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JEL Classifications: O1, I3

Key Words: poverty trap, Ethiopia, multiple equilibria, asset dynamics, regional poverty, sequence of equilibria

1 Introduction

This paper contributes to the empirical analysis of poverty traps by broadening the types of poverty trap concepts examined and introducing new and informative econometric tests.

We begin with a consideration of empirically implementable concepts of what it means to be in a household poverty trap. Recent literature has mainly studied traps to determine the presence of multiple equilibria, which could provide an opportunity to implement policies to push an economy into a self-sustaining higher equilibrium. We contribute to this literature with new strategies for empirical testing for the existence of multiple equilibria. We also present tests for alternative conditions of poverty that are chronic and may represent traps but in a non-classic sense.

In this study, we focus on household assets, rather than consumption or income which have both stochastic and structural components. The noise from the stochastic part of income may generate false positives and false negatives regarding incidence of chronic poverty and poverty traps (Barrett et al., 2006). Since households hold various kinds of assets, we estimate a livelihood-weighted asset index[1] (following Adato, Carter, and May (2006)).

We first show, using a battery of econometric techniques, that our rural Ethiopia panel data set analyzed as a whole suggests the existence of a single stable equilibrium in assets.[2] We expand on previous research that had yielded somewhat inconclusive evidence by introducing new econometric methods to this literature, including a parametric GMM fixed effect model, a local linear regression with explanatory variables, a partial linear mixed model with random effects, and Bayesian penalized spline smoothing. We introduce confidence bands to the poverty traps asset dynamics literature, and also provide credible bands from our Bayesian analysis. Using the bands enables us to make probabilistic statements about whether a potential second stable equilibrium actually exists, and to distinguish equilibria across groups or across time. In addition, we estimate the asset dynamics controlling for explanatory variables in non(semi)-parametric models. By doing so, we can find which variables significantly affect the dynamics. Using the full panel, we do not find an asset poverty trap in the sense that test results point to a single stable equilibrium. However, we hypothesize that conditions in rural Ethiopia likely changed during the period of study. Thus, we split the data into two time intervals, from 1994 to 1999, and 1999 to 2004; we find evidence that a second, higher equilibrium has emerged in the later years of the panel, which we interpret in detail.

We then examine whether poverty traps in Ethiopia occur at a more micro level than can be identified with the pooled nation-wide rural sample. Jalan and Ravallion (2002) introduce an econometric strategy to examine why a region suffers from a poverty trap in a rural China. They conclude that the deprivation of geographical capital causes a geographical trap. Their approach is to test for divergence in consumption dynamics - a sufficient condition for the existence of a poverty trap - which they identify in their data, controlling for household specific latent heterogeneity. Following the Jalan and Ravallion (2002) definition of a geographic trap, we examine whether regional stagnation exists in parts of rural Ethiopia.[3] Three distinct regions are found in our sample, each with distinct farming methods, products, and other characteristics (this is part of the survey design; these regional differences have been utilized in previous research on other topics). We then proceed to estimate the asset dynamics of each region to examine equilibria. We find that one of the three regions (described below) has a very low implied equilibrium (well below the $1.25 PPP poverty line). In addition, we find that the sequential equilibria of this region remains statistically unchanged when dividing the panel into the two five year intervals, despite the upward shift of the asset distribution, while the equilibrium of other regions shift upward.

The remainder of the paper is organized as follows. Section 2 examines concepts of poverty traps and nonlinear income dynamics. An empirical literature review on poverty traps is provided in section 3. Section 4 introduces the Ethiopia Rural Household Survey (ERHS) and a livelihood-weighted asset index. Section 5 shows that, consistent with some of the earlier literature, treating the full data set as homogeneous implies the existence of a single stable equilibrium; this is robust to nonparametric tests that we introduce to this field. In Section 6, we allow for heterogeneity across time and regions. We examine the heterogeneous impact of the slowdown of growth in the later period of the study utilizing nonparametric quantile regression. Then, we present intriguing evidence for the emergence of a second and higher equilibrium in rural Ethiopia. Finally, we show substantial differences in dynamics across regions.

2 Basic Theories of Poverty Traps and Nonlinear Income Dynamics

A substantial tradition in development economics has examined the concept of a poverty trap as a vicious circle. Many theoretical contributions, and more recently some path-breaking empirical work, have studied thresholds in asset or capital accumulation that effectively prevents households from accumulating means for growth. The dynamic growth process with a poverty trap produces multiplicity in the income or asset dynamics. The simplest model of income dynamics can be represented as a nonlinear difference equation:

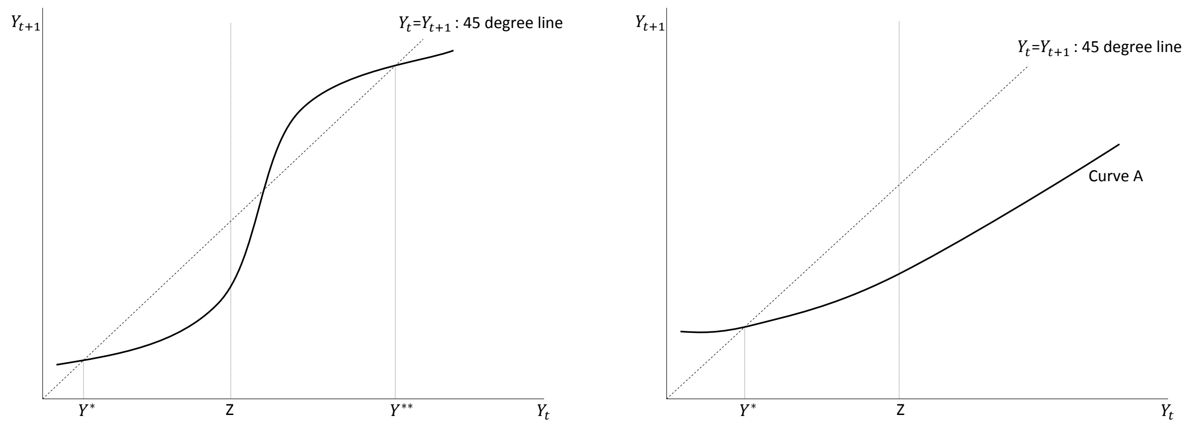
$$Y_{it} = f(Y_{it-1}, X_{it}), \tag{1}$$

where Y_{it} is current household income, X_{it} represents exogenous characteristics, and the function $f(\cdot)$ satisfies $f'(Y_{it-1}) > 0$ and $f''(Y_{it-1}) < 0$. With multiple steady-state equilibria, persistent poverty can be inevitable if any shock reduces current income below the unstable equilibrium.

A number of motivations have been proposed for such nonconvexity: for example the nutritional efficiency wage hypothesis (Leibenstein, 1957; Stiglitz, 1976; Dasgupta, 1997),[4] and liquidity constrained households (Loury, 1981; Galor and Zeira, 1993),[5] among others.[6] These explanations are related to incomplete markets and generate multiple equilibria so that they show how an economy can be trapped in poverty.

Under a threshold model, poor households cannot produce enough human and physical capital to exceed the threshold to escape the lower level equilibrium (known as the poverty trap) and move to the higher-level equilibrium. In this case, a transfer payment may eliminate the low-income unstable equilibrium and enable the poor to escape poverty. A poverty trap is thus viewed as a Pareto-dominated (bad) stable equilibrium, when the preferred equilibrium is available to the same individuals with the same characteristics; it is commonly represented as in Figure 1a.

Note that even if there is only a single stable equilibrium as in Curve A in Figure 1b, although formally different it would also be quite intuitive to use a "poverty trap" terminology to describe a single equilibrium that is below poverty line Z. On the other hand, there is no



(a) Multiple Equilibria

(b) A Single Stable Equilibrium

Figure 1: Dynamic Recursion Curve

reason why the lowest equilibrium in Figure 1a must be below any commonly accepted absolute poverty line Z. Moreover, the emergence of a second, higher equilibrium can actually indicate an improvement in "potential welfare," if under some conditions a household may successfully cross the threshold asset level - perhaps as a result of development assistance. Thus presence of multiple equilibria is not perfectly matched with the broader concepts of poverty traps that would extend to the analysis of other circumstances of chronic, structural poverty.

3 Empirical Literature Review

Empirical research into multiple equilibria in income and asset poverty trap dynamics has only begun fairly recently with contributions by Jalan and Ravallion (2001, 2002); Dercon (2004); Lokshin and Ravallion (2004); Lybbert et al. (2004); Adato et al. (2006); Barrett et al. (2006); Naschold (2009); Campenhout and Dercon (2009). Both parametric and non(semi)parametric estimation methods have been used to estimate poverty dynamics.

Jalan and Ravallion (2001) use a six-year panel of income from four rural provinces (Guangdong, Guangxi, Guizhou and Yunnan) of China to test for nonlinearity in income and expenditure dynamics. They find that the growth rate of household income depends on higher moments of the initial distribution than its mean. That is, initial high inequality of income reduces future growth in mean income. In addition, they find evidence of nonlinearity in income.

Table 1: Summary Table of Literature

	Study	Data	Poverty Trap Concepts	Method	Poverty Trap Findings
Other Data	Jalan and Ravallion (2001)	Six year panel of income from four rural provinces of China	Multiple equilibria in income space	GMM with dynamic panel model	Fail to find multiple equilibria, but find evidence of nonlinearity of income dynamics, implies to a single equilibrium with a slower convergence of the poor
	Jalan and Ravallion (2002)	Six year panel of income from four rural provinces of China, adding geographical dimension	Multiple equilibria in income space	GMM with dynamic panel model	Find evidence of geographic poverty trap by the test for divergence of geographic capital in consumption dynamics, controlling for latent heterogeneity
	Lokshin and Ravallion (2004)	Four year panel from Russia and six year panel from Hungary	Multiple equilibria in income space	Semi-parametric FIML	Fail to find evidence of dynamic poverty trap, but find evidence of nonlinearity of income
	Lybbert et al. (2004)	17-year (1980-97) cattle herd histories for a set of 55 randomly selected households drawn from four communities (Arero, Mega, Negelle and Yabello)	Multiple equilibria in herd space	Nadaraya-Watson estimator (Local constant)	Find evidence of dynamic poverty trap
	Adato et al. (2006)	KwaZulu-Natal Income Dynamics Study (KIDS) in South Africa	Multiple equilibria in asset space	LOESS of 1998 asset indices on 1993 asset indices	Find evidence of dynamic poverty trap
	Barrett et al. (2006)	Rural Kenya and Madagascar	Multiple equilibria in asset space	LOESS of current herd size on 3 month earlier herd size	Find evidence of dynamic poverty trap
	Antman and McKenzie (2007)	ENEU in Mexico	Mutiple equilibria and single stable Equilibrium below poverty line	Dyanmic pseudo-panel method	Find evidence of nonlinearity of income and a single equilibrium above poverty line
	Naschold (2009)	ICRISAT's VLS in India	Multiple equilibria in asset space	Penalized spline with mixed model	Find a single stable equilibrium
Other ERHS	Dercon (2004)	ERHS 1989, 1994/5, 1997	Multiple equilibria in income space	REML	Find β Convergence, Find persistence effect of shocks
	Campenhout and Dercon (2009)	TLU in ERHS 1994, 1994/5, 1995, 1997, 1999, 2004	Multiple equilibria in asset space	Threshold auto-regression model	Find evidence of dynamic poverty trap in TLU
Our Study		ERHS 1994, 1995, 1997, 1999, 2004	Multiple equilibria in asset space	Previously used methods for robustness, nonparametric local linear and quantile regression, and Conditional PDF and CDF with mixed data type	Find nonlinearity of asset dynamics and a single stable equilibrium, and a regional stagnation using evolution of distribution and shift of equilibria over time

Jalan and Ravallion (2002) re-examine the same data as in their 2001 study and present evidence of a geographic poverty trap, meaning that when the consumptions of identical households living in a better-endowed area rise over time, households trapped in geographic poverty remain isolated from the 'rising standard of living.' They find that the effect of average wealth in the county of residence on consumption growth rates at the household level (0.0602) is greater than that of own wealth (-0.0221) in absolute terms, controlling for latent heterogeneity. That is, they find aggregate divergence in consumption dynamics.

Dercon (2004) uses six-village data from the Ethiopia Rural Household Survey to explore the impact of risk on consumption growth paths using a linearized empirical growth model: $\ln y_{it} - \ln y_{it-1} = \alpha + \beta \ln y_{it-1} + \delta Z_{it} + \gamma X_i + u_{it}$. Using the modified specifications of the above baseline model, he finds a persistence effect of famine and rainfall shocks. In addition, road infrastructure is a source of divergence in growth across villages and households.

Lokshin and Ravallion (2004) examine the existence of poverty traps and distribution-dependent growth using a four-year household panel from Russia and six-year household panel from Hungary. In order to resolve endogenous attrition to shocks, they use a system estimator based on semi-parametric full information maximum likelihood. They find evidence of concavity of income for both countries, but they fail to find convincing evidence of a dynamic poverty trap.

Lybbert et al. (2004) use 17-year cattle herd histories in southern Ethiopia to study stochastic wealth dynamics. The most important asset for households is a livestock in this pastoral region. The data they use aggregate heterogeneous livestock into "Tropical Livestock Units (TLU)" via a weighting system. They estimate livestock dynamics using a Nadaraya-Watson estimator of a bivariate case using Epanechnikov kernel with arbitrary bandwidth 1.5. Due to the fact that it is a nonparametric local curvature, they can avoid a local distortion that parametric regression might arise. A limitation, however, is that a local constant estimator such as the Nadaraya-Watson estimator is known to suffer from "boundary bias"(detailed explanations are found in Pagan and Ullah (1999, pp.81-106)). In addition, they don't use an optimal bandwidth from a data driven bandwidth selector such as likelihood cross-validation or plug-in method.[7]

To aggregate a portfolio comprised of multiple assets, Adato et al. (2006), Barrett et al.

(2006), and Naschold (2009) estimate asset-based wellbeing indices by either a regression of expenditure on the household's productive assets or a factor analysis. Based on the indices, they expect that households that suffer from income poverty transitions but not asset losses should not fall into poverty trap. Carter and Barrett (2006) argue that a dynamic asset poverty threshold should be identified to disaggregate the structurally poor into those expected to escape poverty on their own over time. If the dynamic asset poverty line, which is set at an unstable dynamic asset equilibrium, is located far above the level at which it is feasible or rational to accumulate sufficient assets, all the currently structurally poor, and a subset of the non-currently structurally poor would be expected to gravitate to the low level equilibrium. Some but not all studies have identified such a threshold.

Adato et al. (2006) find evidence of an asset poverty trap using the KwaZulu-Natal Income Dynamics Study (KIDS) in South Africa for 1993 and 1998 using bivariate locally weighted polynomial regression methods (LOESS). Barrett et al. (2006) examine rural Kenya and Madagascar to see if there is a poverty trap. They distinguish structural welfare dynamics from stochastic welfare dynamics. They propose a procedure to remove the noise due to stochastic component of income from total income, and estimate both total income dynamics and structural income dynamics regressions using bivariate quadratic LOESS with an optimal, variable span based on cross-validation for each village. They find that the estimated slope is negative from the regression of the total income change on initial income for each village. However, from the estimated structural income dynamics, the estimated line does not have a monotonically negative slope for each village. The dynamics in all five villages have multiple equilibria. In addition, they find multiple dynamic asset and structural income equilibria by estimating an S-shaped curve using both nonparametric and 4th degree polynomial parametric methods.

Naschold (2009) explores household asset poverty traps in rural semi-arid India using semi-parametric and nonparametric estimations, using a 27 year panel data set from the International Crop Research Institute for the Semi-arid Tropics'(ICRISAT) Village Level Studies(VLS). He finds a single stable equilibrium in the VLS data rather than the multiple equilibria he expected, for which he proposes four explanations: First, a social sharing rule and endogenous household composition may hinder asset accumulation. Second, if the time period between observations is short, it is hard to pick up the long run asset dynamics when total asset holdings change slowly. Third, VLS data only contain few richer households since the VLS covers a poor rural population. Fourth, bifurcating equilibrium paths may depend on the quality of the growing season.

Campenhout and Dercon (2009) explore the existence of livestock asset poverty traps in Ethiopia using the Ethiopia Rural Household Survey (ERHS). They use GMM estimation and Threshold Auto-Regression model proposed by Hansen (1999; 2000). They find non-linearities in dynamics of Tropical Livestock Units (TLU) and multiple equilibria of TLU. One of advantage of their method is that it allows us to estimate the speed of convergence, which cannot be computed using nonparametric methods. They find that convergence to the low level equilibrium is almost twice as fast as convergence to the high level equilibrium. In our research, however, we do not limit ourselves to TLU indicators, because our ERHS data primarily cover non-pastoral sites.

4 Data: The Ethiopia Rural Household Survey (ERHS)

This research uses the Ethiopia Rural Household Survey (ERHS); a panel dataset that we selected to study prioritized analysis of a very low income country[8], but one experiencing pro poor growth, to examine conditions under which the poor might be escaping from what had appeared as poverty traps. The multiple waves of this survey is particularly attractive for exploring shifts of equilibria over time.[9]

ERHS is publicly available, and the dataset was used in the form as cleaned by International Food Policy Research Institute (IFPRI). ERHS consists of 15 areas with 1477 households, stratified in three main agro-ecological zones of Ethiopia.[10] Households are selected randomly within each village, stratified by female headed and non-female headed households as well as landless households. Sample population shares are broadly consistent with the population shares in the three main sedentary farming systems, the grain-plow complex highlands, the grain-plow/hoe complex, and the enset growing area. Figure 2 represents the survey sites and 3 categories according to the farming systems in rural Ethiopia.[11] The grain-plow complex highlands area has an ox-plow farming system. Mean recorded rainfall is about 700 to 1200mm, and the main crops are teff and barley. The grain-plow/hoe complex is a very poor and vulnerable area, in

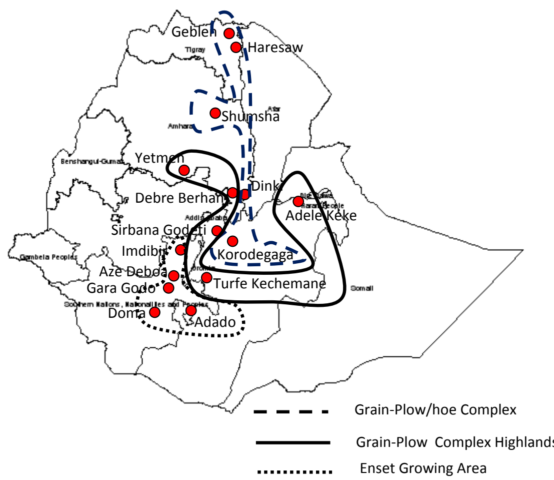


Figure 2: Ethiopia Rural Household Survey Villages

which mainly cereals are grown. It has high variance-excessive or deficient rainfall over time. The enset growing areas have poor environments to grow most crops, and mean recorded rainfall is very high, at over 1500mm. This area is densely populated. Enset and perennial crops are grown; some coffee and cereals are sometimes cultivated.[12] Table 2 shows that there exist large differences in the consumption level according to the farming system regions.

Moreover, we have to note that Ethiopia has a distinctive land institution that may have made poverty more serious. Though utilization of land is a key to economic activity in Ethiopia, like some other countries with socialist backgrounds, land is owned by the state. Three major changes in institutions of land were made after 1991 as summarized in Deininger and Jin (2006): First, regional governments were given the responsibility of enacting laws regarding the nature of land rights, their transferability, and matters of land taxation; second, the frequency of land redistribution was reduced, and third, local governments retained high levels of discretion that allowed them to impose restrictions on land transfers, even though rentals have been officially allowed by the Constitution. Therefore, households have a difficulty in migrating to another region and acquiring land from an other peasant association. In addition, insecure land holdings reduce incentives for farmers to invest in the land, which contributes to the low productivity from land and perpetuating low growth and poverty. Dercon and Ayalew's (2007) findings also support this prediction.[13]

Current income and consumption have been the main wellbeing measure in the previous

Table 2: Consumption per Adult and Asset Index across Farming System Regions

	Full Sample		Grain-plow complex Highlands		Grain-plow/hoe complex		the Enset Area	
	Consumption	Asset Index	Consumption	Asset Index	Consumption	Asset Index	Consumption	Asset Index
Round 1	87.921	1.738	116.196	2.339	79.199	1.513	63.062	1.222
	(93.775)	(.892)	(99.109)	(.758)	(106.501)	(.915)	(55.131)	(.523)
Round 3	81.303	1.970	101.728	2.667	80.277	1.821	57.876	1.290
	(100.152)	(1.333)	(126.993)	(1.367)	(84.951)	(1.076)	(69.225)	(1.095)
Round 4	110.083	2.240	142.456	2.991	98.669	1.858	83.092	1.665
	(115.666)	(1.139)	(156.322)	(1.267)	(84.462)	(.796)	(67.795)	(.618)
Round 5	108.864	2.479	140.231	3.389	110.169	2.410	67.717	1.411
	(98.625)	(1.223)	(113.903)	(1.260)	(94.206)	(.688)	(60.888)	(.561)
Round 6	117.009	2.689	150.971	3.559	106.403	2.545	84.917	1.732
	(124.390)	(1.292)	(161.810)	(1.294)	(93.967)	(1.023)	(81.619)	(.626)
Total	100.45	2.202	129.756	2.963	94.441	2.014	70.842	1.451
	(107.504)	(1.229)	(134.231)	(1.283)	(94.144)	(.986)	(67.800)	(.752)
N	6914	5909	2549	2261	2311	1814	2054	1834

[a] Source: ERHS 1994a, 1995, 1997, 1999, 2004
[b] Standard deviations are in parenthesis.
[c] Groups are constructed based on the farming system.
[d] Consumption per adult is computed using adult equivalent units based on Dercon and Krishnan (1998).
[e] Villages in northern highlands are included in the grain-plow/hoe complex.

literature. Barrett et al. (2006) argue that analysis of solely current flows hinders us from identifying chronic poverty because this measure includes both structural and stochastic components of income. In order to analyze chronic poverty and poverty traps, they suggest using the structural part of income, (i.e., assets).[14] We proceed then to estimate an asset index,[15] which provides a proxy of the household structural income. Table 2 shows the average consumption level and average asset index across each farming system area. Consumption levels show an increasing trend overall (although with fluctuations), while we observe little fluctuation in the asset index, which increases over time. This broad trend holds across the farming system regions. The highlands area with a higher productivity farming system has higher consumption levels and asset index on average. On average, asset indices in rural Ethiopia have increased over time. However, we note that asset indices of the highlands and the hoe areas increase rather steadily over time while that of the enset area exhibits more fluctuation.

5 Analysis of Asset and Consumption Dynamics

While households hold various assets, previous research has focused on tropical livestock units (TLUs) as an asset unit. Given that all land in Ethiopia is state-owned and land sales and rental against fixed payment are banned, livestock can be considered as a key to asset accumulation. But the Ethiopia Rural Household Survey (ERHS) is not a representative sample of pastoralists in Ethiopia. Rather, ERHS can be considered broadly representative of households in non-pastoralist farming system regions as of 1994 (Dercon and Hoddinott, 2009). Hence while we also use TLUs for comparability with previous research, we focus on broader asset indices to estimate asset dynamics, for example to examine if there is a single equilibrium.

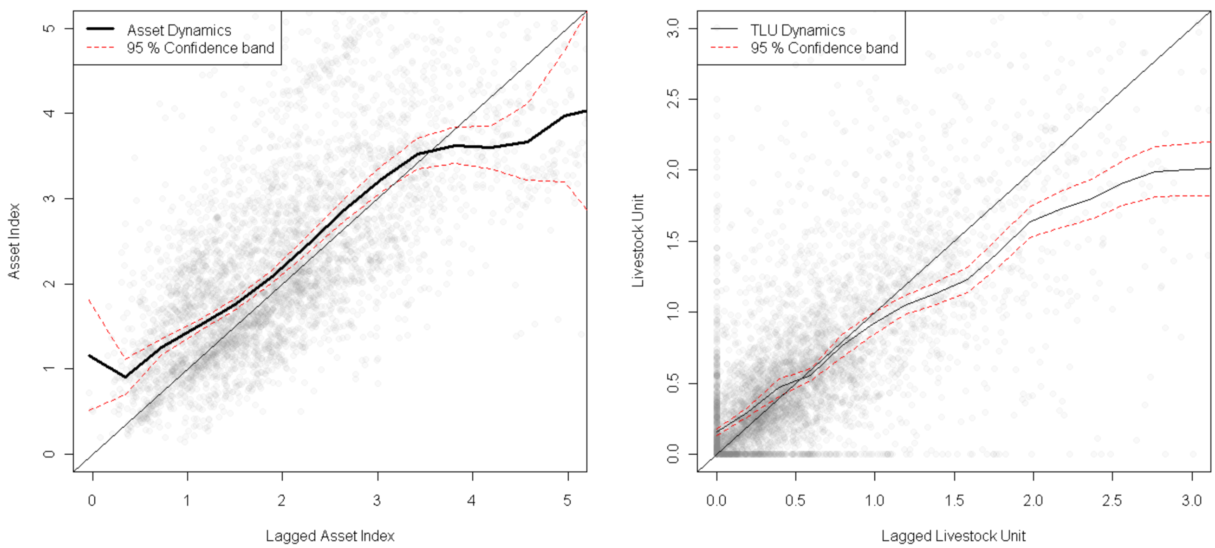
The relationship in nonparametric context is specified by

$$A_{it} = m(A_{it-1}, X_i) + \epsilon_i, \tag{2}$$

where Xs are explanatory variables; age of head, household size, and gender of household head.[16] Using pooled data, we estimate the equation (2) above.

Figure 3a shows the estimation results of equation (2), which is a multivariate nonparametric model having explanatory variables with continuous and categorical variables while most previous literature estimates a bivariate model. Our local linear regression adapts Epanechnikov kernel for continuous variables and a variation on Aitchison and Aitken's (1976) kernel for a categorical variable, i.e., gender of head. We use data driven methods of fixed type bandwidth,[17] selected by likelihood cross-validation (LCV) based on Hurvich, Simonoff, and Tsai's (1998) AIC$_c$.[18] Confidence bands are generated by bootstrap resampling with independent non-identical distribution, which admits general heteroscedasticity of unknown form.[19] From Figure 3a, we observe a single stable equilibrium around 3.6, which represent about 6 Birr per adult per day. It may correspond to a poverty equilibrium, depending on how the poverty line for Ethiopia is set.[20]

In addition, Figure 3b exhibits TLU dynamics, in which we don't control for the explanatory variables analogous to what was done in Lybbert et al. (2004). They use an arbitrary sized bandwidth, but we use adaptive nearest neighbor bandwidth for the TLU estimation.[21] From the local linear regression, we find a single stable equilibrium. In addition, we also adapt Bayesian penalized spline and a partial linear mixed model as robustness check methods in the Appendix B1 and B2. From them, we find a single stable equilibrium as well. Finally in Appendix B3, for comparability with previous methods, we present parallel results using a parametric approach. Although, as explained in the appendix, the nonparametric approach is generally preferred, the broad, qualitative conclusions of the two approaches are very similar.



(a) Asset Index

(b) TLU

Figure 3: Asset Dynamics

6 Regional Stagnation

In order to consider the possibility of a regional stagnation in structural income, we examine the three farming system regions in Ethiopia.[22] We employ local linear regressions and Bayesian penalized Spline smoothing. Descriptive statistics in Table 2 show that the enset area has the lowest consumption and asset index level among the three regions. Utilizing the nonparametric and semiparametric methods that we used in the previous section, we investigate whether or not there exist a regional stagnation.

We first establish that growth has been strong throughout the income distribution (in fact exhibiting clearly pro poor growth in the earlier years of the panel) consistent with First Order Stochastic Dominance (FOSD). We then consider how to evaluate the possible existence of a regional stagnation in structural income even under these circumstances using two concepts: evolution of distribution over time which we apply in section 6.1; and the concept of shift of equilibria over time as we employ in section 6.2. We find that the household structural income distribution has improved over time in terms of FOSD. We also indicate that the households' structural income dynamics have changed over two time intervals. These changed dynamics produce the shift of equilibria over time as well. Under the evolution of structural income distributions of all regions over time, if we don't observe positive shifts of equilibria in a region over time while positive shifts of equilibria are observed in other regions, then the region without the shifts of equilibria (i.e., converging to the same equilibrium over time repeatedly), we conclude, is in stagnation. Based on this definition, we first estimate a Rosenblatt-Parzen type density function (PDF) and cumulative distribution function (CDF) of asset indices over time, adapting the Maasoumi, Racine, and Stengos's (2007) kernel methods. Furthermore, we investigate whether there exists a difference between the asset dynamics of each region in rural Ethiopia.

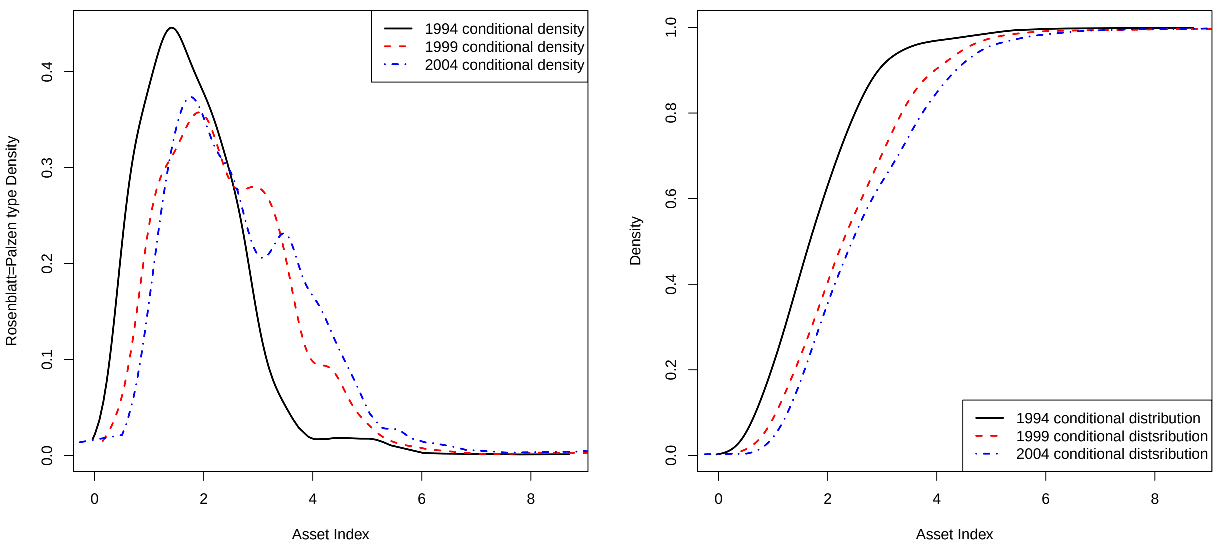
The remainder of this section is organized as follows. First we estimate conditional densities and distributions of the asset index over time in the following section 6.1. In section 6.2, we investigate how the asset dynamics and their equilibria have changed over time. In section 6.3, we explore which among the three studied regions has the lowest level of equilibrium. The region having the lowest equilibrium may be the strongest candidate for a regional stagnation problem. Finally, we examine whether a regional stagnation exists in section 6.4.

6.1 Evolution of Cross-sectional Distribution

We note that mean regression approaches have limitations for analyzing the extreme quantile of the income distribution. For example, we hardly identify the incidence of growth of the poor over time from the mean regression approach. Here we analyze cross-section distributions of asset indices and their evolution.

We use the probability density function (PDF) and cumulative distribution function (CDF) of asset indices to analyze how distribution evolves over time. We adapt the Maasoumi, Racine, and Stengos (2007) kernel methods that they applied to cross-country data, and estimate Rosenblatt-Parzen type density estimates. As in the previous nonparametric estimation, we use data driven methods of bandwidth selection, i.e., likelihood cross-validation (LCV).

Figure 4 provides density functions and distribution functions for all years. The density is a conditional asset index density conditional on year only.[23] The density function in Figure 4a is not symmetrical, and becoming less concentrated. It suggests the forming of a bimodal distribution, which is difficult to examine using traditional conditional mean regression techniques.



(a) Evolution of PDF

(b) Evolution of CDF

Figure 4: Evolution of Asset Index Distributions

The advent of bimodality suggests the multiple equilibria in the asset dynamics. Figure 4b represents that the distribution in 2004 *first order dominates* the distributions of other years. Hence we conclude that Ethiopia rural households have clearly improved over time. Given that FOSD implies SOSD, the households of ERHS in 2004 have second-order stochastic dominance over them in earlier years. That is, inequality has decreased over time while incomes have risen, in the manner of pro poor growth. Inequality indices in Table A1-2 also conform with our findings.

6.2 Shift of Equilibria

Thus far, we have identified the dynamics asset equilibria implied by the merged data set as a whole, but as conditions change, particulary as technology progress in rural Ethiopia proceeds, the nature of dynamic asset equilibria may change with it. In most previous literature (Adato et al., 2006; Barrett et al., 2006), only two data points have been used in exploring asset dynamics, but we estimate the following equation (3) using data points over time. Hence we have an opportunity to study a sequence of implied equilibria.

$$A_{i,t} = f(A_{i,t-5}) + \gamma X_i + e_i, \tag{3}$$

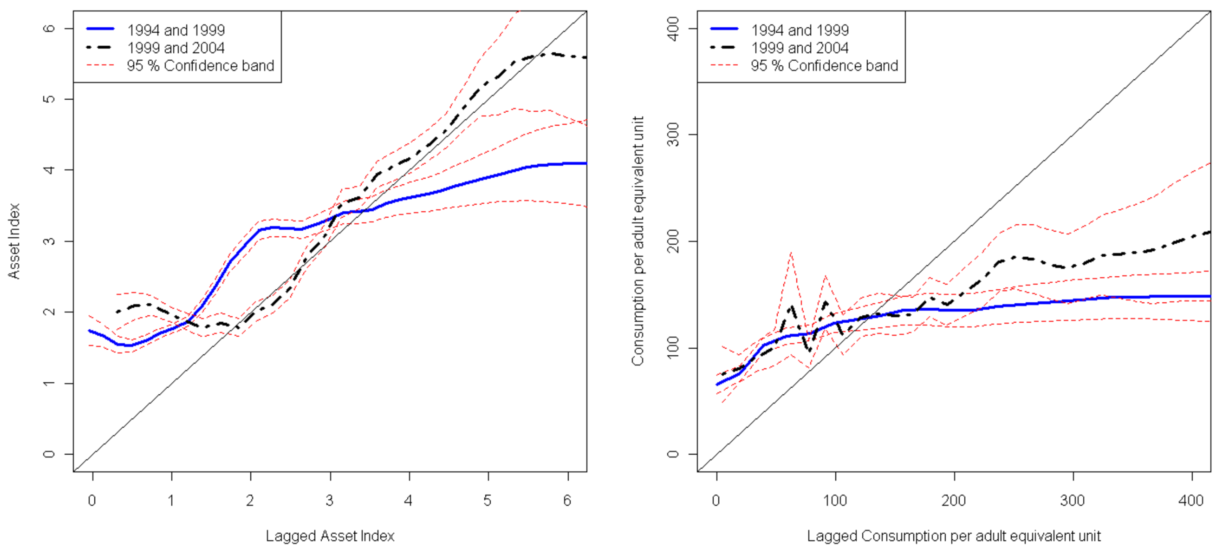
where $A_{i,t-5}$ is an lagged asset index of i, and t represent data time points (1999 and 2004), $f(\cdot)$ is an unknown functional form, and X_i contains explanatory variables.[24] The estimation method is the local linear kernel regression with Epanechnikov kernel. Bandwidths are selected by the LCV.

Figure 5 shows the evolution of equilibria in asset and consumption space. The equilibrium for *consumption* does not vary over time; nor do the paths of dynamics for consumption significantly differ between 1994 to 1999, and 1999 to 2004.[25] But the paths of *asset* dynamics are statistically significantly different from each other, as are the equilibria. The 1999 to 2004 path of asset dynamics gives evidence compatible with the emergence of a second equilibrium in structural income, while the 1994 to 1999 path does not.[26]

Furthermore, the asset index represents the structural part of income while consumption includes both stochastic and structural part of income as Barrett et al. (2006) point out. Figure 4 and 5a imply that the dynamics of the structural part of incomes are changed with the evolution of asset distributions over time. However, the consumption dynamics in Figure 5b do not appear to have changed over the two time intervals while asset distributions have apparently evolved (their equilibrium is not changed over time). The evidence suggests that when examining current consumption, the changes in the structural part of income is masked by the changes in the stochastic part of income. The implication is that in examining poverty persistence, generally it would be more reliable to examine asset dynamics than consumption dynamics.[27]

In Figure 6 the growth incidence curves are provided, which indicate that rural Ethiopia has experienced pro poor growth over time;[28] we observe pro poor growth in both assets and consumption from 1994 to 2004. This finding conforms with other evidence of pro poor growth in rural Ethiopia.[29] In particular, there was a large growth between 1994 to 1999 in rural Ethiopia in both structural income and consumption.

Figure 6a indicates that both lower and higher percentiles of the income distribution exhibit



(a) Shift of Asset Dynamics

(b) Shift of Consumption Dynamics

Figure 5: Shift of Equilibria in Asset and Consumption

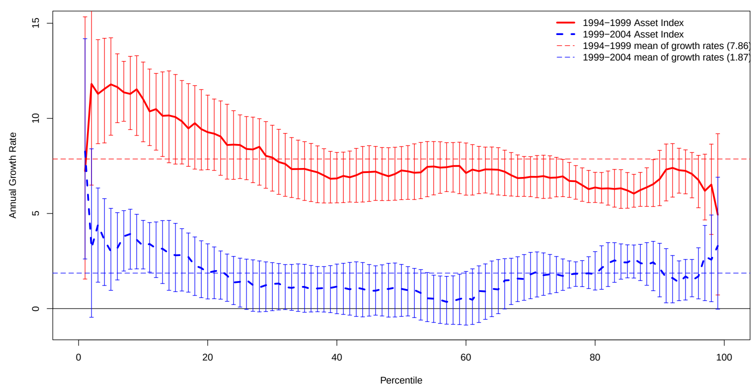
positive growth from 1999 to 2004, while the middle percentiles have little growth.[30] This may indicate that the distribution of structural income has been in the process of evolving from a unimodal one to a bimodal one in rural Ethiopia.[31] These findings conform to the implications of the evolution of distributions over time as presented in the previous section 6.1. However, throughout the distribution, we see essentially no income growth from 1999 to 2004 as seen in Figure 6b; this helps explain why there was no difference in the path of consumption dynamics from 1994 to 1999 and 1999 to 2004 in Figure 5b.

Figure 5a is intrinsically a representation of a mean regression. It hardly represents the dynamics of the households located in extreme percentiles of the income distribution. The dynamics of the households located in the lower percentile of the income distribution may well be different from those in the higher percentiles of the income distribution. Hence, we adapt a nonparametric quantile regression proposed by Li and Racine (2008).[32] Figure 7 shows asset index dynamics of the 25th percentile and 75th percentile nonparametric quantile regression. The bandwidth selection method for our kernel quantile regressions follows the case of conditional PDF estimation making use of the Hall et. al. (2004) bandwidth selector.[33]

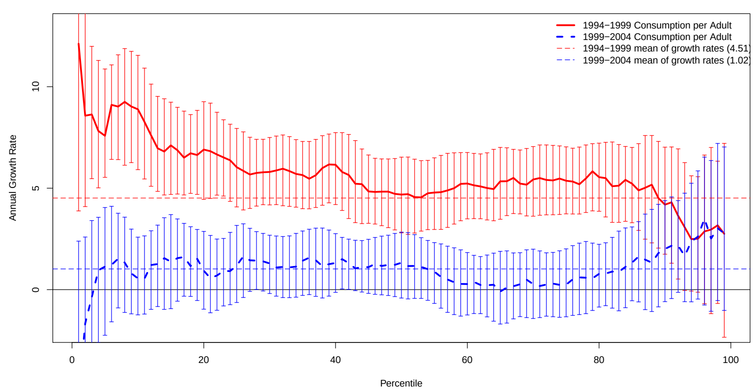
Figure 7a shows that the 1999 to 2004 path has a lower equilibrium than the 1994 to 1999

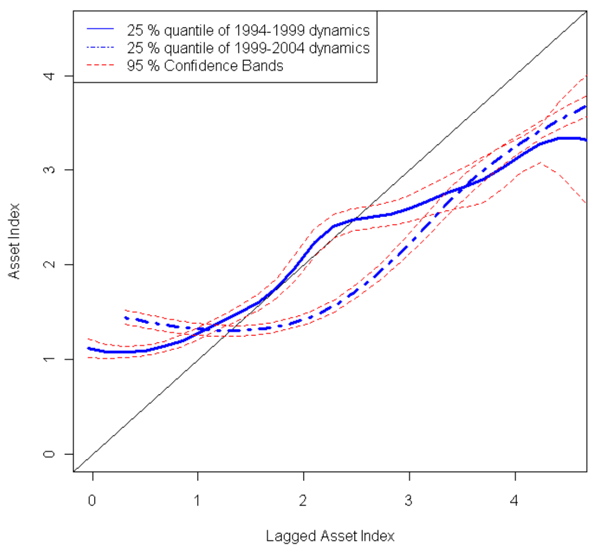
Figure 6: Evolution of Growth Incidence Curves

(a) Asset Index

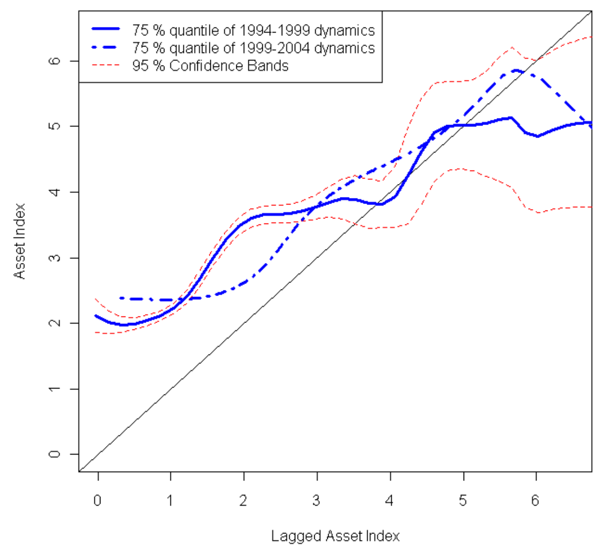


(b) Consumption per Adult





(a) 25 % Nonparametric Quantile Regression

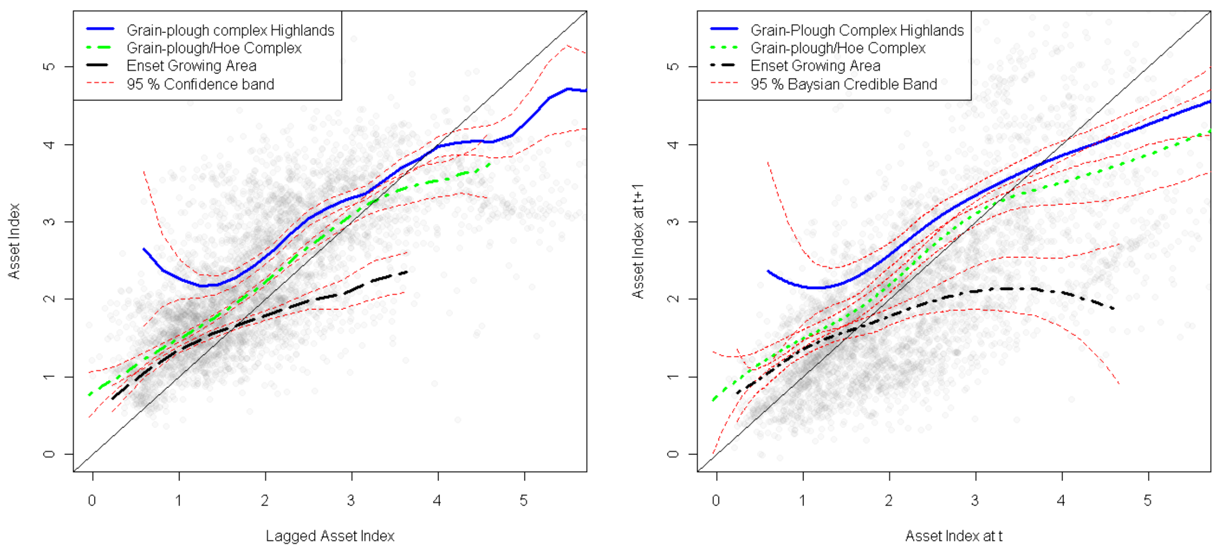


(b) 75 % Nonparametric Quantile Regression

Figure 7: Shift of Equilibria in Asset Along Distribution

path, while Figure 7b shows that both paths have (statistically) the same equilibrium.[34] Figure 7 indicates that households in the lower percentiles of the income distribution have a lower equilibrium asset level in the later period, while households in the higher percentiles of the income distribution do not. This phenomena may be related to the appearance of bifurcation of the economy in rural Ethiopia from 1999 to 2004. In addition, the lower growth rate of the lower percentiles from 1999 to 2004 as seen in Figure 6a may drive the result that 1999 to 2004 asset dynamics of the 25th percentile quantile regression has a lower equilibrium than 1994 to 1999 dynamics as seen in Figure 7a.

In conclusion, the evidence indicates that there was not only a pro poor growth in rural Ethiopia but also transition of the economy from a unimodal distribution of the structural income to a bimodal distribution. We note that the decrease in growth rates during the time interval from 1999 to 2004, relative to the interval from 1994 to 1999, negatively affects the lower income households, but not the higher income households.



(a) Local Linear Regression

(b) Bayesian Spline

Figure 8: Comparison of Equilibria across Farming System Regions

6.3 Comparison of Equilibria among Farming System Regions

To find a candidate region suffering from a regional stagnation, we estimate $A_{it} = m(A_{it-1}) + \varepsilon_i$ at each farming system region by both local linear regression and Bayesian spline that we used in the previous section.[35] Figure 8a and 8b shows asset dynamics across the three farming system regions. The enset growing area has the lowest single stable equilibrium and their dynamics are distinguished from the other areas' statistically significantly.[36] From the partial linear mixed model, we also observe that the enset growing area has the lowest equilibrium. The results are shown in Figure A4-5 in the Appendix. All the estimation methods above indicate that the enset area has the lowest equilibrium, around 1.7 livelihood-weighted asset index units. Translating this number into Purchasing Power Parity (PPP) provides \$1.18 per day.[37]

6.4 Regional Stagnation: The Enset Area

We find that rural Ethiopia has been in the process of evolving in terms of the structural income distribution. By estimating the cross-section models over time, we have observed the shift of short-term equilibria in the case of using all information of the areas we study in section 6.2. In addition, we find that the enset area has the lowest equilibrium among the three regions as

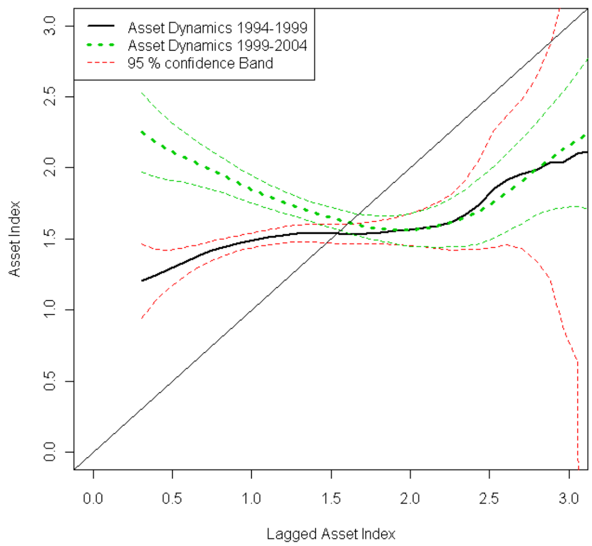


Figure 9: Shift of Asset Dynamics: the Enset Growing Area

in section 6.3.

Comparing results from each period to period transition, we find that equilibria are not statistically significantly different in the enset area (see Figure 9). By contrast, Figure 5a and Figure 4 using the full data implies different equilibria over time, and evolution of asset distribution, respectively.[38] The enset growing area is the most deprived area, which has poor environments to grow most crops. Moreover, the institutions of Ethiopia hinder households' mobility between regions as mentioned previously.[39] After crossing the 45 degree line, their dynamic paths overlap. Before crossing the 45 degree line, the dynamics differ due to the pro poor growth in rural Ethiopia in the 1994-1999 period. Even though the dynamics of the poor groups differ, both the 1994 to 1999 and 1999 to 2004 dynamic paths have a statistically identical single stable equilibrium. We may interpret this stability of the equilibrium as implying a regional stagnation.[40] Moreover, the implied equilibrium of around 1.7 is lower than $1.25 a day in Purchasing Power Parity.[41]

In conclusion, we find that the decrease in the growth rates affects the lower income households negatively, but not the higher income households. In addition, we find that the most deprived area is in a regional economic stagnation.

7 Concluding Remarks

This paper has presented three ways to characterize the existence of a poverty trap: as inferior outcomes in multiple equilibria environments; as impoverished single equilibria; and more generally as a sequence of low income equilibria without a positive trend. The recent literature has concentrated almost exclusively on the first characterization (multiple equilibria). Low-income single equilibria are another traditional way of thinking about poverty and also add value. The third characterization (a sequence of implied equilibria) has not been introduced in the previous literature. We employed household survey data from rural Ethiopia to investigate the presence of poverty traps according to each of these characterizations.

Examining the first five-year period, we find strongly pro poor growth. Indeed, this was one reason for our selection of these data to study poverty dynamics. In some contrast, the second five years evidenced reduced growth, with weaker evidence of pro poor growth.

In this research, unlike a number of previous studies, we found only very limited evidence of multiple equilibria utilizing the nationally representative rural sample as a whole. With our battery of tests, we would certainly have identified the second (or additional) equilibria if it were present. This is not due to oversampling of very poor people; the data set comprise a random sample of households in the region. On the other hand, rural Ethiopia is a very poor environment, so there may be very few or no observations of income levels high enough for the higher equilibrium to "form" (or to emerge empirically). But, as incomes rise a second, higher equilibrium may emerge. In fact, some intriguing evidence that this is a possibility was found when we split the sample into two equal time periods. We present evidence of a shift toward a bimodal asset distribution consistent with the emergence of multiple equilibria (and indeed an examination of comparative growth rates is suggestive that a second equilibrium is indeed in the process of formation). In particular, using nonparametric bootstrap methods over the second five-year period, we find two statistically significant stable equilibria. These findings open up a new avenue for research on the dynamic nature of changes in equilibria over time, and indeed the potential opening up of additional equilibria in the process of structural transformation, or of the transition of regions out of structural poverty and into new opportunities for improved livelihoods.

The decrease in growth rates in the second time interval may differentially affect the dynamics of the poor households. We adapt nonparametric quantile regression techniques and estimate 25th and 75th percentile quantile regressions. For the 25th percentile quantile regression, the equilibrium of the second time interval is lower and statistically different from the first time interval. In contrast, for the 75th percentile quantile regression, the equilibrium of the later periods is not statistically different from that of the earlier periods. Although we cannot demonstrate causality, this suggests that the decrease in growth rates during the time interval from 1999 to 2004, relative to the interval from 1994 to 1999, negatively affects only the poor, but not the non-poor, in the long run equilibrium.

Finally, we split the sample into three agro-ecological regions. We broaden the analysis to consider an extended poverty trap concept, in which implied equilibria are potentially shifting over time in general, but for a sequence of implied equilibria the poor remain in poverty throughout the sequence. We find that the most deprived region is (repeatedly) in a low-level stagnant equilibrium in this sense.

In sum, under an expanded range of poverty trap concepts, splitting the data into time intervals allowed improvements in the characterization of the dynamics of extreme poverty. Analyzing sequences of single but low equilibria, and allowing for shifts of dynamic income paths, highlighted a larger set of potential "poverty trap" conditions.

In fact, while more research is needed, the analysis provided hints that a mechanism for escape from structural poverty is the emergence of a second equilibrium when one had not existed previously.

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Appendix A

A1 Descriptive Statistics

Table A1-1: Descriptive Statistics

	Mean	Standard Deviation
Tropical Livestock Units	.6203018	.675447
Land (Hectare)	.3552366	.4073929
Education Years of Head	1.365327	2.537335
Age of Head	48.25934	15.61703
Male Head(=1)	.8029042	.3978405
Number of working age	2.933062	1.73045
Number of children	2.911103	2.01198
Number of oxen	.6514964	1.011109
Productive Asset Value	57.57634	383.2702
Transfer income[d]	9.277428	44.10967
Off-farm income(=1)	.440765	.4965228
Number of Crop Trees(Coffee, Enset, Eucalypts)	54.59048	222.4116
N	5647	

[a] Descriptive Statistics is for Parametric Regression in section B3

[b] All money values are adjusted to 1994 price.

[c] All assets are in terms of per adult equivalent units.

[d] Transfer income includes remittances, gifts, or other transfers.

Table A1-2: Inequality Measures from 1994 to 2004

	1994	1999	2004
Gini index	0.2799	0.2592	0.2510
Generalized Entropy: I(0)	0.1474	0.1224	0.1029
Theil's T: I(1)	0.1260	0.1079	0.0987
Coefficient of Variation	0.5059	0.4639	0.4600

[a] Source: ERHS 1994, 1999, and 2004.

[b] Based on estimated asset index, authors calculate it.

A2 Estimation Results

Table A2-1: System GMM Estimation

	Δ ln Consumption per adult	
Lag of ln Consumption per adult	-0.766**	(0.280)
Land per adult	0.0960+	(0.0522)
Livestock unit per adult	0.139**	(0.0321)
Education year of Head	0.0138	(0.00952)
Off-farm Income(=1)	0.0230	(0.0260)
Number of Enset	0.0000907**	(0.0000315)
Number of Eucalyptus	0.0000498**	(0.0000173)
Number of Coffee	-0.0000174	(0.0000423)
Gender of Head	0.0795*	(0.0384)
Age of Head	0.000384	(0.00797)
Squared Head Age	-0.0000185	(0.0000739)
Household Size	-0.0722**	(0.0119)
round 3(=1)	-0.325**	(0.0628)
round 4(=1)	0.0508	(0.0921)
round 5(=1)	-0.0536	(0.0453)
village 1(=1)	-0.151	(0.0962)
village 2(=1)	-0.275	(0.192)
village 3(=1)	-0.434*	(0.183)
village 4(=1)	-0.150*	(0.0737)
village 5(=1)	0.0529	(0.0556)
village 6(=1)	0.231**	(0.0596)
village 7(=1)	0.0279	(0.0695)
village 8(=1)	-0.245	(0.195)
village 9(=1)	-0.0530	(0.0911)
village 10(=1)	-0.571**	(0.215)
village 11(=1)	-0.369*	(0.169)
village 12(=1)	-0.277*	(0.117)
village 13(=1)	-0.462	(0.299)
village 14(=1)	-0.239	(0.176)
Constant	3.813*	(1.479)
N	4555	
AR(1) test		P-value=0.019
AR(2) test		P-value=0.475
Hansen J stat.	$\chi^2_{(4)}$=4.74	P-value=0.315

[a] Standard errors in parentheses

[b] Source: ERHS 1994a, 1995, 1997, 1999, 2004

[c] $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

A3 Figures

Figure A4-1: Asset Dynamics with Stationary Bootstrap Confidence Band

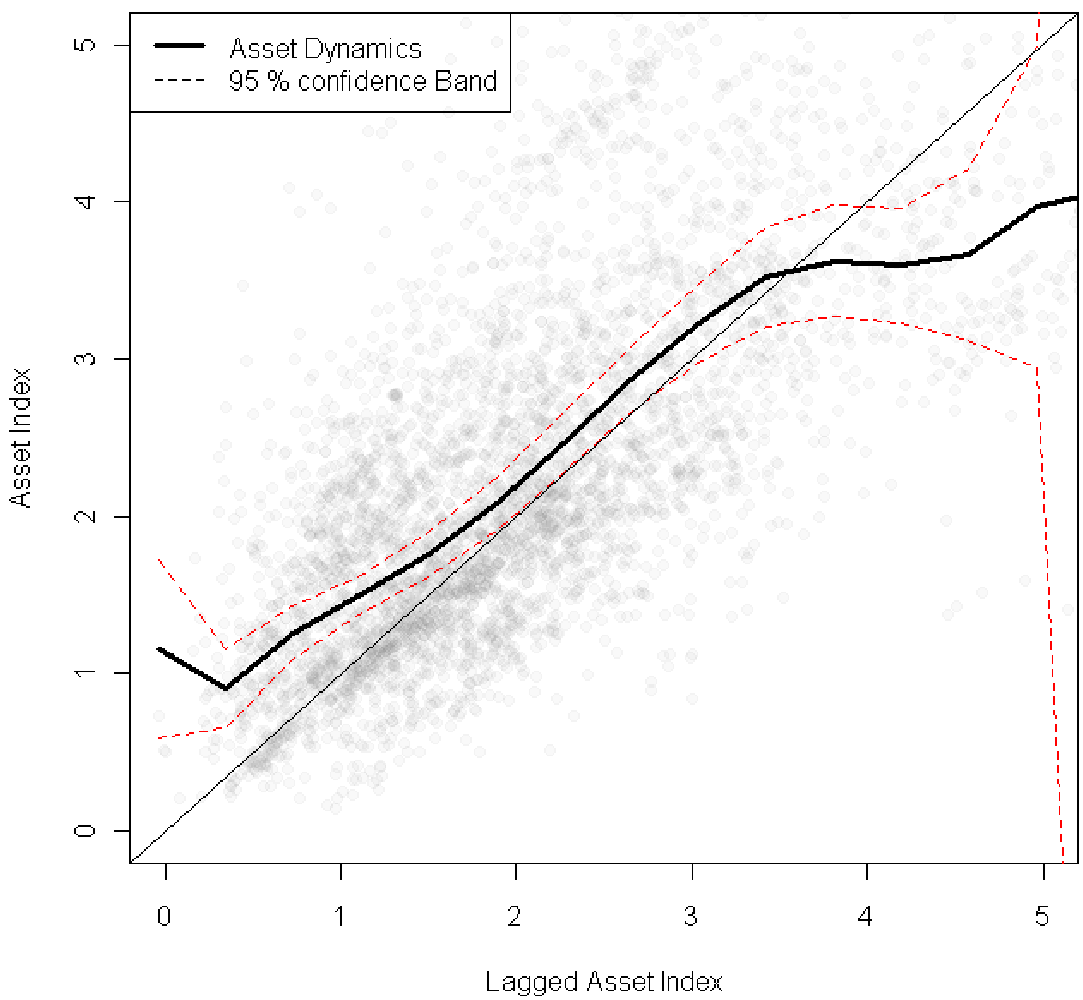


Figure A4-2: Simultaneous Confidence Band with Mixed Model

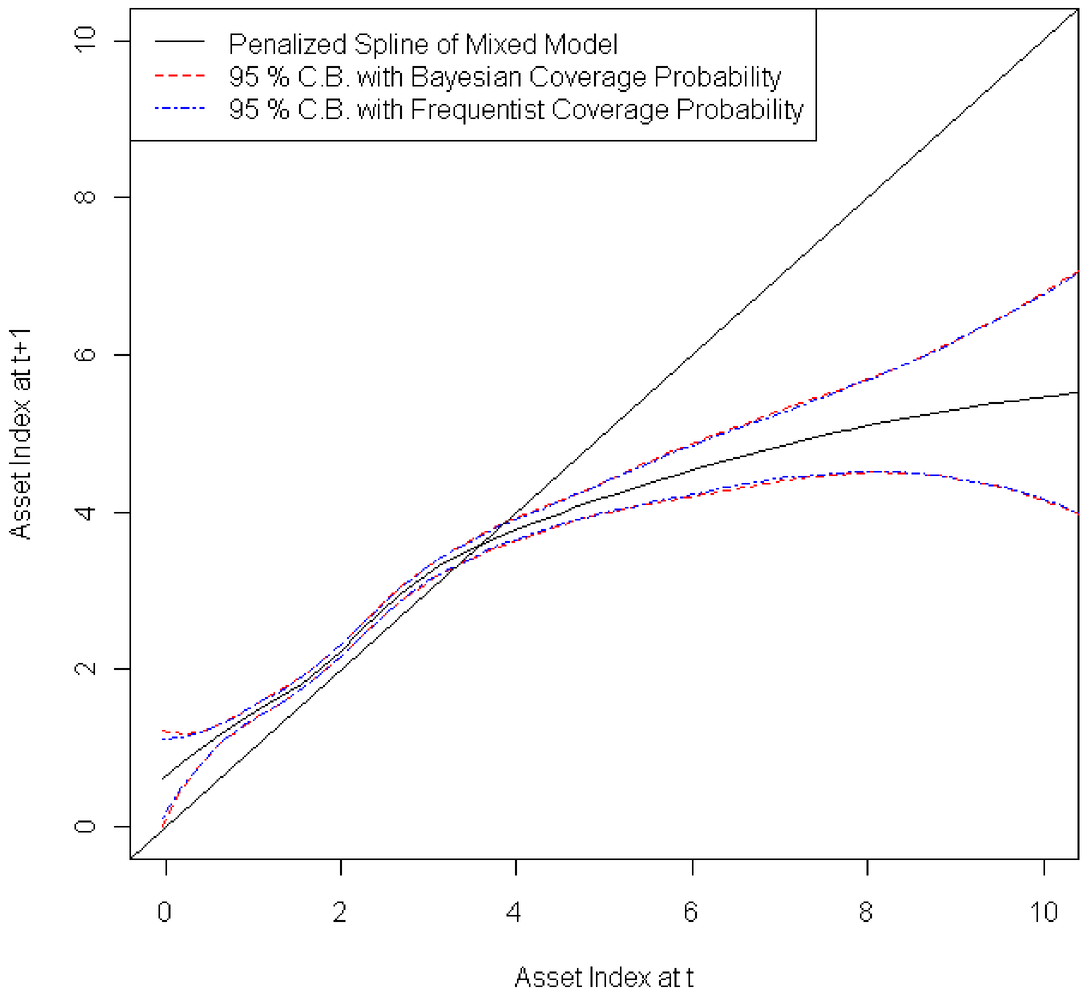


Figure A4-3: Shift of Asset equilibria with Explanatory Variables

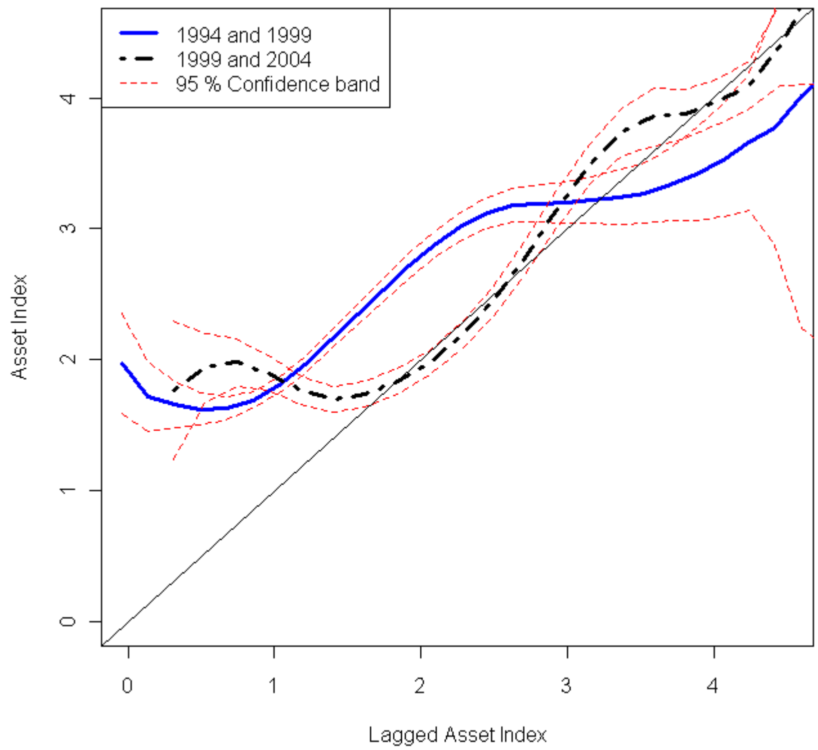


Figure A4-4: Asset Index Distributions by Regions for Round 1, 5, and 6

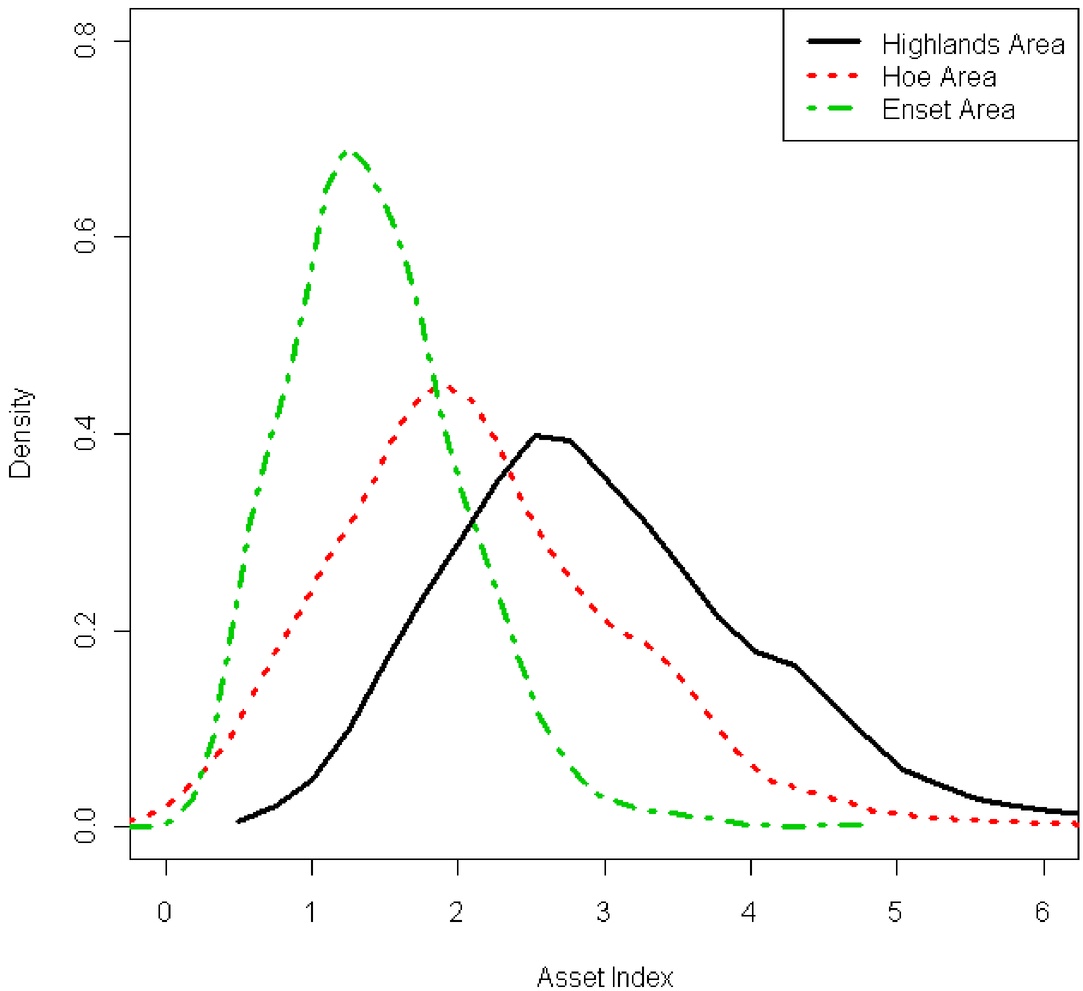


Figure A4-5: Farming System Region with Partial Linear Mixed Model

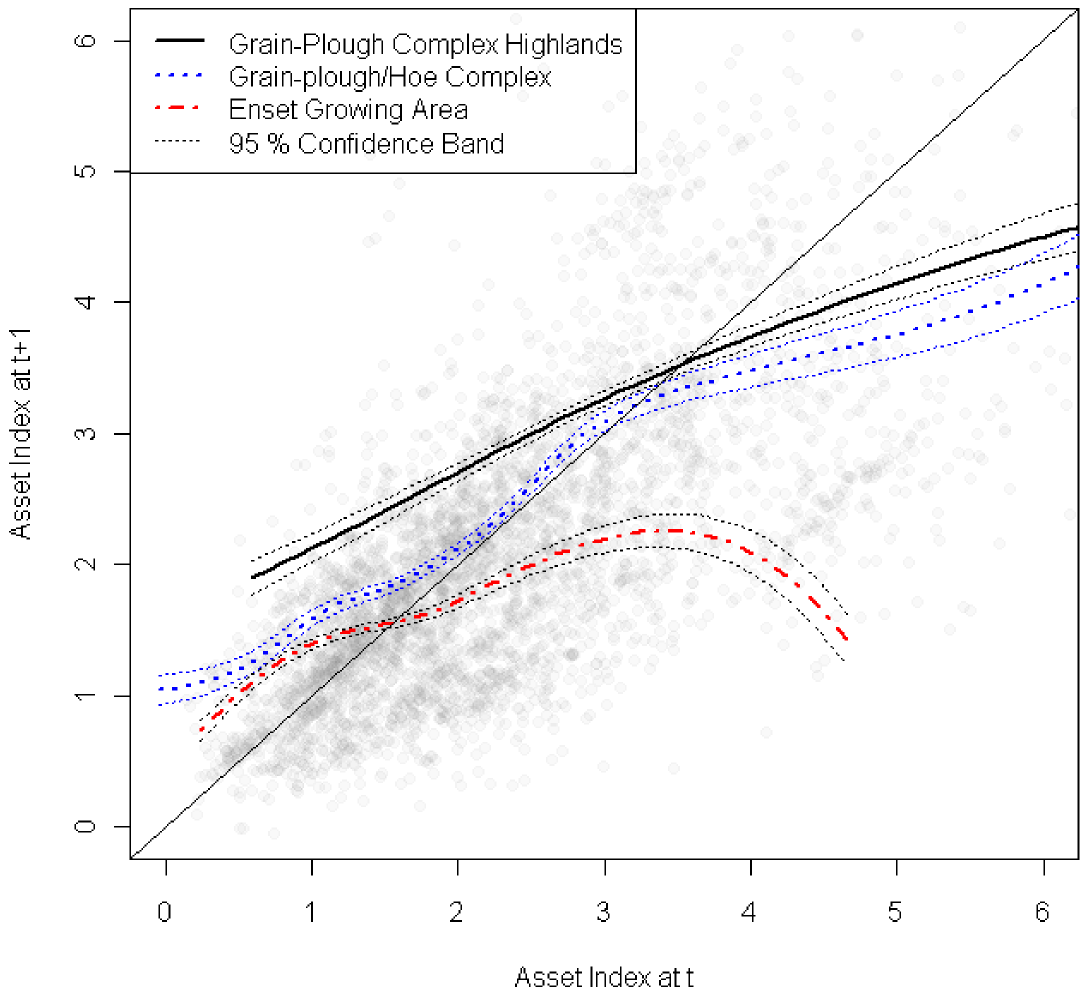
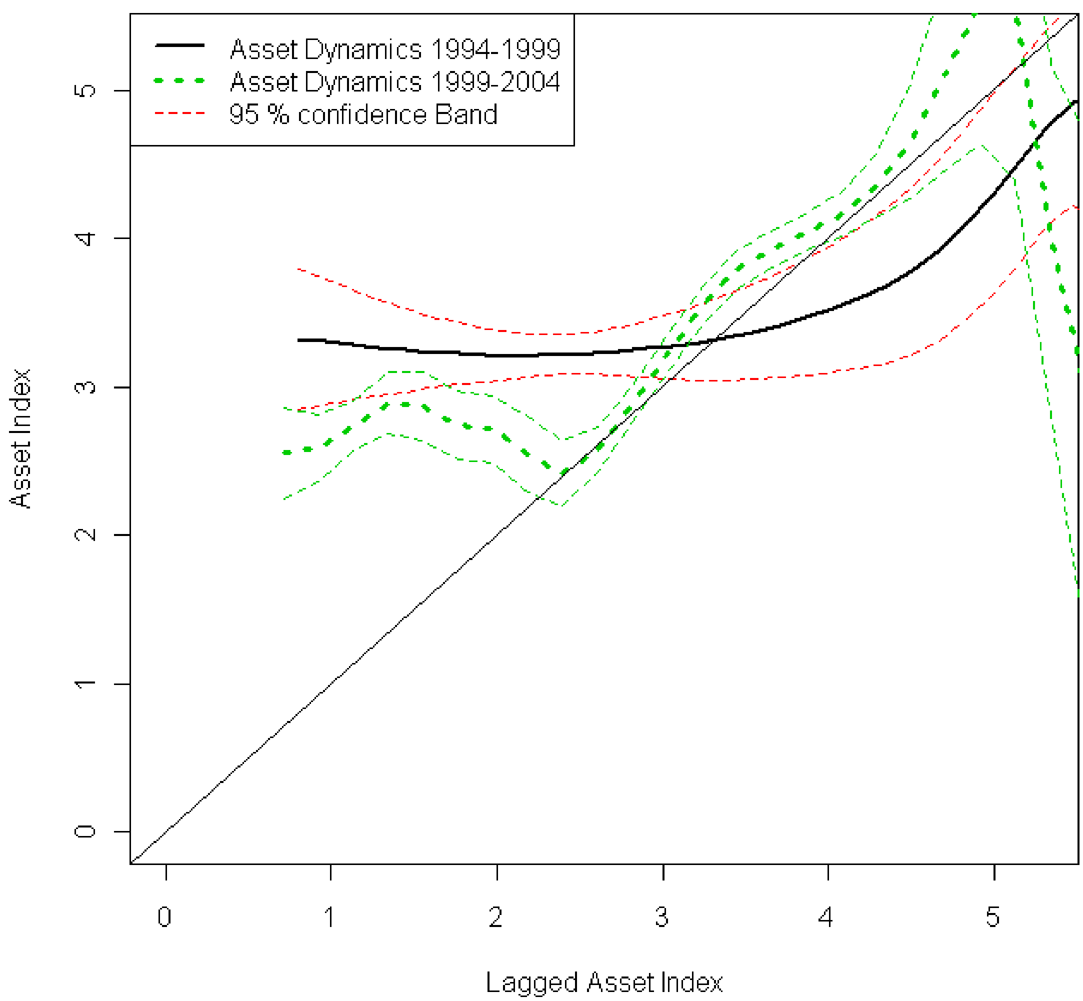


Figure A4-6: Shift of Asset Dynamics: the Highlands Area



Appendix B: Robustness Check

B1 Asset Dynamics with Bayesian Penalized Spline Smoothing

Penalized splines can be viewed as a Best Linear Unbiased Predictor (BLUP) in a mixed model framework . The pth degree spline model for the asset index is

$$A_{it} = \beta_0 + \beta_1 A_{it-1} + ... + \beta_p A_{it-1}^p + \sum_{k=1}^{K} u_k (A_{it-1} - \kappa_k)_+^p. \tag{4}$$

Since the function $(A_{it-1} - \kappa_k)_+^p$ has $p-1$ continuous derivatives, higher orders of p lead to smoother spline functions.[42]

Penalized Spline provides automatic smoothing parameter choice via restricted maximum likelihood (REML) estimation of variance components. It also allows for combination of smoothing with random effects for longitudinal data. An advantage of the penalized splines over other splines is that it avoids the roughness of the fit because it constrains the knots' influence.

As usual, confidence bands for nonparametric regression requires us to see if the bands are centered properly.[43] Here we use Bayesian inference because the bias from measurement error can be automatically adjusted from the Bayesian framework as shown in Berry et al. (2002). Also the smoothing parameter λ is automatically selected, which is also helpful to resolve the bias from measurement error.[44] Hence, we adapt Bayesian inference for penalized spline regression.

Krivobokova et al. (2009) propose "simultaneous Bayesian credible bands" derived from MCMC simulation output. In this framework, we use truncated line basis with degree 2. Consider the regression model

$$y_i = \beta_0 + \beta_1 x + \sum_{k=1}^{K} u_k (x - \kappa)_+^2 + \varepsilon_i, \tag{5}$$

where ε_i are $i.i.d.N(0, \sigma_\varepsilon^2)$ and $\theta = (\beta_0, \beta_1, u_1, ..., u_K)^T$ is the vector of regression coefficients, and $\kappa_1 < \kappa_2 < ... < \kappa_K$ are fixed knots. The following priors are assigned to the error variance σ_ε^2 and the prior variance σ_θ^2: $\sigma_\varepsilon^2 \sim IG(0.001, 0.001)$ and $\sigma_\theta^2 \sim IG(0.001, 0.001)$.[45] The construction of Bayesian credible bands is based on the posterior distribution and the

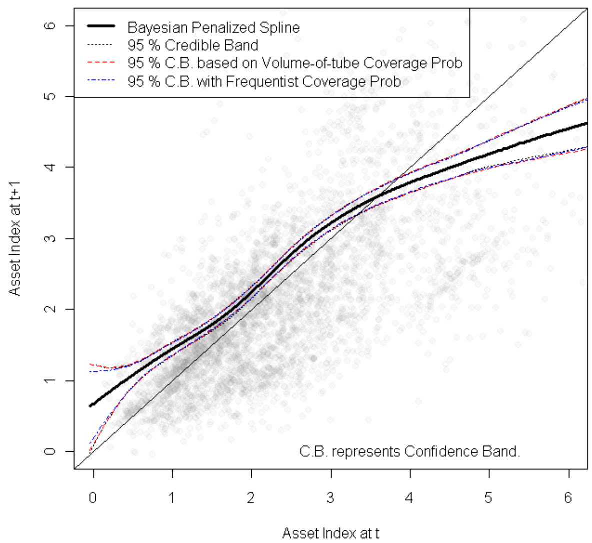


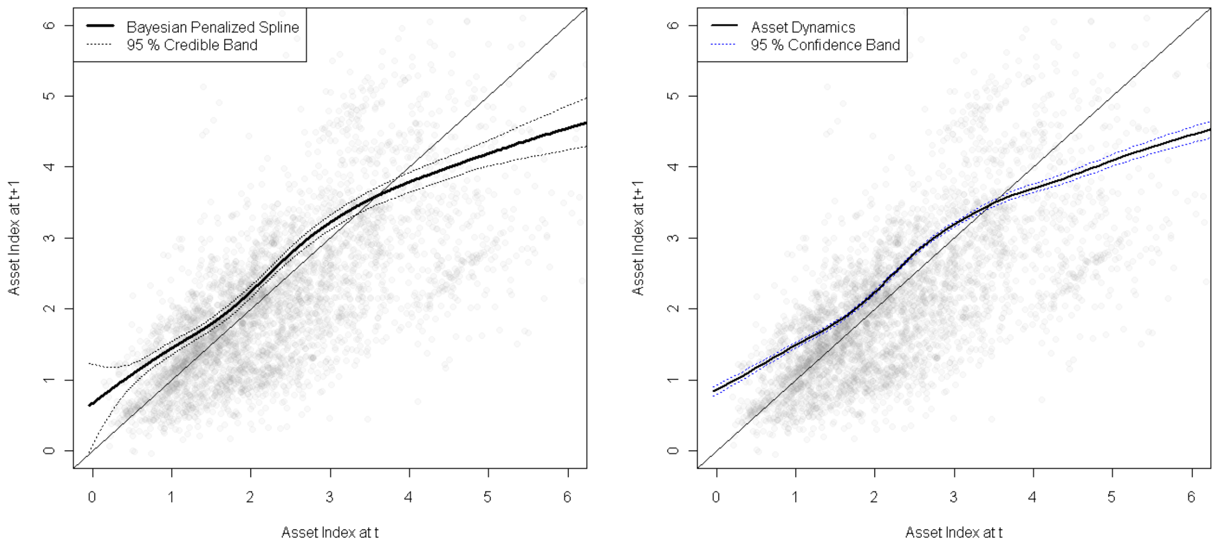
Figure B1-1: Simultaneous Confidence Bands for Penalized Splines

confidence region I_α is defined in terms of the posterior distribution of $\mathbf{f} = f(x_1), ..., F(X_N)^T$, given the observed data Y, that is, $P_{\mathbf{F}|Y}(\mathbf{f} \in I_\alpha) = 1 - \alpha$. Their simultaneous credible band does not depend on a specific point estimator due to the full utilization of the posterior sample information while Crainiceanu et al. (2007) fail to use the full posterior distribution information contained in the sample.[46] In addition, they find that the results from the volume of tube formula for the mixed model formulation of penalized splines are nearly identical to the fully Bayesian framework, but with considerably less computational costs.[47]

Figure B1-1 shows the confidence bands from the different several approaches. They are quite similar, although the frequentist confidence band (CB) is a little narrower than the Bayesian credible band. Since the Bayesian inference is known as most conservative, we will adapt Bayesian inference in the bivariate case. Figure B2-1a shows the Bayesian penalized spline with 95 % credible band, which conforms to the nonparametric local linear regression results in Figure 3a. Thus we treat this approach as a method to robustness check.

B2 Asset Dynamics with a Partial Linear Mixed Model

The studies on the nonparametric estimation of panel data models have been rare. This is due to the invalidity of first-difference to remove individual specific effects. Instead of a nonpara-



(a) Bayesian Spline without covariates

(b) Random Effect Mixed Model

Figure B2-1: Spline Regression

metric approach, in this case we use a partially linear model with random effects. This model is considered "semiparametric" because the model has both parametric components, T_{ij} and X, and a nonparametric component, $f(A_{it-1})$. Here, the T_{ij} represent time dummies taking account of time specific effects and X represents our explanatory variables.

$$\begin{aligned} A_{it} &= \beta_0 + U_i + X\alpha + \sum_{t=3}^{T} \beta_t T_{it} + f(A_{it-1}) + \varepsilon_{it}, \quad 1 \le i \le N, \quad 2 \le t \le T \\ U_i &\sim_{iid} N(0, \sigma_u^2), \quad \varepsilon_i \sim_{iid} \quad N(0, \sigma_\varepsilon^2), \end{aligned}$$

where U_i is a random household effect and X includes gender of head, age of head, illiteracy status, and household size.[48]

Figure B2-1b shows the results of partial linear model with explanatory variables. We find the existence of a single stable equilibrium, which is the same finding as our other estimation methods. One of advantages comparing to nonparametric model is that this method allows us to have point estimates of explanatory variables. Table B2-1 reports the coefficients of the linear part of model. The coefficient of illiteracy trap status is marginally significantly negative on income. Household size significantly affects negatively at any conventional level, while age of head affects positively.

Table B2-1: Partial Linear Mixed Model: All Samples

	Coefficient	S.E.
Intercept	0.9721**	(0.074650)
Round 3(=1)	0.1293**	(0.039550)
Round 4(=1)	0.1196**	(0.040190)
Round 5(=1)	0.1224**	(0.041380)
Illiteracy Trap(=1)	-0.0599+	(0.031680)
Household Size	-0.0559**	(0.005424)
Male head(=1)	-0.0447	(0.039430)
Age of Head	0.0034**	(0.001014)

[a] Standard errors in parentheses

[b] Number of Knots is 34.

[c] Source: ERHS 1994a, 1995, 1997, 1999, 2004

[d] + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

B3 Parametric Estimation Approach for Consumption

We explored asset dynamics using estimated asset index (structural income) in the previous section. However, many studies in various applications have either examined consumption or income flow dynamics (Jalan and Ravallion, 2001, 2002; Lokshin and Ravallion, 2004; Dercon, 2004). Since it is widely argued that consumption is usually measured with less error than income, we estimate consumption dynamics to examine whether a single equilibrium exists in rural Ethiopia using the dynamic fixed effect Generalized Method of Moment(GMM) model.[49] Since most panel data have small T, Jalan and Ravallion (2001, 2002) and Lokshin and Ravallion (2004) use GMM estimators in allowing for nonlinear income dynamics in a cubic function of the lagged dependent variable.[50]

$$y_{it} = \beta_0 + \beta_1 y_{it-1} + \beta_2 y_{it-1}^2 + \beta_3 y_{it-1}^3 + X\alpha + u_i + e_{it}, \tag{6}$$

where y represents consumption per adult and X is a set of household characteristics.[51]

However, a finding nonlinearity of income does not guarantee there is multiple equilibria. For a given income mapping $y_{it} = f(y_{it-1})$ of the cubic specification, the sufficient condition for the existence of poverty trap based on the threshold model is

$$f_i'(y_{it-1}|_{y_{it}=y_{it-1}}) > 1, \tag{7}$$

where y is consumption per adult. If this condition is satisfied, we may observe multiple equilibria. This property has a root in the macro growth model. Hence, Equation (7) can be explained by the following specification, which is also used by Jalan and Ravallion (2002) and Dercon (2004), to see whether an equilibrium is converging or bifurcating.

$$\ln y_{it} - \ln y_{it-1} = \beta_0 + \beta_1 \ln y_{it-1} + X\alpha + u_i + e_{it}, \tag{8}$$

where y represents consumption per adult and X is a set of household characteristics including gender of head, age of head, age squared, household size, hectares of land owned (de facto), livestock units, head education year, an off-farm income dummy, and number of main trees. We also include time dummies and location dummies to control for the time and location specific effects respectively. With $\hat{\beta}_1 < 0$ the dynamics are converging. But the dynamics are diverging with $\hat{\beta}_1 > 0$.

Descriptive statistics of data used in this estimation are reported in Table A1-1 in the Appendix. Tropical Livestock Units (TLU) are small since the survey covers non-pastoral areas. The average education of the household head is very low, about 1 year. Table A2-1 in the Appendix reports the estimates from system GMM. All explanatory variables and the dependent variable are adjusted into per adult equivalent units. The coefficient of lag of consumption per adult is significantly negative, which implies that the consumption dynamics converge to a single stable equilibrium. We find that consumption dynamics are significantly determined by the amount of assets including land, trees, and livestock units.

Parametric GMM IV estimation might be of value in our context. However, the weak instrumental variable problem can appear when the observed data are highly persistent as in Blundell and Bond (2000). As a result, the lagged values of the variables are weakly correlated with the difference regressors. Hence, it is important to confirm whether the lagged instrumental variables are valid when using the differenced GMM proposed by Arellano and Bond (1991). In addition, Bun and Windmeijer (2010) show that the system GMM proposed by Blundell and Bond (2000) may not be free from a weak instrument problem under conditions that the variance of the unobservable individual specific effects and idiosyncratic errors are the same in the covariance stationary panel data AR(1) model. Moreover, due to the bifurcation characteristics of unstable equilibria, the observations near an unstable equilibrium may not be picked up by the polynomial, as Barrett (2005) and Naschold (2009) point out, but instead they enter as positive autocorrelated or heteroscedastic error.

In addition, they have two intrinsic limitations though parametric estimations are reasonable as far as they go. The estimation results above may obscure the income dynamics for households located in the lower tails of the income distribution since all estimation results are just evaluated at the conditional mean. The conditions of the lower income households below the mean cannot be easily captured. Moreover, parametric estimations lose the flexibility of the functional shape, while nonparametric estimations do not. Although most previous literature finds nonconvexity of income and consumption dynamics using polynomial parametric models, some part of the dynamics may not be nonconvex. Nonparametric estimation helps to avoid parametric functional shape constraints. Hence, we are using non/semi-parametric regression and nonparametric quantile estimation method as a vehicle to explore the asset dynamics as experienced by the households in the lower tails of the income distribution.

Notes

[1]The asset index enables a reduction of dimensions. We compare results with changes in consumption dynamics between time intervals in section 6.2.

[2]We adapt alternative estimation methods utilizing the GNU Software R for statistical computing and graphics using ConfBands (Krivobokova et al., 2009), np (Hayfield and Racine, 2010), plm (Croissant, 2010), quantreg (Koenker, 2009), and SemiPar (Wand et al., 2005) packages.

[3]Our aim is not to find the cause of the geographic trap. Instead, we examine features of an economy (Ethiopia in our case) in which regions may be in a stagnation, while other regions are showing growth.

[4]Under the assumption that labor productivity and earnings are zero at a low but positive level of consumption, the worker will be productive only if consumption rises above a threshold level.

[5]The household is only willing to give up current consumption to invest if its income exceeds a critical threshold level.

[6]There exist other explanations of poverty traps such as dysfunctional institutions (Bowles, 2006), neighborhood effects (Borjas, 1995; Sampson and Morenoff, 2006), incomplete markets including household and government impatience (Azariadis, 2006), kin systems (Hoff and Sen, 2006), and social interaction effects such as peer and role model effects (Durlauf, 2006).

[7]If a bandwidth approaches to ∞, the estimates are represented by a straight line.

[8]According to International Monetary Fund's World Economic Outlook Database, purchasing power parity per capita income of Ethiopia is $360 in 1994. By 2004, the purchasing power parity income per capita had risen to $560.

[9]We exclude Round 2 primarily due to problems of comparability. The survey was conducted in the Bega (long dry) season (in 1994/5). Seasonal analysis using the panel revealed rather large seasonal fluctuations in consumption, seemingly linked to price and labor demand fluctuations (Dercon and Krishnan, 2000a,b; Dercon, 2004). In Round 4, six villages were also surveyed in the Bega period.

[10]According to Dercon and Hoddinott (2009), the Westphal (1976) and Getahun (1978) classifications are used to divide Ethiopia into agro-ecological zones based on the main farming systems.

[11]The regional borders of the map are drawn by package "*maptools*" in R using the data of Global Administrative Areas from " `http://www.gadm.org`". The regions are based on prior research on Ethiopia; see Dercon and Hoddinott (2009, p.9).

[12]In addition, this area includes Doma, which is resettlement area.

[13] Dercon and Ayalew (2007) use the Ethiopia Rural Household Survey (ERHS) between 1994 to 2004 to examine whether land rights affect household investment decisions.

[14] Barrett et al. (2006) note that under serially independent stochastic components, poor draws in one period are offset by better draws in subsequent periods and vice versa; moreover, stochastic incomes are likely to exaggerate income inequality in cross sectional analysis; finally, using current income may generate spurious economic mobility in longitudinal analysis.

[15]Following Adato et al. (2006), we estimate the following equation:

$$\Lambda_{ivt} = \sum_j \beta_j (A_{ijvt}) + \sum_{j,k} \beta_k (A_{ijvt})(A_{ikvt}) + \sum_j \alpha_j H_{ijt} + \sum_{v,t} \delta_v (\Psi_v)(\Upsilon_t) + \sum_v \phi_v \Psi_v + \sum_t \gamma_t \Upsilon_t, \tag{9}$$

where Λ_{ivt} is household consumption expenditure divided by the money value of the household's subsistence needs. We use a value of 50 Birr per month per adult: Dercon and Krishnan (1998, p.10) calculated the average food poverty line using the ERHS price survey for 1994 as 40.7 birr per adult equivalent unit; consumption is adjusted to the 1994 price. The dependent variable equals one if consumption exactly equals the poverty line. The coefficients of the regression give the marginal contribution to livelihood of the j different assets. A_{ivt} includes the key asset variables–human capital (education year of household head) and productive capital (hectare of land, tropical livestock units, total number of crop tree, and value of productive assets) per adult, where the adult equivalent unit is adopted from Table A.5 of Dercon and Krishnan (1998, p.44). The regression includes household characteristic variables, H_{it}: gender of head and age of head. In addition, all asset variables are second order polynomially expanded and interacted. To control for location and time specific effects, village and time dummies are included. In addition, the interacted terms of time dummies and village dummies are included to control for village specific transitory effects.

[16]Before applying local linear regression following the tradition in the previous literature, we test the null hypothesis that the following parametric linear model, (10), is correctly specified using the consistent model

specification test described in Hsiao et al. (2007) that admits both categorical and continuous data. Most previous studies with a parametric estimation method use third degree polynomial function of parametric method (see, for example, Jalan and Ravallion (2004) and Lokshin and Ravallion (2004)). Barrett et al. (2006) use a 4th degree polynomial function.

$$A_{it} = \beta_0 + \beta_1 A_{it-1} + \beta_2 A_{it-1}^2 + \beta_3 A_{it-1}^3 + \beta_4 A_{it-1}^4 + X\alpha + \epsilon_i, \tag{10}$$

where X includes age of head, household size, and gender of head. This linear model is rejected by the data (the test statistic J_n is 11.65779 and the p-value for the null of correct specification is 0.00, which is estimated by 400 bootstrap replications.). Hence we estimate this relationship using kernel methods. In the traditional nonparametric approach including plug-in rules for bandwidths, the presence of qualitative variables requires splitting of data into subsets containing only the continuous variables of interest because general formulas are not available from the plug-in rules for mixed data. However, in our analysis we do not have to split the sample as we adopt the cross-validation approach recently proposed by Hall et al. (2004) and Li and Racine (2004). Thus our estimation provides an efficiency gain from the sample size over previous research using a split sample.

[17]Here we use fixed type bandwidths, which are constant over the support of the variables. The fixed type bandwidths of asset index, age of head, gender of head, and household size for asset index dynamics are respectively: 0.3429, 3.5533, 0.25, and 1.8770. The total number of observations used are 4,400 ; and the adjusted R-squared is 0.5635.

[18]Likelihood cross-validation (LCV) results in estimates that are close to the true density in terms of the Kullback-Leilber information distance $\int f(y|x) \log \frac{f(y|x)}{\hat{f}(y|x)} dy$ where $f(y|x)$ represents the conditional density function. Details are found in Silverman (1986, pp.52-55).

[19]We use 500 replications. We also estimate confidence band based on Politis and Romano's (1994) stationary bootstrap to take care of "cross correlation". The results are reported in Figure A4-1 in the Appendix.

[20]The 6 Birr per adult per day is computed based on household consumption expenditure divided by the money value of the household's subsistence needs. We set 50 Birr as the subsistence needs when we estimate a livelihood asset index. That is, the implied consumption expenditure per adult at equilibrium is 3.6×50=180 Birr per month. Each adult equivalent unit consumes $1 per day using an annual official exchange rate, which is about 6 birr per dollar in 1994 according to the IMF *International Financial Statistics*. In 2004, the rate was 8.65 birr. Using World Bank purchasing power parities (PPP) conversion factors (http://www.worldbank.org/data), 2.4 Birr is equal to $1 in 1994. Thus, the long-run equilibrium represents $2.5 in terms of PPP. As can be seen in Figure 3a, most current incomes are far below this equilibrium value.

[21]Adaptive nearest-neighbor bandwidths change with each sample realization in the set, x_i, when estimating the density at the point x. Using an adaptive nearest neighbor bandwidth type helps avoid undersmoothing in some part of the range and oversmoothing in another, but the computational time burden is very heavy.

[22]The three areas are the grain-plow highlands, the grain-plow/hoe complex, and the enset growing area, as shown in Figure 2. A regional stagnation means that a region is in stagnation, even if other regions are not.

[23]Following Maasoumi et al. (2007), by modelling the joint distribution of asset index and year and then conditioning on year, we obtained a kernel density estimate having improved finite sample properties relative to the traditional univariate kernel density using the split subset of the data.

[24]There is an analogy here to a typical income growth regression such as applied to cross-country growth studies by Barro (1991).

[25]Confidence bands are estimated by 500 bootstrap replications.

[26]Again there is an analogy to the development of a national economy. Azariadis and Stachurski's (2003; 2005) conclude that the long-run income distribution is unimodal, but that bimodality appears during the transition. We observed that the distribution of asset index has bimodality in the previous section 6.1.

[27]As a robustness check, we estimate the specification with control variables. Figure A4-3 in the Appendix shows the asset dynamics, in which we control for the average of age of head and household size between the two periods, and gender of the household head. The estimated results show essentially the same pattern.

[28]The growth incidence curve (GIC) proposed by Ravallion and Chen (2003) calculates the growth rates in consumption per capita at each percentile point along the consumption distribution.

$$g_t(p) = \frac{y_t(p) - y_{t-n}(p)}{y_{t-n}(p)}, \tag{11}$$

where $g_t(p)$ is the growth rate in expenditure y of the pth percentile between t and $t-n$. If the growth rates are positive at all percentiles up to some poverty line z, then poverty has fallen for all poverty lines up to z and growth has been pro poor up to point z. The rate of pro poor growth is defined as the area under the GIC up to point z. We obviously face a higher rate of pro poor growth if the GIC shifts upward at all points along the expenditure distribution up to point z. Hence, the rate of pro poor growth represents the absolute expenditure or income growth of the poor.

[29]This is noted by Dercon (2000, pp. 18-19) and Geda et al. (2009, pp. 964-966).

[30]Note: Confidence bands are computed by 1000 bootstrap replications.

[31]Inequality measures in Table A1-2 indicate a decrease in inequality, which may be attributed to the relatively higher growth for the poor.

[32]The previous literature (Yu and Jones, 1998; Honda, 2000) does not include discrete components as explanatory variables. Also He, Ng, and Portony (1998) and He and Ng (1999) examine nonparametric quantile estimation using smoothing splines. The spline method is much faster than kernel methods in computing time while it is hard to get data driven smoothing parameters in an additive spline quantile model by minimizing Schwarz Information Criterion (SIC) (Koenker, 2010, p.15).

[33]Details are in Li and Racine (2008, pp.6-7).

[34]We use a fixed type of bandwidth, which is estimated by likelihood cross-validation (LCV), utilizing a Gaussian kernel. In addition, we don't estimate the bootstrap confidence band of the 1999 to 2004 path because it already passes through the confidence bands of the 1994 to 1999 path.

[35]For simplicity, we do not include the explanatory variables.

[36]The confidence bands are also estimated by 500 bootstrap replications in the local linear case. The Bayesian credible band is estimated using 20,000 sampling and 2,000 burn-in.

[37]We use the same conversion factor as in endnote 20.

[38]Fixed type bandwidth are selected by likelihood cross-validation. We use lag of asset index, age of head, gender of head, and household size as explanatory variables. Bandwidths are 0.3284975, 9.2659938, 0.2495202, 2.5481930 respectively in the 1994 to 1999 path. The 1999 to 2004 path uses the same methods.

[39] Jalan and Ravallion (2002) also point out that a reason of a geographic poverty trap is "restrictions on labor mobility."

[40]As a robustness check, we explore whether the dynamics of other areas also converge to the same equilibrium over time or not, estimating the same model above for the highlands area. The estimated dynamics are in Figure A4-6 in the appendix, which provides different dynamics from Figure 9 for the enset area. The results also support that only the enset area has experienced a regional stagnation among other areas.

[41]The implied equilibrium is approximately \$1.18 a day in terms of PPP.

[42]Detailed explanations are found in Ruppert(2003) p.108-110.

[43]Thus, most researchers use bootstrap or Bayesian inference.

[44]Berry et al. (2002) concluded that, "measurement error has large effects on both bias and variance, and a smoothing parameter that is optimal for correctly measured covariates may be far from optimal in the presence of measurement error."

[45]The prior distribution of β_0, and β_1 is centered at zero with a standard error equal to 1000. The parametrization of the Gamma(a, b) distribution is chosen so that its mean is $a/b = 1$ and its variance is $a/b^2 = 10^3$.

[46]The advantages of their approach are found in Krivobokova et al. (2009, pp.8-10).

[47]The volume of tube formula is found in Krivobokova et al. (2009, pp.10-11).

[48]We also estimate the same specification without explanatory variables. The estimated results are shown in Figure A4-2 in the Appendix. The Bayesian band (dashed red line) is a little wider than frequentist (dashed dotted blue line). The difference is ignorable.

[49]The dynamic fixed effect GMM estimation, proposed by Arellano and Bond (1991) and Arellano and Bover (1995), has three advantages: first, when time invariant village or household characteristics may be correlated with the explanatory variables, the unobservable household fixed effects can be removed; second, when a lagged dependent variable causes autocorrelation, the first-difference lagged dependent variable can be used as instrumental variables for its past values; and third, usual panel dataset has small time (T) dimension and a large individual (N) dimension. In panel data with large T a shock to a village specific effect will decline with time so that the GMM estimator does not provide much gain in efficiency.

[50] Lokshin and Ravallion (2004) point out that Arellano and Bond (1991) and Arellano and Bover (1995) fail to control for panel attrition, which may well be endogenous to the shocks and household characteristics. Fortunately, ERHS has a small attrition rate of about 5% each round. Dercon and Hoddinott (2009) point out that small attrition is likely due to the fact that households cannot obtain land when moving to other areas.

Moreover, results from Lokshin and Ravallion (2004) indicate that estimates of nonlinearity in income dynamics for Russia and Hungary are robust to allowing for endogenous attrition.

[51]In addition, following the specification of Jalan and Ravallion (2001) and Lokshin and Ravallion (2004), Antman and McKenzie (2007) point out that one cannot obtain consistent estimates of β_1, β_2, and β_3 with measurement error in income. Antman and McKenzie (2007, pp. 1061-1063) present how inconsistent estimates are produced with large measurement errors in income. Plausibly, the ERHS has relatively small measurement errors because the recall periods of the questions in the questionnaire is relatively short and there is time for close attention of surveyers.