms (referred to as the $1/day measure). In August 2008, the World Bank released its current absolute poverty measure of $1.25 a day measured in 2005 prices (Ravallion and Chen 2008). Other concepts of a poverty line focus on some income level below which a proportion of the poorest people in a population lie.

other welfare markers. Other studies, such as Sahn and Stifel (2000, 2003) and Little, Barrett, and Carter (2006), base their asset poverty measures on an index generated using factor analysis. Factor analysis generates an asset index from the variance-covariance matrix associated with a bundle of assets owned by a household. This approach is based on the assumption that there exists some unobserved common factor (*c*) (for example, household welfare in Sahn and Stifel [2003]) that explains the variation in assets owned by a household. With both the common factor (*c*) and the coefficient explaining the relationship between asset ownership and the common factor (β) unavailable, identification of the variance in asset ownership ($\Omega = \beta\beta'\sigma_c^2 + \Psi$)[3] requires a normalization of the relevant parameters—either the variance of the common factor (σ_c^2) or the squared coefficient ($\beta\beta'$). This normalization makes it difficult to interpret the coefficient on the common factor (β).

While useful and appropriate for specific applications, neither the use of a unidimensional asset measure nor the use of factor analysis jointly addresses the possibility of nonlinearities and complementarities among assets. In a mixed farming system, multiple assets (land, livestock, tools) can be significant sources of income, and the returns to one asset (say, tools) might be affected by the presence of another specific asset (say, livestock). Imperfect markets in rural areas compound this problem by making assets less liquid and thereby leaving some households with less productive combinations of assets than others. Similarly, although procedures such as factor analysis enable the identification of some key assets, they do not distinguish between the relevance of assets at different levels of endowment, nor do they provide an easily interpretable measure of the contribution of various assets to household well-being. Another distinction between our analysis and most of the studies that use factor analysis or study assets in developing countries is our particular focus on household productive assets (land, livestock, farm implements, and so on.) rather than wealth indicators such as the presence of a latrine or the type of roof.

This study applies a translogarithmic functional form to explore possible nonlinearities and multidimensionality in the relationship between assets and consumption with easily interpretable coefficients.[4] Omitted-variable bias arising from unobserved factors presents a second challenge to estimating the relationship between assets and expenditures. Critical unobserved village characteristics could include cultural practices, specific agricultural activities, and environmental particularities, while unobserved household characteristics might be savings habits as well as asset and production managerial ability. Panel data with fixed effects (FE) models enable the recovery of consistent estimates of coefficients when there are unobserved household characteristics associated with some explanatory variables as well as the outcome variable. However, FE models do not permit the recovery of estimates on time-invariant unobservables at the village level (for example, villagewide soil condition). Consequently, this study exploits panel data to capture village and household effects by using a modification of the Hausman-Taylor instrumental variable (HTIV) method. We use a three-stage least squares instrumental variables (generalized instrumental variable [GIV]) estimator to produce unbiased and consistent coefficient estimates for the various assets and asset interactions with proper standard errors for inference. The panel data structure also enables us to validate the methods by comparing actual dynamics of asset accumulation and expenditures with those implied by the poverty classification scheme based on assets.

[3] This is obtained by specifying assets a_t as $a_t = \beta c_t + u_t$ with the variance of these assets expressed as $E(a_i' a_i') = E[(\beta c_t + u_t)(\beta c_t + u_{t'})']$, which is Ω.

[4] This approach is similar to that used in Adato, Carter, and May (2006), but that work uses a polynomial expansion rather than a translog form to capture nonlinearities and the interactions among different assets.

3. ANALYTICAL FRAMEWORK

The theoretical framework guiding most asset-based poverty measures is presented in Carter and May (1999), while Carter and Barret (2006) and Mogues (2006) present the theory on the dynamics of asset poverty. Empirical work begins with a specification of the relationship between assets and expenditures. For example, Adato, Carter, and May (2006) estimate the following relationship:

$$L_{it} = \sum \beta_j (A_{it}) A_{ijt} + e_{it}, \qquad (1)$$

where L_{it} is the scaled consumption expenditure of household *i* in period *t* and is measured as the ratio of consumption expenditures to an income poverty line ($L_{it} = \frac{c_{it}}{\underline{c}}$). β_j is the coefficient of the current asset *j* owned by household *i* in time *t*, A_{ijt} is the amount of asset *j* owned by household *i* in time *t*, A_{it} is the total amount of assets the household owns, and e_{it} is the time- and household-specific error term. By using a polynomial expansion in the estimation of (1), Adato, Carter, and May (2006) estimate interaction effects among different asset types as well as nonlinearity in the effects of specific assets. The estimates of β_j are then used to calculate the asset index for a household as: $\Lambda_{it} = \sum \hat{\beta}_j (A_{it}) A_{ijt}$, where Λ_{it} is the asset index, and the weight given to each type of asset in the index is derived from the regression of scaled consumption expenditures on assets.

In this formulation, a value Lit of 1 implies that a household is exactly on the poverty line, while a household with $L_{it} < 1$ is poor and one with $L_{it} > 1$ is nonpoor. The following analysis uses a translog specification such that the reference point is zero. Thus Λit = 0 is the threshold value separating the asset poor from the asset nonpoor.

Extending the previous literature, this model accounts for unobserved village characteristics in the study area and incorporates a proxy for social capital to capture this nontangible asset. Accounting for unobserved village characteristics was based on both practical and econometric considerations. The geographical dispersion of the study villages creates differences in weather, topography, proximity to markets, and quality of infrastructure that could cause varying returns to the same assets. Specification tests conducted on the pooled ordinary least squares (POLS) analysis revealed the presence of time-invariant unobserved characteristics that if not accounted for would render the model estimates biased and inconsistent.[5] Consequently, this study derives an asset index by first estimating:

$$L_{ivt} = \sum_j \beta_j (A_{ijvt}) + \sum_{j,k} \beta_k (A_{ijvt})(A_{ikvt}) + H_{it} + \Psi_v + D_t + \varepsilon_{ivt} \qquad (2)$$

for all assets *j* and *k* in peasant association *v*, where L_{ivt} and $\beta_j (A_{ijvt})$ are as previously defined and ε_{ivt} is an error term. β_k is the coefficient of the squared asset and asset interaction terms, H_{it} is a vector of household demographic characteristics, and Ψ_v and D_t are peasant association and time dummy variables that are included to capture location-specific unobserved characteristics and time-specific events that may affect the per capita returns to assets. The asset index for each household (Λ_{ivt}) is the estimated value of (2).

[5] A simple test of the significance of village dummies added to the original explanatory variables resulted in a chi-squared value greater than 700 with the probability of the critical value being greater than the calculated value equal to zero. Thus we reject the null hypothesis that the coefficients of these village means are equal to zero, indicating the presence of significant unobserved village characteristics.

4. DATA AND MODEL SPECIFICATION

Data for this study are drawn from the Ethiopian Rural Household Survey (ERHS). The ERHS dataset contains detailed information on consumption expenditure, assets, and agricultural activities and is the product of efforts by Oxford University, the University of Addis Ababa, and the International Food Policy Research Institute (IFPRI). The survey covered 15 peasant associations (groups of villages) across four regions, with a sample of 1,477 households in 1994 (twice), 1995, 1997, 1999, and 2004. Though the ERHS is not fully representative of rural Ethiopia, the15 peasant associations were selected to cover the main farming systems in the country, including grain-plow areas of the northern and central highlands, enset [6] growing areas, and sorghum-hoe areas (Dercon and Krishnan 1998). This paper focuses on the ERHS data for the period 1994 to 2004, supplemented with qualitative information gathered during interviews with key informants in each of the ERHS peasant associations (PAs) in 2007.

The data used in estimating equation (2) were from six rounds of the ERHS. The assets used in this model fall into six categories: land, livestock, implements, other physical assets (such as jewelry), social capital, and education. Measurement of physical assets was based on the estimated value in Ethiopian birr (EB) of land, implements (tools), livestock, and other physical assets. The livestock variables, also expressed in birr value, are divided into draft animals (oxen), dairy cattle, pack animals (mules, horses, and donkeys), and other animals (chicken, goats, and rams). Asset values were calculated each year and adjusted by a consumer price index.

Data on the value of livestock and other assets reflect self-reporting by respondents. As the reliability of such estimates is questionable, average unit values of each asset type (goat, plow, and so on.) were calculated for each village based on the survey responses. Land in Ethiopia is not bought and sold but allocated by the government, so ascertaining land values was difficult. However, land rental has become more common since 1991 (when the previous prohibitions on land leasing were lifted). A suggested value from Pender and Fafchamps (2001) of 352 EB per hectare in 1993/94 is used as a basis for estimating land rental values, and this value is adjusted yearly by the consumer price index.[7]

Human assets were measured through maximum years of education of a household member, and social assets were proxied through memberships in local savings and credit clubs (equbs). Dummy variables were added for villages and for the survey rounds (1994a, 1994b, 1995, 1997, 1999, and 2004). The specification included additional controls for age of household head (in years); gender of household head (1 if male, 0 otherwise); whether someone in the household worked off the household farm (1/0); whether a family member participated in a food-for-work program (1/0)[8;] and variables for the number of household members under 15 years old, 15–65 years old, and over 65. The dependent variable was measured as per capita value of consumption expenditures relative to the poverty line. The ERHS dataset includes a poverty line that was calculated for 1994 using a cost-of-basic-needs approach and consisting of a food and nonfood component (Dercon and Krishnan 1998). For later years, the poverty line is deflated by a yearly adjusted price index (MOF 2006). Because unobserved village characteristics such as land quality, availability of infrastructure, and proximity to a market center could affect the return to assets, village dummy variables were included in the model. Additionally, time dummies were added to capture variations across time. Excluding the dummy variables, data were transformed into log form, adding 1 to the initial values of independent variables due to the frequency of zeros in the raw data.

Household assets (A) are expected to contribute positively to household productive capacity and expenditures. The law of diminishing marginal returns implies a positive relationship between assets and scaled per capita expenditures but a negative sign on the squared term. Male-headed households are expected to be better off economically than female-headed households. We expect negative coefficients on the children and elderly variables, as these household members tend to increase consumption without

[6] Enset (*Ensete ventricosum*), commonly known as "false banana," is a traditional staple crop in the densely populated south and southwestern parts of Ethiopia.

[7] Although land in the descriptive statistics is expressed in area to give intuition about small landholdings, all empirical estimations were run with the value of land calculated as land area multiplied by rental value adjusted by the consumer price index.

[8] Food-for-work programs are geared toward providing a safety net for the poorest of the poor in the event of adverse shocks while investing in the production or maintenance of valuable public goods (roads and bridges, schools, and natural resources) that are necessary to stimulate productivity and thus increase aggregate income (Quisimbing 2003).

being able to contribute equivalently to income generation. However, if workers are productive, additional working-age members should contribute positively to household income and expenditures.

With a mean monthly consumption expenditure per capita of about 87 EB (about $1/day in purchasing power parity [PPP] terms),[9] households in the ERHS sample are quite poor on average (Table 1). There is wide variation in physical assets. Most assets are negatively skewed, but with enough values at the extreme ends to guard against outlier problems. About 80 percent of households are male headed, with a mean household size of around seven members. The average duration of schooling for the most educated household member is about seven years, which is just about primary school education.

Multiple specification tests were applied to identify a consistent and asymptotically efficient estimator for this study. A test for serial correlation[10] based on Wooldridge (2002) indicated serial correlation, revealing that the POLS estimates are potentially biased and inconsistent. With a chi-squared statistic of 835.81 (p-value = 0.00), we also reject the Breusch and Pagan Lagrange multiplier test for random effects, which indicates that the variance of the error term is not zero and the random effects (RE) model is superior to the POLS. An RE framework puts the unobserved characteristic c_i into the error term. Thus, though potentially more efficient, the RE model is only consistent if $E(x_{it}, c_i) = 0$.[11] However, further tests indicated endogeneity due to unobserved characteristics invalidating the RE model in favor of the fixed effects (FE) model, which is consistent in the presence of unobserved time-invariant characteristics.[12]

One major drawback of using the FE estimator is the loss of estimators for time-invariant variables. Furthermore, FE models ignore variability across households, which is important for our research purpose. Thus, this study uses the generalized instrumental variables (GIV) estimator, which is also the efficient general method of moments (GMM) estimator to estimate the coefficients associated with the explanatory variables in equation (2).

This approach comprises a three-stage least squares instrumental variable estimation based on the Hausman-Taylor instrumental variable (HTIV) technique. It uses means and deviation from means as instruments for time-invariant and time-varying endogenous variables, respectively (Hausman and Taylor 1981). The analysis uses the GMM estimator to account for nonspherical errors by incorporating an optimal weighting matrix that is a consistent estimator of $(Var[(1/n)(Z'\varepsilon)])^{-1}$, where $(Z'\varepsilon) = 0$ is the relevant orthogonality condition.

[9] One U.S. dollar is equivalent to 9.8 Ethiopian birr (EB). The PPP conversion factor is approximately 0.25.

[10] This test is performed by adding the lagged value of the error to the rest of the regression and testing for the significance of the coefficient of the lagged error term. With an F-statistic of 83.39 (p-value of 0.00), we reject the null hypothesis H0:coefficient on the lagged residual = 0, which is equivalent to no serial correlation.

[11] where e_{ivt} in equation (2) is a composite error ($e_{ivt} = c_i + u_{it}$) due to the unobserved time-invariant characteristic.

[12] This test is equivalent to testing the joint significance of the means of various explanatory variables added to the POLS model. The chi-squared statistic was 723 with probability of being less than the critical value equal to zero. Thus the null hypothesis of insignificance is rejected, indicating the presence of unobserved characteristics.

Table 1. Descriptive statistics

Variable	Mean	Standard Deviation	Min.	Max.
Scaled Consumption[a]	0.30	0.59	-2.7	1.83
Monthly Expenditure per Capita 1994 (value[b])	84.51	77.54	1.49	819.39
Expenditure per Capita 1995 (value[b])	85.69	86.00	1.15	982.34
Expenditure per Capita 1997 (value[b])	87.49	78.07	2.95	912.51
Expenditure per Capita 1999 (value[b])	101.02	90.99	2.97	735.35
Expenditure per Capita 2004 (value[b])	92.79	99.56	2.79	696.72
Total Livestock (value[b])	1,186.45	1,743.74	0.00	14,710.80
Draft Animals (value[b])	333.01	620.99	0.00	5,837.03
Dairy Animals (value[b])	628.85	1,104.62	0.00	8,964.11
Pack Animals (value[b])	101.96	265.98	0.00	3,217.25
Other Livestock (valueb)	130.60	280.80	0.00	4,921.66
Farm Tools (value[b])	98.26	200.19	0.00	2,214.90
Other Physical Assets (value[b])	284.47	630.64	0.00	7,575.00
Number of Children (<15)	2.86	2.04	0.00	17.00
Number of Working Adults (15–65)	3.14	1.84	0.00	15.00
Number of Elderly (>65)	0.76	1.33	0.00	9.00
Household Size	6.70	4.08	1.00	30.00
Highest Education of Any Household Member (years)	6.89	4.75	1.00	13.00
Age of Household Head (years)	47.76	15.66	15.00	105.00
Land (area)	1.88	2.65	0.00	40.50
Draft Animals (0/1)	0.47	0.50	0	1
Other Livestock (0/1)	0.56	0.50	0	1
Pack Animals (0/1)	0.35	0.48	0	1
Dairy Animals (0/1)	0.67	0.47	0	1
Social Capital (membership in local organization)	0.10	0.30	0.00	1.00
Male Household Head (0/1)	0.79	0.41	0.00	1.00
Village 1	0.06	0.24	0.00	1.00
Village 2	0.05	0.22	0.00	1.00
Village 3	0.07	0.25	0.00	1.00
Village 4	0.06	0.23	0.00	1.00
Village 5	0.05	0.21	0.00	1.00
Village 6	0.09	0.29	0.00	1.00
Village 7	0.07	0.25	0.00	1.00
Village 8	0.07	0.26	0.00	1.00
Village 9	0.08	0.27	0.00	1.00
Village 10	0.08	0.27	0.00	1.00
Village 11	0.06	0.24	0.00	1.00
Village 12	0.06	0.23	0.00	1.00
Village 13	0.07	0.26	0.00	1.00
Village 14	0.08	0.27	0.00	1.00
Village 15	0.05	0.22	0.00	1.00

Source: Generated by the authors using Ethiopian Rural Household Survey (ERHS) data 1994–2004. Sample size is 1,190 each year..

a Relative consumption expenditure is as earlier defined; log of consumption per capita relative to the poverty line with reference point being 0.

b All values measured in Ethiopian birr, deflated to 1994. Official exchange rate in 1994 was 6 birr / U.S. dollar.

Attrition in the sample is low, with information available each year for about 88 percent of households. In 1999 there is information for 94 percent of the households interviewed in 1994. This removes concern for endogeneity of village characteristics. Also, since land is not bought and sold in Ethiopia, we also consider land to be exogenous. In essence, the HTIV approach applied here is similar to a FE estimation, with the added value of including time-invariant village effects. Consequently, our instrumental variables estimator can be expressed as

$$\hat{\beta}_{GIV} = \hat{\beta}_{GMM} = (X'M\Omega M'X)^{-1} X'M\Omega M'Y$$

$$\hat{\beta}_{GIV} = \hat{\beta}_{GMM} = \left(X'\hat{W}^{-1}Z(Z'\hat{W}^{-1}Z)^{-1}Z'\hat{W}^{-1}X\right)^{-1} X'\hat{W}^{-1}Z(Z'\hat{W}^{-1}Z)Z'\hat{W}^{-1}Y,$$

where Ω is the optimal weighting matrix, which is a consistent estimator of $\left(Var[(1/n)(Z'\varepsilon)]\right)^{-1}$.

To implement the GMM estimation, equation (2) was estimated first by the pooled two-stage least squares (2SLS). Using the residuals from the pooled 2SLS, scalars $\hat{\sigma}_u$ and $\hat{\sigma}_c$ were obtained as

$$\hat{\sigma}_u^2 = \frac{\sum_i \sum_t \hat{u}_{it}^2}{nT - k}, \text{ and}$$

$$\hat{\sigma}_c^2 = \frac{\sum_{i=1}^{n} \sum_{t=1}^{T-1} \sum_{s=t+1}^{T} \hat{u}_{it}\hat{u}_{is}}{\left(nT\left(T-1\right)/2\right) - k},$$

where n is the number of individuals, T is the number of periods, and k is the number of estimated parameters. These two estimates were then used to construct

$$\hat{\lambda} = 1 - \left(\frac{1}{1 + T\sigma_c^2 / \sigma_\varepsilon^2}\right)^{\frac{1}{2}},$$

which is used to adjust the individual means over time. The adjusted means are then subtracted from the dependent, explanatory, and instrumental variables (Hausman and Taylor 1981). These transformed variables (deviations from the adjusted mean over time) are used in a pooled 2SLS estimation, which provides the efficient GMM estimator with standard errors that are asymptotically valid for inference (Wooldridge 2002; Hausman and Taylor 1981; Im et al. 1999. The GMM approach yields consistent estimates of all desired coefficients and correct standard errors for further inference. In this study, the standard errors are also robust to both heteroskedasticity and autocorrelation.

For comparison, results of an FE specification (which we know is consistent in the presence of unobserved time-invariant household characteristics) are presented also. These results are very similar to the GIV, but the significance of the village and time dummy variables in the GIV suggests that the simple FE model could suffer from omitted-variable bias. Hence the GIV is preferred. As an alternative to the GIV and FE approaches, the difference or system GMM estimators could also be employed.[13] Because the survey rounds in this analysis were not evenly spaced over time, the results of the dynamic panel model are less credible than those of the GIV method. Results are nonetheless presented together with the FE and GIV estimation for comparison.

Model Estimation and Interpretation

Estimation of (2) began with a full translogarithmic specification in assets. As is frequently the case, the polynomial expansion model exhibited considerable multicollinearity. Thus, using a stepwise selection approach and consideration of likely interaction relationships between assets, the model was constructed as shown in Table 2a. As can be seen in Table 2a, the F-statistic indicates that joint significance of the

[13] See Anderson and Hsiao (1981); Arrelano and Bond (1991); Arrelano and Bover (1995); and Blundel and Bond (1998) for a detailed explanation of the GMM estimator and Roodman (2006 for its implementation.

explanatory variables and all estimated coefficients that were individually statistically significant were either of the expected sign or have a sign that can be plausibly explained. Among the physical assets, land area is positive and significant in its squared term, with a coefficient of about 0.02. This unexpected result of increasing returns to land could be driven by limited variation in land size at lower levels of landownership. Mean land size for the entire sample is 1.88 hectares. Similar findings occurred for physical assets such as jewelry, which are only statistically significant in the squared form. The coefficients on household tools were significant, positive, and large in value. The regression results indicate the importance of livestock, consistent with other studies in rural areas in Sub-Saharan Africa. Livestock such as sheep and goats, generally perceived as easily disposable assets, were found to be positively associated with consumption expenditure. A 1 percent increase in livestock value corresponds to a 0.05 percent increase in consumption relative to the poverty line. Unlike land, other physical assets and most livestock follow the expected pattern of diminishing marginal returns with significant and negative coefficients on the squared terms. After controlling for various household characteristics and removing the time-invariant unobserved variables, the sex of the household head and education are not significantly different from zero. The insignificance of education probably reflects the generally low level of education attained in the sample.

Table 2a. Hausman Taylor instrumental variable model estimates: Dependent variable is household scaled consumption expenditures

	Generalized Instrumental Variables Estimation+		**Fixed Effects Panel**		**Dynamic Panel Estimation**	
	Coef.	**P>Z++**	**Coef.**	**P>Z++**	**Coef.**	**P>Z++**
Landholdings (hectares)	0.03	0.42	0.02	0.55	-0.06	0.23
Farm Tools (values)	0.11	0.00	0.08	0.02	0.09	0.10
Draft Animals (values)	0.09	0.00	0.08	0.00	0.01	0.82
Dairy Animals (values)	0.04	0.08	0.04	0.10	0.10	0.03
Pack Animals (values)	0.07	0.02	0.07	0.03	0.21	0.01
Other Livestock (values)	0.05	0.02	0.03	0.16	0.02	0.59
Education	-0.01	0.45	-0.01	0.52	-0.03	0.22
Other Physical Assets	-0.01	0.41	-0.01	0.41	0.06	0.07
Land*Tools	-0.00	0.00	-0.01	0.15	-0.01	0.28
Land*Draft Animals	0.00	0.15	0.00	0.88	0.00	0.29
Tools*Livestock	0.00	0.96	0.00	0.33	-0.01	0.14
Memberships	0.15	0.00	0.15	0.00	0.32	0.00
Off-Farm Activities	0.13	0.00	0.13	0.00	0.10	0.02
Land squared	0.02	0.01	0.00	0.97	0.03	0.05
Tools squared value	0.01	0.75	0.00	0.96	0.01	0.61
Other Livestock squared value	-0.01	0.17	0.00	0.54	0.00	0.76
Other Physical Assets squared	0.01	0.02	0.01	0.03	0.01	0.38
Dairy Animals squared value	-0.01	0.29	-0.01	0.31	-0.02	0.11
Pack Animals squared (values)	-0.02	0.05	-0.02	0.08	-0.07	0.01
Draft Animals squared value	-0.03	0.00	-0.03	0.00	-0.01	0.45
Male head	0.04	0.37	-0.05	0.36	0.05	0.70

Table 2a (contd.)

	Generalized Instrumental Variables Estimation+		Fixed Effects Panel		Dynamic Panel Estimation	
	Coef.	P>Z[++]	Coef.	P>Z[++]	Coef.	P>Z[++]
Age	-0.04	0.01	-0.03	0.10	-0.14	0.01
Working-Age Household Members	-0.19	0.00	-0.18	0.00	-0.23	0.00
Children under 15	-0.16	0.00	-0.16	0.00	-0.15	0.00
Elderly over 65	-0.00	0.85	0.00	0.92	-0.03	0.23
Nonfarm Activities	0.04	0.34	0.03	0.43	-0.04	0.51
Food-for-Work Program	-0.08	0.09	-0.08	0.14	-	-
Constant	0.28	0.00	0.00	0.98	0.24	0.43
Round 2	0.32	0.00	0.32	0.00	0.32	0.00
Round 3	0.20	0.00	0.21	0.00	0.22	0.00
Round 4	0.15	0.00	0.16	0.00	0.06	0.25
Round 5	0.32	0.00	0.33	0.00	0.27	0.00
Round 6	0.02	0.75	0.04	0.44	-0.10	0.17
Village 1	-	-			-0.27	0.19
Village 2	-0.02	0.68			0.23	0.31
Village 3	-0.13	0.01			-0.98	0.00
Village 4	0.25	0.00			0.06	0.71
Village 5	0.11	0.03			-0.19	0.51
Village 6	0.23	0.00			0.22	0.23
Village 7	0.37	0.00			-	-
Village 8	0.20	0.00			-0.25	0.21
Village 9	-0.10	0.04			-0.59	0.01
Village 10	0.15	0.00			-0.18	0.46
Village 11	-0.14	0.00			-0.83	0.00
Village 12	0.02	0.72			-0.52	0.03
Village 13	-0.02	0.71			-0.95	0.00
Village 14	-0.18	0.00			-	-
Village 15	-0.02	0.66			-0.97	0.00
Adjusted R^2	0.20		0.11			
Number of observations	7,161				7,042.00	
F-statistic	30.62					
Probability>F	0.000					

Source: Generated by the authors from STATA regression estimations using Ethiopian Rural Household Survey (ERHS) data.
Note: Continuous variables were transformed into logarithms. “Coef.” refers to coefficient.

Households with more children tend to have lower per capita consumption, but the presence of elderly members does not have a statistically significant effect. The negative and significant coefficient on the number of working-age adults in a household indicates widespread underemployment. Households with members employed as farm laborers or in other wage-earning activities tend to have higher consumption. Social capital appears to be a significant asset, with membership in local savings and credit groups (equb) increasing consumption expenditures by about 15 percent. Finally, village characteristics appear to be significant drivers of consumption in rural Ethiopia, indicating that location-specific issues are important for households' ability to generate income. Interpretation of the coefficients on the village dummy variables is relative to village number 1 (Harresawe), which was dropped from the GIV estimation.

The GIV estimators are only consistent if independent variables are exogenous in the model. Following Wooldridge (2002, p. 285), we test for exogeneity of the various assets by including the lead values (t + 1) of variables in the FE model.

$$L_{ivt} = \beta_0 + \sum_j \beta_j \ln A_{ijt} + \frac{1}{2}\sum_j \sum_k \beta_{jk} \ln A_{ijvt} \ln A_{ikvt}$$

$$+ \sum_j \delta_j \ln A_{ijt+1} + \frac{1}{2}\sum_j \sum_k \delta_{jk} \ln A_{ijvt+1} \ln A_{ikvt+1} + c_i + u_{it}$$

Significance of the δ coefficients would indicate a violation of the strict exogeneity assumption. The tests for strict exogeneity reveal that all but the dairy livestock variable were exogenous after conditioning on the household fixed effect.[14] One solution to this problem would be the use of the lagged value as an instrument, as in the dynamic panel framework of the Arrelano and Bond GMM estimator (Arrelano and Bond 1998). This approach yielded a statistically significant coefficient (at 1 percent) with a larger magnitude than that of the GIV estimation. However, because the lag lengths are uneven in the sample, the dynamic panel results are problematic. Hence the analysis focuses on the GIV estimation and uses its more conservative estimates concerning the effect of dairy livestock.

The various conditions necessary to justify the use of the GIV approach model are satisfied. The first-stage results of the GIV estimation reveal F-statistics associated with all the asset variables significantly larger than 10 (Table 2b. Furthermore, as shown in Table 2b, we reject the test for weak instruments based on the Shea partial R-squared statistic. Shea (1997) showed that given more than one endogenous variable and a set of instruments, it is possible to still have a high R-squared in the first stage but a poor instrumental variable estimator if, for example, two instruments are highly collinear. Shea's partial R-squared is thus a measure of instrument relevance that takes intercorrelations among instruments into account. We also reject the underidentification tests based on the Anderson canonical test and the Anderson-Rubin test of insignificance of the endogenous variables in the model.[15] Finally with a Hansen J statistic of 0.49 (p-value = 0.4387), we fail to reject the Hansen J test of overidentifying restrictions, indicating the validity of our instruments. The null hypothesis is that the instruments are valid, that is, uncorrelated with the error term. Under the null, the test statistic is distributed as chi-squared in the number of overidentifying restrictions. Based on these tests, we conclude that the model is estimated properly.

[14] The F-statistic associated with the test of the significance of the lead of the dairy variable was 3.19 (p-value = 0.07). Thus we can reject the null of exogeneity only at 10 percent significance. For other variables, we fail to reject the null hypothesis that the lead values were equal to zero.

[15] With an Anderson canonical correlation likelihood ratio statistic of 3800.40 (p-value = 0), we reject the null hypothesis of underidentification. Consequently, with an F-statistic of the Anderson-Rubin test of joint significance of end of 14.51 (p-value = 0.00), we reject the null hypothesis that the endogenous variables are inappropriately included in the main equation.

Table 2b. Shea partial R-squared, traditional R-squared, and first-stage F-statistic

Variable	Shea Partial R^2	Partial R^2	F-statistic	P-value
Draft Animals	0.91	0.82	1637.2	0.00
Dairy Animals	0.89	0.79	1121.9	0.00
Pack Animals	0.85	0.78	912.2	0.00
Other Livestock	0.70	0.84	1564.5	0.00
Education	0.95	0.95	4541.6	0.00
Nonfarm Activities	0.89	0.92	975.8	0.00
Food-for-Work Program	0.89	0.91	1239.0	0.00
Other Physical Assets	0.88	0.84	1241.8	0.00
Land*Tools	0.54	0.73	316.4	0.00
Land*Draft Animals	0.73	0.75	561.2	0.00
Tools*Livestock	0.78	0.78	777.6	0.00
Memberships	0.93	0.93	2020.4	0.00
Off-Farm Activities	0.84	0.86	2464.1	0.00
Tools squared	0.84	0.80	448.3	0.00
Other Livestock squared value	0.67	0.81	735.7	0.00
Other Physical Assets squared	0.87	0.83	1067.7	0.00
Dairy Animals squared value	0.89	0.80	1020.7	0.00
Pack Animals squared (values)	0.85	0.80	787.2	0.00
Draft Animals squared value	0.91	0.83	1364.7	0.00

Source: Generated by the authors using Ethiopian Rural Household Survey (ERHS) data 1994–2004.

Asset Index Calculation and Tests for Multiple Equilibria and Poverty Traps

If assets offer positive but diminishing marginal returns, one would expect a household's assets to grow over time, but at a decreasing rate until the return on assets is absorbed into regular household consumption and a steady state equilibrium is achieved. Across households, diminishing returns would imply convergence to the same equilibrium. If, however, assets exhibit locally increasing returns to scale, then households that lack some minimum asset level may be trapped in a low-level equilibrium, while other households with assets above that threshold will experience growth to a higher equilibrium. Tests for multiple equilibria in asset dynamics can therefore be used to identify poverty traps.

Given the asset index values calculated from regression equation (2), estimation of the relationship between initial and future asset levels can be used to empirically test for the existence of bifurcated asset dynamics and the Micawber threshold. The nature of the question requires use of flexible estimation techniques that can allow for nonlinear relationships. Both nonparametric and parametric estimations are applied to test for the existence of multiple equilibria in asset index dynamics between 1994 and 2004. Tests are based on the null hypothesis that:

> ***Ho****:* Asset dynamics in rural Ethiopia exhibit bifurcation, indicating multiple equilibria and the existence of a Micawber threshold in assets, below which households cannot grow out of poverty.
> ***Ha****:* No bifurcation exists in asset dynamics in rural Ethiopia, indicating convergence of assets over time.

Nonparametric estimation is based on a running line smoother to estimate the dynamics of the household asset index between 1994 and 2004.[16] This procedure sorts the data by the *x*-variable (asset index in 1994) and forms local neighborhoods consisting of an (*x*; *y*) pair together with the *k* nearest *x*-neighbors on either side of *x* (Sasieni 1995). The default value of *k* is defined to be $N^{0.67}$, where N is the number of observations. Data are sorted according to the *x* variable, and the subscripts refer to the ordered data. The running line smoother estimates the corresponding value of *y* for each i^{th} ordered data point using its nearest neighbors from $i - k$ to $i + k$. Figure 1 below provides the results of the nonparametric estimation of the asset index dynamics.

From Figure 1, there is a tangency between the estimated function and the 45° line at about 0.14, indicating a low-level equilibrium, and another tangency at about 0.98, indicating a high-level equilibrium. At about 0.5 there is an unstable equilibrium called the Micawber threshold. In this case, a household with an initial asset index value of less than 0.5 would be expected to converge back to the low equilibrium of 0.14. Households with initial asset values in excess of 0.5 would be expected to converge to an asset index value of about 0.98. Based on the estimation and the associated 95 percent confidence interval, we fail to reject our null hypothesis of bifurcation and multiple equilibria. Results indicate that households with initial asset levels that are near the asset poverty line are unlikely to attain the higher equilibrium. The low-level equilibrium of asset index = 0.14 corresponds to monthly consumption of about 52 EB per capita, while the high equilibrium (asset index = 0.98) implies monthly per capita consumption of 123 EB. This difference of about 70 EB ($25 PPP) exceeds the average per capita consumption level of a household on the poverty line (46 EB).

To support the nonparametric results, the relationship between current and future values of the asset index is estimated through least squares estimations. Estimations were run with bootstrapping to account for the fact that the asset index used in the estimation was the predicted value of an earlier estimation. Figure 1 suggests that the relationship between the assets in 1994 and those in 2004 is nonlinear. Thus the asset dynamics are specified as:

$$\Lambda_{ivt+1} = \Sigma\gamma_k\Lambda_{ivt}^{\,j} + Z_{itv} + e_{ivt}\,, \tag{3}$$

where $j = 1 \ldots n$, and Z_{itv} represents controls that might affect asset accumulation separately from affecting the return on the assets in question. These controls include the sex of the household head, the age of the household head, the squared age of the household head (for life-cycle effects), and household size.[17] As seen in Figure 1, the presence of multiple equilibria implies the existence of points where[18]

$$(1 - \gamma_1)\,\Lambda_{ivt} - \gamma_2\Lambda_{ivt}^{\,2} - \gamma_3\,\Lambda_{ivt}^{\,3} - Z_{itv} = 0 \tag{3a}$$

or

$$(\gamma_1 - 1)\,\Lambda_{ivt} + \gamma_2\Lambda_{ivt}^{\,2} + \gamma_3\,\Lambda_{ivt}^{\,3} + Z_{itv} = 0 \tag{3b}$$

If there are multiple equilibria, one would expect to find multiple solutions (values of Λ_{ivt}) to solve (3b) (Ravallion 2001; Mogues 2006). If there is a low equilibrium and a high equilibrium, with an unstable equilibrium in between, then the curves intersect at three points: two points where

[16] This procedure is almost identical to the traditional locally weighted regression (LOWESS) but unlike the LOWESS it does not permit arbitrary weights.

[17] Because the asset index was generated with a two-stage least squares instrumental variable estimation, which took into account time and village-level effects as well as other controls, most of the necessary variables that could be underlying a household's asset accumulation and decumulation as well as unobservable time- or weather-related factors have been accounted for.

[18] The minimum polynomial expansion necessary to find multiple equilibria is a cubic polynomial. Equating the cubic polynomial to a 45°-line equation ($\Lambda_{ivt+I} = \Lambda_{ivt}$) gives $\Lambda_{ivt+i} = \gamma_1\Lambda_{ivt} + \gamma_2\Lambda_{ivt}^{\,2} + \gamma_3\Lambda_{ivt}^{\,3} + Z_{itv} + e_{ivt} = \Lambda_{ivt+i} = \Lambda_{ivt}$, which can be expressed as $\Lambda_{ivt+i} - \gamma_1\Lambda_{ivt} - \gamma_2\Lambda_{ivt}^{\,2} - \gamma_3\,\Lambda_{ivt}^{\,3} - Z_{itv} - e_{ivt} = \Lambda_{ivt+i} - \Lambda_{ivt}$ or $\Lambda_{ivt+i} - \gamma_1\Lambda_{ivt} - \gamma_2\Lambda_{ivt}^{\,2} - \gamma_3\,\Lambda_{ivt}^{\,3} - Z_{itv} - e_{ivt} = \Lambda_{ivt+i} - \Lambda_{ivt}$

$$\gamma_1 + 2\,\gamma_2\,\Lambda_{ivt} + 3\gamma_3\Lambda_{ivt}^{\;2} \le 1, \tag{3c}$$

indicating that the curve is falling at that point,[19] and one point where

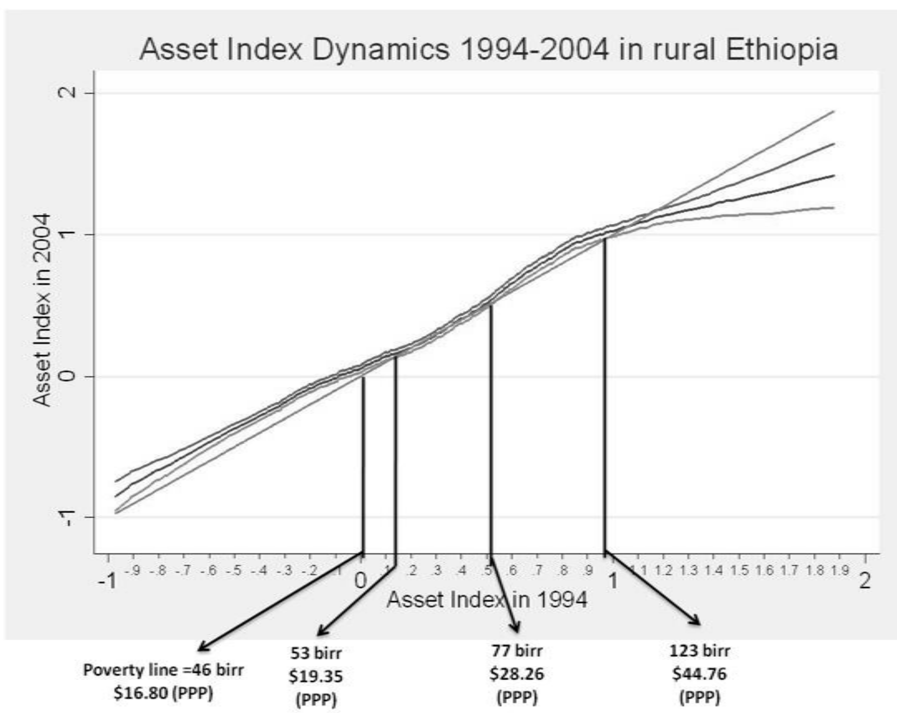
$$\gamma_1 + 2\,\gamma_2\,\Lambda_{ivt} + 3\gamma_3\Lambda_{ivt}^{\;2} \ge 1, \tag{3d}$$

indicating that the curve is upward sloping, which would be at the Micawber threshold. We first estimate equation (3) and then explore whether the points described by equations (3c) and (3d) exist.

Specifications for estimating (3) were developed in two ways. First we use a fractional polynomial regression equivalent to equation (3) without the matrix of household controls (Z_{ivt}). Allowing the program (STATA) to determine the order that best fits the data, we estimate equation (3) and generate the predicted values, which are plotted with the confidence interval evaluated at the mean of the data. The second method uses a stepwise approach guided by the Akaike Information Criterion and the Bayesian Information Criterion compared models with n = 2 – 4. The identified model was:

$$\Lambda_{ivt2004} = \Lambda_{iv1994} + \Lambda_{iv1994}^{\;2} + \Lambda_{iv1994}^{\;3} + lnhhsize_{itv} + Sexhead_{itv} + Agehead + Agehead^2 + e_{ivt} \tag{4}$$

Figure 1. Asset index dynamics in rural Ethiopia



Source: Generated by the authors using Ethiopian Rural Household Survey (ERHS) data 1994–2004.
Note: The center line is the estimated line with the two outer lines being the 95% confidence interval band

Table 3a shows that the coefficients on the base and squared asset index value in 1994 are positive, indicating increasing returns to scale rather than the diminishing returns to assets associated with convergent asset dynamics. The negative cubic term indicates an S-shaped curve. As can be seen from Figure 2, the parametric estimates confirm that we cannot reject the hypothesis of bifurcated asset dynamics. There are two stable equilibria within the 95 percent confidence interval of the estimated line,

[19] This is the slope of equation (3b).

one around zero and the other about two times the static asset poverty line, consistent with the nonparametric estimates.

Table 3a. Parametric estimates of asset index dynamics

Dependent Variable = Asset Index in 2004 (AI 2004)	Coefficient	Bootstrapped Standard Errors
Asset Index in 1994	0.975***	0.032
Squared 1994 Asset Index	0.0939*	0.045
Cubed 1994 Asset Index	-0.131**	0.049
Male-Headed Household	0.009	0.022
Household Size	-0.129***	0.020
Age of Household Head	-0.269***	0.047
Squared Age of Household Head	0.0541***	0.010
Constant	0.489***	0.032
Number of observations	1,190	
Wald $chi^2(8)$	3,388.22	
Prob > chi^2	0	
R-squared (adjusted R-squared)	0.72 (0.71)	

Source: Generated by the authors from STATA regression estimations using Ethiopian Rural Household Survey (ERHS) data.
Note: *means significant at 10 percent, **means significant at 5 percent, ***means significant at 1 percent

Disaggregating by peasant association results indicates that some villages exhibit multiple equilibria while others exhibit convergence (see Table 4a). Moreover, levels of convergence vary widely across villages. Villages characterized by better infrastructure and proximity to markets (for example, Sirba, Shumsheha, and Debre Berhan) converge at two times higher than the static poverty line, while other villages with very poor infrastructure and rugged terrain that are also drought prone and remotely located (for example, Harresawe, Geblen, and Gara Godo) converge at or below the static asset poverty line. Villages such as Yetmen, Turufe Kechema, and Aze Deboa exhibit multiple equilibria. In Turufe Ketchema and Aze Deboa, there is a low-level equilibrium at around 0 and a higher one at about 0.9. In Yetmen, there appears to be a low equilibrium at around 0.2 and a higher one around 0.5. As in the general case, the parametric and nonparametric estimates yield similar results for most villages, with Sirba and Adado the only exceptions. This is shown in Figure 3.

Table 4a. Asset dynamics by farming system

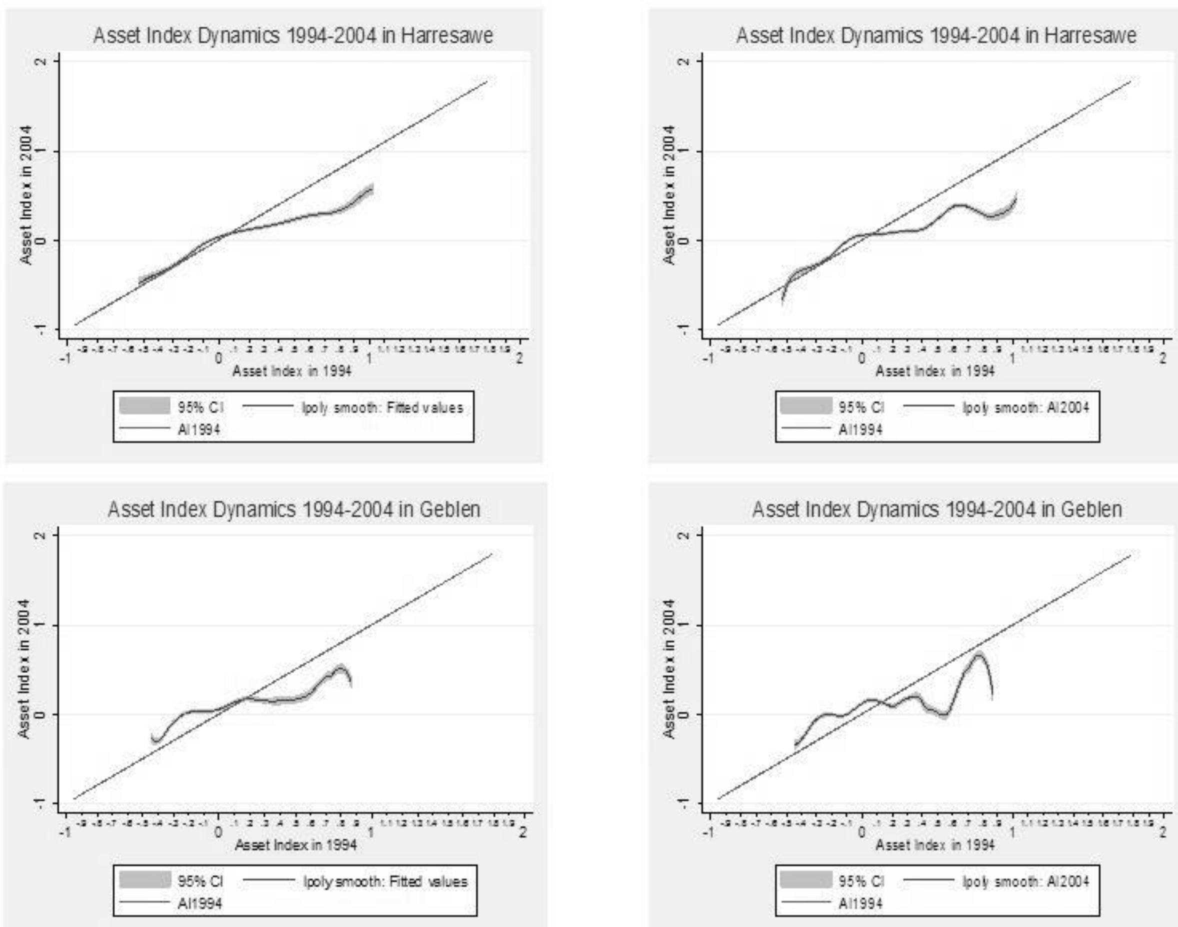
Farming System	Equilibrium 1	Equilibrium 2
Enset	0.00	
Teff	1.10	
Chat	0.55	
All cereals	0.25	0.85
Peasant Association		
Harresawe	0.10	
Debre Berhan	1.10	
Tufrufe Kechema	0.05	0.85

Source: Generated by the authors using Ethiopian Rural Household Survey (ERHS) data 1994–2004.
Note: Although estimations were performed for all peasant associations, only a subset for which results were consistently confirmed are shown to reflect different types of equilibria.

Similarly, disaggregation by farming system (Table 4a) reveals convergence at a high equilibrium for teff, which is a major food crop in urban centers in Ethiopia but a major cash crop for rural farmers (World Bank 2002). The chat farming system, which is also commercialized, exhibits convergence at about 1.5 times the poverty line. For the enset farming system, we find weak evidence of multiple equilibria. There is a low equilibrium at around zero and a higher one at 0.5. For cereals, we see evidence of a low equilibrium at about 0.25 and a higher one at about 0.85. The multiple equilibria found in cereal farming systems could reflect distinct paths for farm households that are able to commercialize activities and others that produce almost exclusively for home consumption.[20]

Figure 3. Village-level asset index dynamics: Parametric and nonparametric estimations of village asset dynamics

Village Dynamics from Parametric Estimation	Village Dynamics from Nonparametric Estimation



[20] In Ethiopia, some cereals such as maize and barley are food crops, while others such as teff are cash crops for rural farmers (World Bank 2002 . For enset, the higher equilibrium might be capturing farmers within such systems who grow other cash crops, probably coffee.

Figure 3. Continued

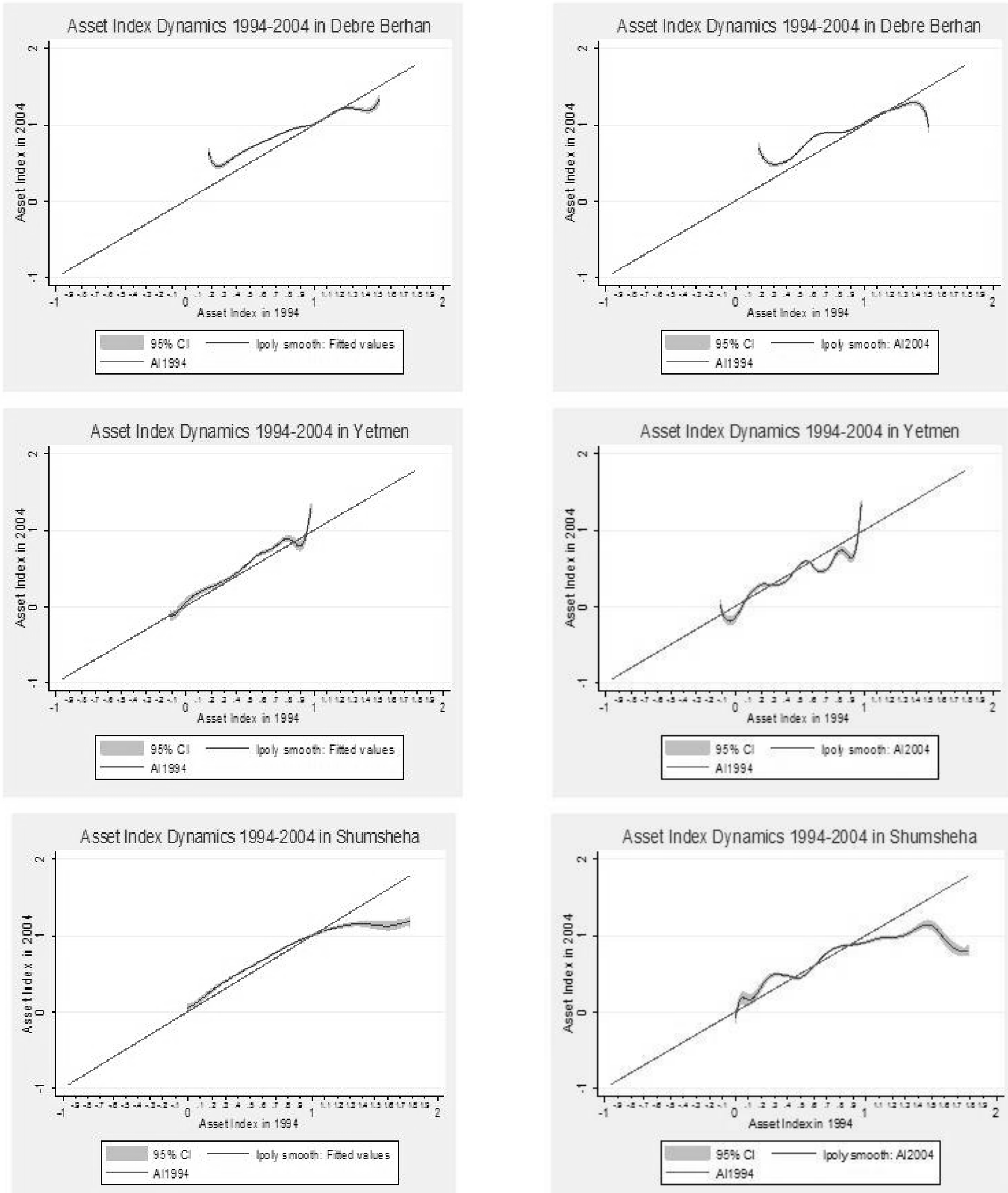


Figure 3. Continued

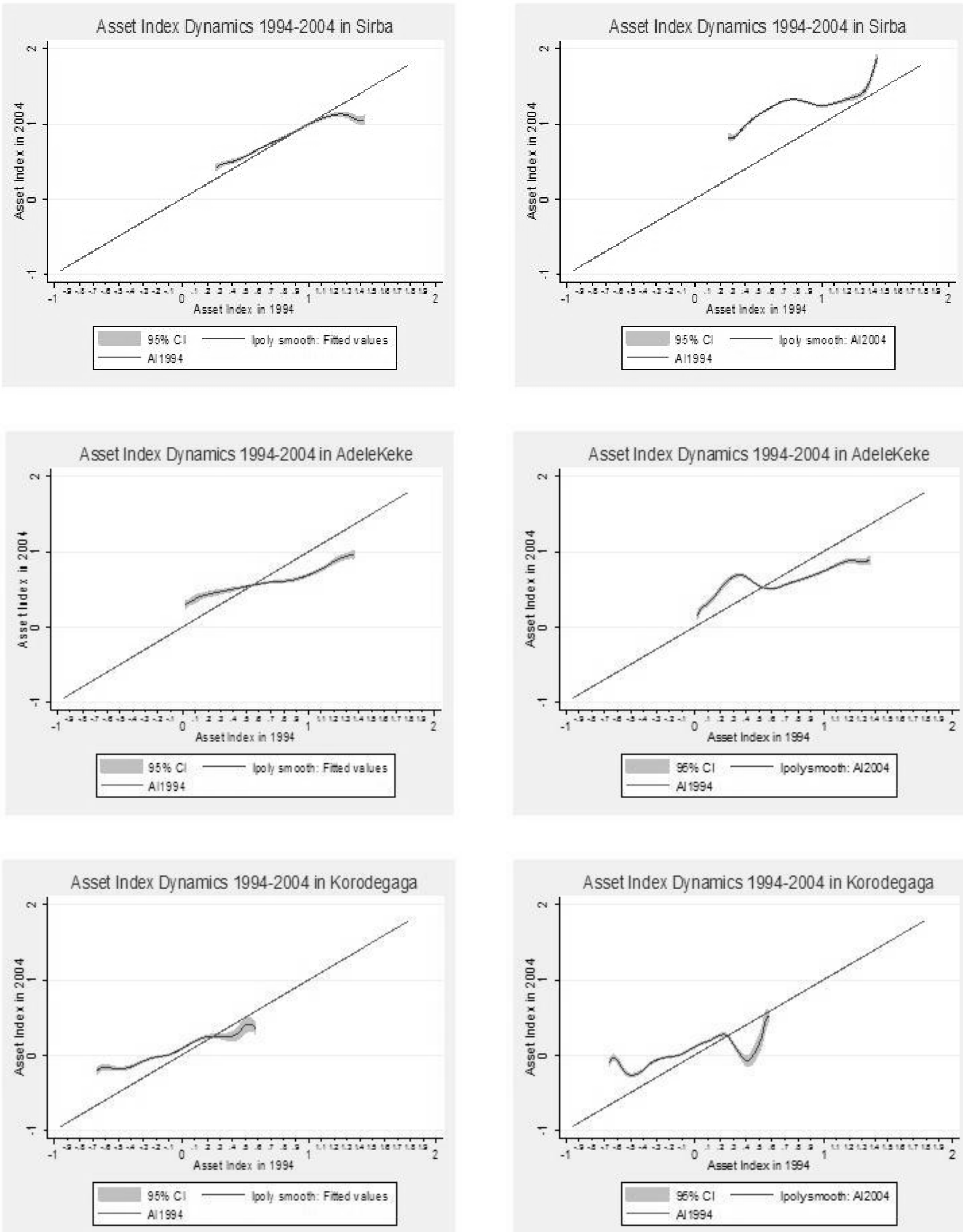


Figure 3. Continued

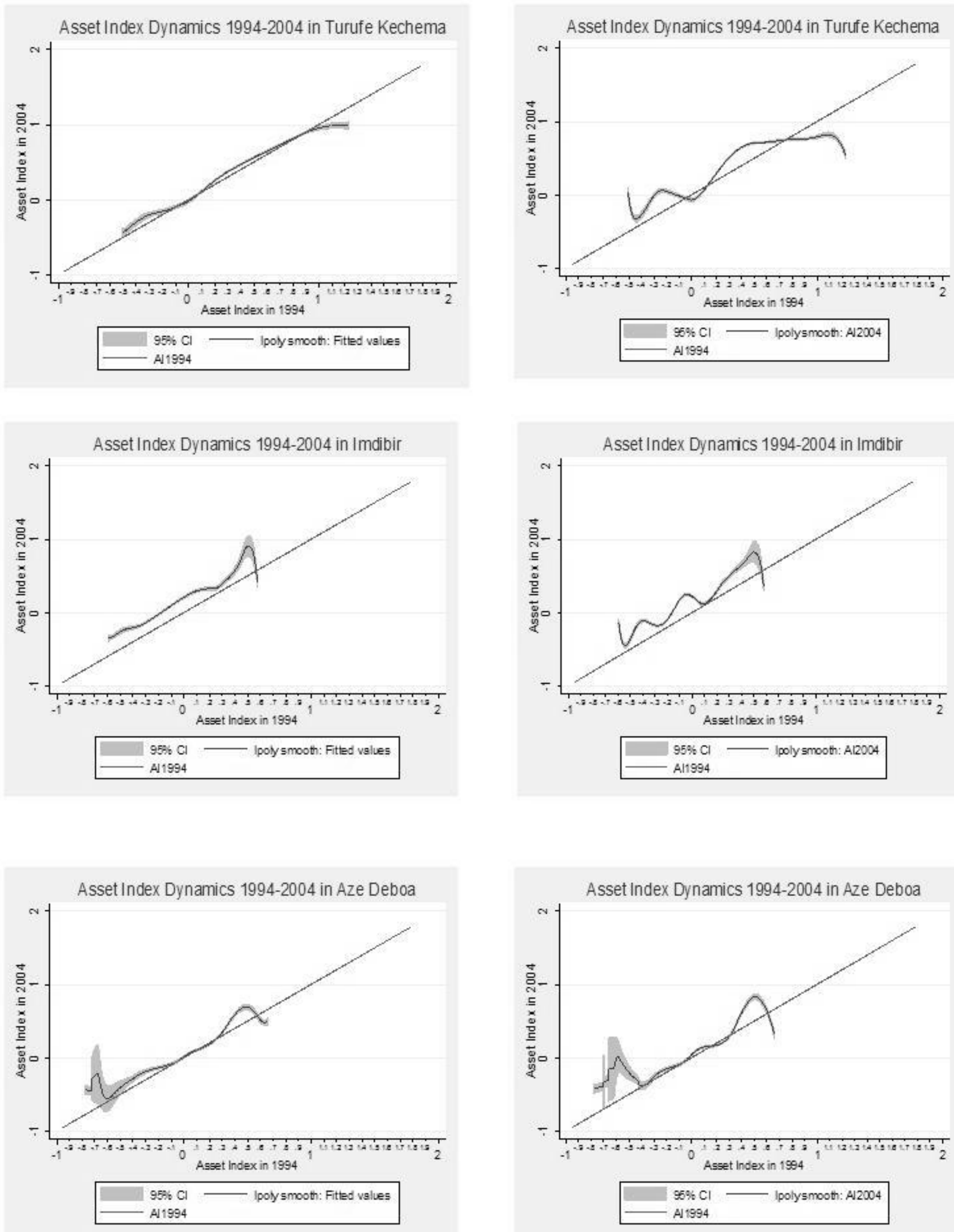
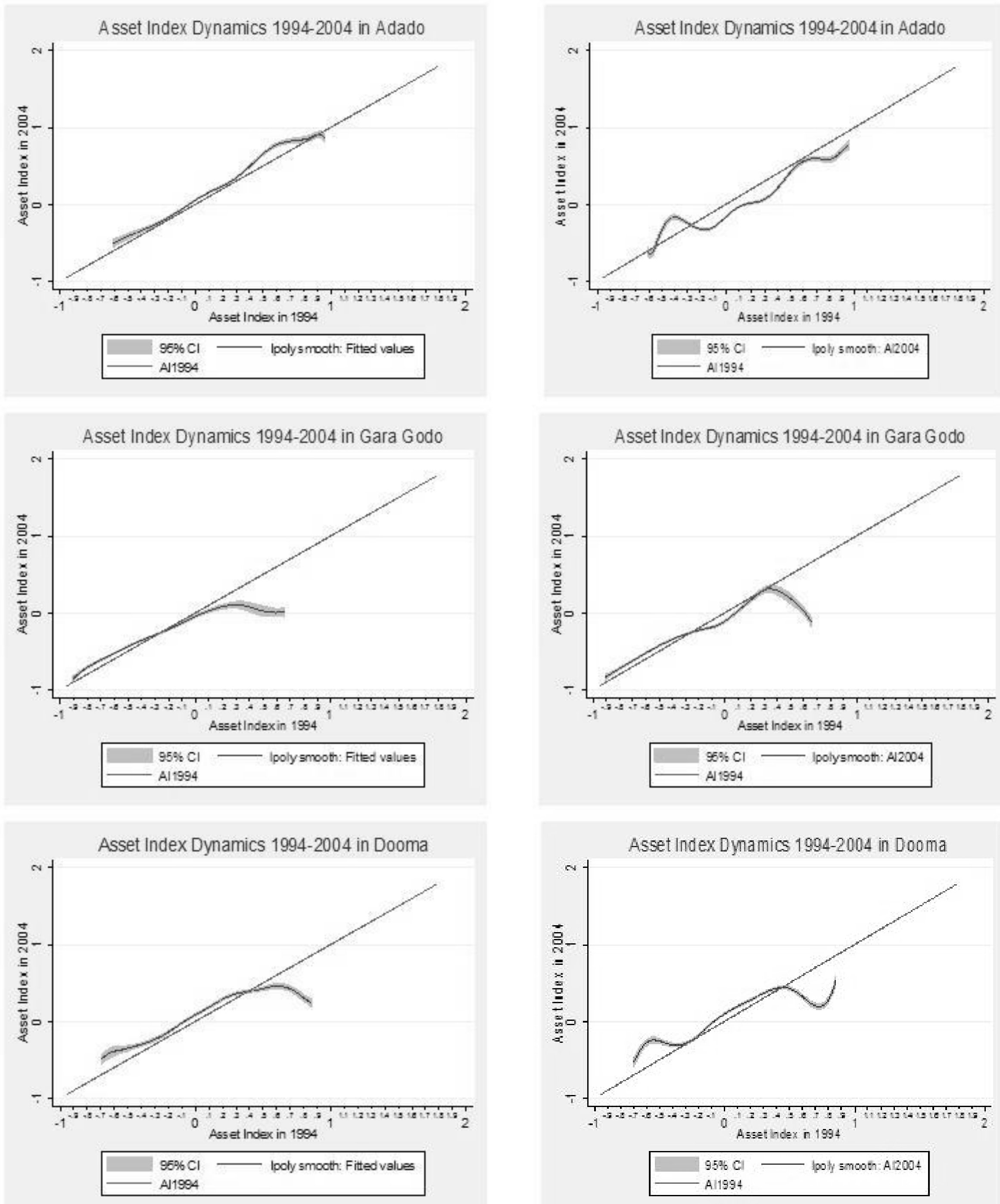


Figure 3. Continued



Source: Generated by the authors using Ethiopian Rural Household Survey (ERHS) data 1994–2004.

Asset Index Dynamics, Shocks, and Social Capital

Vulnerability and shocks are of critical importance in the dynamics of assets and potential poverty traps. To examine these factors we first explore the role of social capital, which can cushion the effects of vulnerability on asset dynamics. We use a household's membership in a local savings and credit organization as an indicator of access to social capital. The parametric results in Table 4b indicate that social capital is positively associated with future assets. Households that participate in local credit and savings organizations show a convergence in the asset index, whereas those that do not participate exhibit bifurcation and multiple equilibria. This was concluded based on fractional regression results shown in Figures 4a and 4b.

As an indicator of household shock, we consider the distressed sale of livestock for purchase of food, repayment of loans, or health expenses in 1999. We then consider the effect of this shock on the household's asset index in the presence or absence of social capital. Households that face a shock but do not have access to social capital display evidence of bifurcation, while those with access to social capital show evidence of convergence.[21] These results reveal the importance of vulnerability and social capital in the development and evaluation of programs to address or prevent the persistence of poverty and poverty traps.

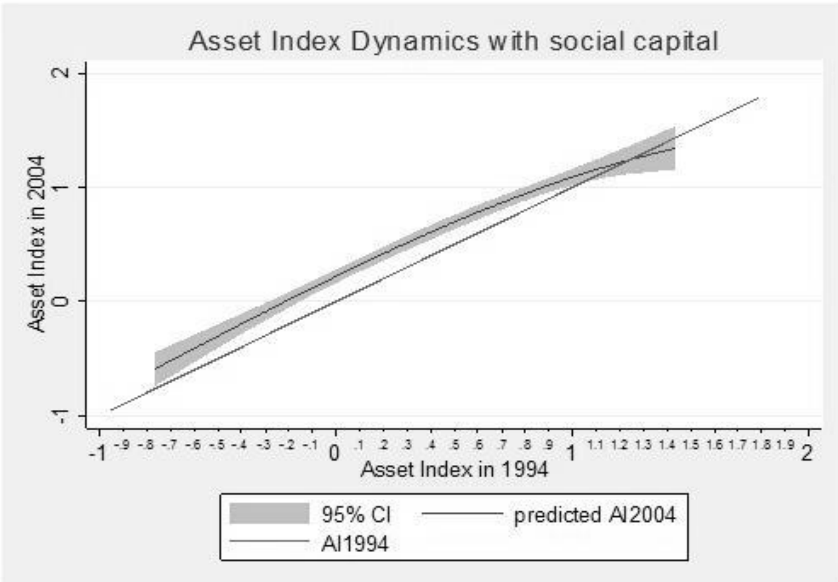
Table 4b. Parametric estimations with social capital

Dependent Variable = Asset Index in 2004 (AI 2004)	Coefficient	Bootstrapped Standard Errors
AI 1994	0.972***	0.031
AI 1994^2	0.079*	0.044
AI 1994^3	-0.125***	0.047
Male-Headed Household	-0.001***	0.022
Household Size	-0.134	0.020
Age of Household Head	-0.299***	0.046
Squared Age of Household Head	0.061***	0.009
Social Capital	0.174***	0.022
Constant	0.490***	0.070
Number of observations	1,190	-
Wald $chi^2(9)$	3,360.58	-
Prob > Wald chi^2	0	-
R-squared	0.701	
Adjusted R-squared	0.6998	-

Source: Generated by the authors from Ethiopian Rural Household Survey (ERHS) data 1994–2004.

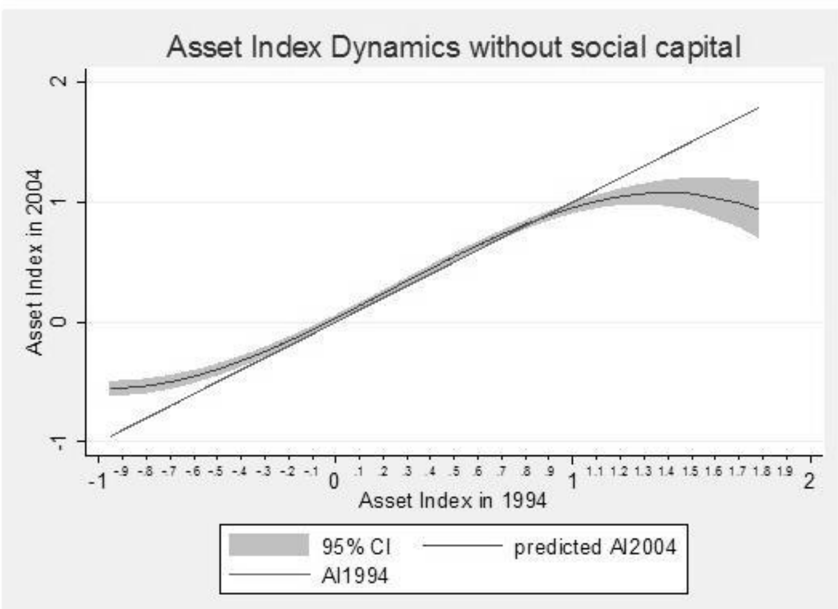
[21] This was concluded based on results from fractional regression estimations similar to those in Figure 4; they are not included due to space considerations but are available from the authors upon request.

Figure 4a. Asset dynamics with social capital



Source: Generated by the authors using Ethiopian Rural Household Survey (ERHS) data 1994–2004.

Figure 4b. Asset dynamics without social capital



Source: Generated by the authors using Ethiopian Rural Household Survey (ERHS) data 1994–2004.

A Comparison of the Asset and Income Poverty Measures

The credibility of the asset index and the estimated asset dynamics can be assessed by considering the predictive capacity of the index. Validation here is based on analysis of transition matrixes and the Thiels U statistic. Tables 5 and 6 present transition matrixes for expenditures-poverty status and asset-poverty status between 1994 and 2004. In principle, the asset poverty measure should capture the structural nature of poverty. Therefore, one would expect the transition matrix for asset poverty to exhibit lower levels of mobility than the matrix for expenditures poverty. As expected, Table 6 shows considerable instability in expenditures poverty over time. Although the total number of households in poverty is fairly stable between the periods (460 households in 1994 and 402 households in 2004), only 46 percent of the households in expenditures poverty in 1994 were still in poverty in 2004; 249 households moved out of expenditures poverty while 191 households fell into that status. Table 6 reveals greater inertia in the asset poverty status. The total number of households in asset poverty changes only from 513 in 1994 to 498 in 2004, and 81 percent of the asset-poor households in 1994 remain in that status in 2004. This greater stability suggests that the asset index is reflecting the structural causes of poverty rather than stochastic factors that can cause expenditures to rise above or fall below the poverty line.

Table 5. Expenditure poverty transition matrix

	Expenditure Poor 2004	Expenditure Nonpoor 2004	Total	% Transitioning
Income poor 1994	211	249	460	54
Income nonpoor 1994	191	539	730	26
Total	402	788	1,190	

Source: Calculated by the authors using Ethiopian Rural Household Survey (ERHS) data 1994–2004.

Table 6. Asset poverty transition matrix

	Asset Poor 2004	Asset Nonpoor 2004	Total	% Transitioning
Asset Poor 1994 ($\Lambda<0$)	418	95	513	19
Asset Nonpoor 1994 ($\Lambda>0$)	80	597	677	12
Total	498	692	1,190	

Source: Calculated by the authors using Ethiopian Rural Household Survey (ERHS) data 1994–2004.

Finer parsing of the transitions reveals that the expenditures-poor households that moved out of expenditures poverty tended to be those with exceptionally high asset index values. Ninety-six of the 460 households that were in expenditures poverty in 1994 had asset index values above the poverty line. Eighty-one percent (78) of these households were expenditures nonpoor in 2004, compared to 45 percent (171 out of 364) of the expenditures-poor households that were also asset poor. Meanwhile, the households that fell into expenditures poverty between 1994 and 2004 tended to be asset poor in 1994. In 1994, there were 149 households that were asset poor but consuming above the expenditures poverty line. In 2004, 56 percent (83) of these households had fallen into expenditures poverty. This compares to 19 percent of asset nonpoor households falling into expenditures poverty between 1994 and 2004. These differential rates of transition all suggest that the asset index is capturing the structural forces behind poverty and could therefore be used to identify households at risk of poverty and those that are in chronic poverty.

Another validity check for the asset index is to examine its internal consistency concerning asset dynamics. If the asset index is accurately capturing dynamics, then households identified as being below the Micawber threshold in 1994 would be expected to remain below that threshold in 2004, unless they received exogenous transfers of some kind. Table 7 shows that 81.48 percent of the households below the Micawber threshold in 1994 remained there in 2004, and none of the households in this status in 1994 achieved the higher-level equilibrium. Meanwhile, one would expect households that were at or above the higher-level equilibrium in 1994 to remain above the Micawber threshold in 2004. As Table 7 shows, this is the case for 99 percent of the households.

Table 7. Asset poverty transitions: Micawber thresholds

	Below MT – 2004	Above MT but below high equilibrium –2004	Above high equilibrium – 2004	% in expected poverty category
Below MT – 1994	81.48%	18.52%	0.00%	**81.48**
Above MT but below high equilibrium – 1994	14.88%	62.15%	22.98%	**85.12**
Above high equilibrium – 1994	0.68%	36.99%	62.33%	**99.32**

Source: Calculated by the authors using Ethiopian Rural Household Survey (ERHS) data 1994–2004.
Note: "MT" refers to the Micawber threshold.

While the transition matrixes suggest that the asset index is reflecting structural features of poverty, they do not provide any test of statistical significance. In addition to the transition matrixes, we validate the asset poverty measure using the Theils U statistic to evaluate the in-sample and out-of-sample predictions of the asset poverty model and to compare its predictive power to that of an expenditures poverty measure. For the in-sample prediction, we compared the predicted value of the asset poverty index for each year, $\Lambda_{ivt.}$, to the actual household consumption level relative to the poverty line. We used the Thiels U statistic (Ui), which measures the prediction accuracy of a forecasting model. This is provided in equation (5), where A_i is the actual value and P_i refers to the predicted value from the model. A Thiels U statistic as shown in equation (5) lies between 0 and 1. The closer to 0 the statistic is, the more accurate the prediction of the model. For the out-of-sample prediction, we estimated the asset index using data from 1994 to 1999 (excluding 2004) and then compared the predicted value of the asset poverty index from that estimation to the actual household consumption relative to the poverty line in 2004.The U statistic associated with this model is 0.48 for the in-sample predictions and about 0.47 for the out-of-sample predictions.

$$Ui = \frac{\left[\frac{1}{n}\sum_{i=1}^{n}(A_i - P_i)^2\right]^{1/2}}{\left[\frac{1}{n}\sum_{i=1}^{n}A_i^2\right]^{1/2} + \left[\frac{1}{n}\sum_{i=1}^{n}P_i^2\right]^{1/2}} \tag{5}$$

To compare the asset index and the expenditure poverty measure, we use the Thiels U statistic to measure the accuracy of their status prediction (that is how well they predict whether a household would be poor or not in the future). To compare the predictive power of the asset poverty measure and the income poverty measure, we consider the poverty status in time (t – 1) as the prediction (P_i) and the actual poverty status in time t as A_i. We find that the Thiels U statistic (Ui) for the income measure prediction is 0.51, while for the asset measure it is 0.29. We also tested the predictive accuracy of the asset poverty measure in time (t – 1) for the *income* poverty status in time t and find that the asset measure predicts income poverty status much more accurately than does the income measure, with a Theils U statistic of 0.25 compared to 0.51 (Table 8).

Table 8. Results of Thiels U statistic calculations

Measure	No. of Observations	U Statistic
In-sample prediction	1,190	0.475
Out-of-sample prediction	1,190	0.469
Asset prediction of asset-poverty status	1,190	0.294
Income prediction of income-poverty status	1,190	0.505
Asset prediction of income-poverty status	1,190	0.246

Source: Calculated by the authors using Ethiopian Rural Household Survey (ERHS) data 1994–2004.

This result further confirms that the asset-based measure is better able to capture structural poverty (which is more likely to be persistent) than is a consumption-based measure. It supports the findings from transition matrixes that the asset poverty measure enables us to identify the structurally poor households that might reveal a nonpoor poverty status by their consumption in one period, but lack the asset base to sustain such consumption and thus are expected to move back to their expected poor status.

5. SUMMARY AND CONCLUSION

Using a GIV regression model, this paper estimated the relationship between household assets and consumption expenditures. Results show that physical and human assets are good predictors of consumption expenditures in rural Ethiopia, and that village characteristics are significant in explaining household relative consumption expenditures. Results indicate that various assets such as land and agricultural implements revealed increasing returns to scale rather than the usual diminishing returns of livestock and jewelry.

In this paper, regression results were used to estimate an asset index for poverty classification and to categorize households based on the structural nature of their poverty status. The results of this classification approach reveal that though the asset-based approach is not in conflict with the income-based poverty measurement, it is more informative as it enables a better understanding of the nature, dynamics, and persistence of households' poverty status. In addition to developing the static asset poverty measure, this paper also explored the dynamics of the asset index to test for the existence of multiple equilibria in the asset growth path in rural Ethiopia. We fail to reject the existence of multiple equilibria, identifying a low equilibrium at slightly above the asset poverty line and a higher equilibrium at about two times the asset poverty line with monthly per capita expenditure of about 123 EB ($44.76, PPP).

An important contribution of this analysis is the provision of empirical evidence that the asset-based poverty classifications consistently predict future poverty status more accurately than do traditional income-based measures. Thus, an asset-based measure could be used to more carefully describe rural poverty, to target poverty interventions, and to more accurately assess the impact of those interventions. In particular, baseline data on assets could be used to more accurately identify households to target for specific programs, while ex post data on assets could indicate the impacts of interventions more clearly than can expenditures data in isolation. The study finds evidence of geographic poverty traps and farming-system-related poverty traps, indicating the impact of infrastructure and access to commercialization opportunities on the ability of farmers to make meaningful investments and grow out of poverty.

This study also shows that contextual setting is important in asset poverty measurement. Although land is often thought to be a critical asset, the research findings in rural Ethiopia show that livestock, household tools, and social networks are more important. It is only at larger land sizes that land becomes very important. This is probably partly due to the small land sizes owned by the majority of farmers (hence the limited variation at low levels) as well as the low quality of land (which many farmers complained about) such that larger land sizes are needed for satisfactory production. Livestock would thus naturally be more important, since these animals are a source of manure for soil fertility as well as a means of traction and transportation; and social networks would be important to deal with various shocks and to supplement productive resources. These results indicate a need for further attention to the problems of limited land size and soil fertility in Ethiopia, including strategies for replenishing soil fertility as well as expanding nonfarm activities. This research also calls for greater attention to the rearing of livestock, including a better understanding of the challenges faced by rural sedentary farmers in rearing livestock (such as limited grazing land and expensive fodder), and to increasing access to improved livestock services for crossbreeding and animal health.

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