Institute for International Economic Policy Working Paper Series
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Multidimensional Poverty and Interlocking Poverty Traps: Framework and Application to Ethiopian Household Panel Data

IIEP-WP-2011-04

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June 10, 2011

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*Send correspondence to ssmith@gwu.edu. We would like to thank Shahe Emran, James Foster, John Hoddinott, Takashi Kurosaki, Travis Lybbert, and participants at the Northeast Universities Development Consortium Conference at MIT (Nov. 2010), and seminars at GWU, Korea Institute for International Economic Policy (KIEP), Korea Institute for Industrial Economics and Trade (KIET), and Samsung Economic Research Institute (SERI) for valuable comments. Research support from the Institute for International Economic Policy at GWU is gratefully acknowledged.

Abstract: This paper examines the impact and potential interactions of health, education and consumption dimensions of persistent poverty at the household level. Our application is to indictors of assets, undernutrition, and illiteracy drawn from the Ethiopia Rural Household Survey (ERHS) panel data set. We develop a framework for operationalizing the concept of multidimensional traps, involving two or more simultaneous distinct poverty dimensions of persistent poverty; these include a subset of cases in which an interlocking poverty trap is effectively formed as a result of deprivations functioning as complements. We test an implication of the multiple trap framework by comparing structural income dynamics across groups. We find that in the poorest of the three main agro-ecological regions in Ethiopia, those with both chronic undernutrition and illiteracy have the lowest implied equilibrium; those with one of these chronic conditions have intermediate (but still deeply poor) equilibria; and those without either condition have the highest asset equilibrium. Evidence for complementarity of persistence across dimensions of poverty - what we term an interlocking poverty trap - is found in only a limited number cases, however. We present several robustness checks for our results.

JEL Classifications: O1, I3

Key Words: Poverty, poverty trap, Ethiopia, multidimensional poverty, interlocking poverty, regional poverty, literacy, undernutrition, asset dynamics

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1 Introduction

Conditions of poverty often appear to be the very conditions that make escape from poverty so difficult: challenges posed by such self-reinforcing mechanisms, often called vicious circles, or poverty traps, are an enduring theme of the poverty and development literature. A substantial body of economic theory has demonstrated the essential logic of this possibility. But taken as a whole, empirical findings on whether poverty traps actually exist have been inconclusive. Recently, the focus of the poverty measurement literature has turned from single to multiple dimensions of poverty (Alkire and Foster, 2011). This paper extends the analysis of one poverty trap to simultaneous potential traps, and introduces an econometric analysis of multiple dimensions of chronic poverty and potentially interlocking poverty traps.[1]

In recent years multiple and interlocking poverty traps have been used as a case-study based term for a region, village, or family with two or more distinct poverty problems. Plausibly, the simultaneous presence of different types of poverty traps makes poverty reduction for the extremely poor more difficult. For example, low farm assets, poor nutrition, and illiteracy may each cause income gains to be slow. Moreover, relaxing one of these constraints may result in few gains because another constraint is quickly reached; and then progress on the first problem may even be undermined or reversed. These conditions may reinforce each other; in a well-known framework (Dasgupta, 1993), saving to build assets may be difficult when food is the priority (which we may call a low asset trap), but poor nutrition itself keeps productivity and hence incomes low (an undernutrition trap).[2]

Based on insights gained from their direct field experience and other reported case studies, and some evidence on impact, policymakers and practitioners have often implemented approaches to help address poverty which is multidimensional in character, taking into account that some dimensions of poverty may essentially interact so as to reinforce the chronic incidence of some or all of the individual dimensions. Among government-sponsored programs, Mexico's pioneering Opportunidades-Progresa and many subsequent conditional cash transfer programs operate on the assumption that undernutrition, poor-health, low schooling, and child labor are interrelated. The interrelated provision of income support, health, and schooling is a common feature of these programs. A number of well-known NGOs providing microfinance such as BRAC have integrated provision of credit with health, training, education, and legal services.[3] Grameen, despite sometimes being described as a "minimalist" supplier of credit alone, has in fact also provided training, and encouraged behavioral change. There is some evidence that integrated programs can be effective.[4] But the econometric literature to date has not systematically analyzed the incidence of multiple dimensions of poverty that can be mutually reinforcing.

Our approach is to test an implication of the multidimensional trap framework by comparing structural income dynamics across groups. We find that in the poorest of our three regions, those with both chronic undernutrition and illiteracy have the lowest implied equilibrium; those with one of these chronic conditions have intermediate (but still deeply poor) equilibria; and those without either condition have the highest asset equilibrium. Our methods may be useful in other settings to inform program design and policy priorities.

The remainder of the paper is organized as follows. Section 2 covers basic theories of multidimensional poverty traps. We examine how multidimensional poverty traps may be mutually reinforcing given complementarities of inputs in household production functions. An empirical literature review on poverty traps is presented in section 3. In section 4, we introduce the Ethiopia Rural Household Survey (ERHS) and provide descriptive statistics for our main indicators of interest. Section 5 examines problems of identifying differences in implied equilibria for all households, combined from all the agro-ecological regions, in either illiteracy or undernutrition traps. Section 6 utilizes semi- and non-parametric methods to distinguish regional and subgroup cases where no multidimensional poverty is present, where multidimensional poverty is present but these traps do not exhibit complementarity, and where complementarity among poverty traps are present. Furthermore, we investigate the plausibility that two or more traps are mutually reinforcing; we adopt the term "interlocking" poverty traps for this type of interaction. We conclude in section 7.

2 Multidimensional Poverty Traps: Conceptual Framework

Poverty traps have been studied within consumption and asset space as a vicious circle, or Pareto-dominated equilibrium. Many theoretical contributions have studied thresholds in asset or capital accumulation that effectively constrain the household from further growth of income as seen in Figure 1. Proposed explanations of thresholds are various: for example, nonlinearity in the relationship between nutrition and productivity (Leibenstein, 1957; Stiglitz, 1976; Dasgupta, 1997), and liquidity constraints faced by households (Loury, 1981; Galor and Zeira, 1993), among others. These explanations are related to incomplete markets and under some conditions generate multiple equilibria so that poverty can be persistent if any shock reduces current income below the unstable equilibrium. A parallel tradition has in effect treated curve A in Figure 2 as a single-equilibrium poverty trap with convergence to a low-level equilibrium below the poverty line Z.[5]

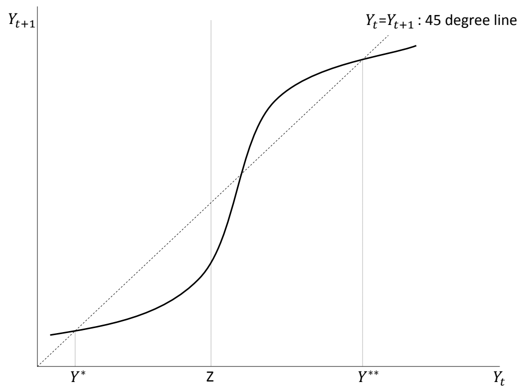


Figure 1: Multiple Equilibria

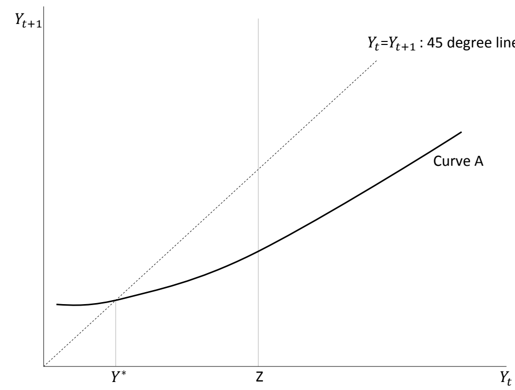


Figure 2: Single Stable Equilibrium

The presence of multiple deprivations also appears in basic assets, education and/or health components of the new United Nations Development Programme Multidimensional Poverty Index, that reflects the view that poverty is multidimensional, incorporating multiple aspects. (See Anand and Sen (1997), Alkire and Foster (2011), and UNDP (2010).) In the dual cut-off method, for each household it is first determined whether deprivation in each element is sufficiently severe to be deemed deprived in that element (in UNDP practice this indicator is binary but it could be made continuous with a set threshold such as z-scores as we use in this paper). But only when a sufficient number of deprivations have been counted are individuals in the family deemed multidimensionally poor. This procedure results only in a measure of the existence and extent of poverty. However, it is plausible that severe and chronic deprivation in more than one dimension interacts and increases the difficulty of moving out of poverty across each of the component deprivation. Thus, this paper is complementary to the new research on multidimensional poverty and contributes to taking a step beyond measuring multidimensional poverty to examining its potential effects. These effects are likely to differ depending on the type and severity of the deprivations and the degree to which they interact (or act as complements in keeping individuals trapped in poverty).

Moving from concepts of poverty measurement to an examination of conditions under which some forms of poverty traps may emerge, we start with the observation that, potentially, characteristics of asset equilibria differ across regions and across types of deprivations. Moreover, an economy that behaves with the properties of a local trap given current conditions may not behave similarly after conditions change (such as a sufficient increase in average national income raising demand, or newly available farming technologies). In this regard, observing poverty traps in more than one asset or welfare indicators in one region may predict more poverty persistence than in another region with just one deprivation, when other conditions in the wider economy improve. Moreover, an estimated equilibrium above the poverty line for a given region may effectively assume that complementary factors are correspondingly increased, but in the presence of other constraints the poor may be prevented from acquiring the needed achievements, such as acquiring requisite complementary skills.

With these motivations, we proceed to expand the one dimensional model of income dynamics to a multidimensional model. Defining household assets broadly to include human capital and other resources, the following is the system of household asset growth functions.

$$\begin{pmatrix} Y_{it} \\ R_{1it} \\ R_{2it} \\ \vdots \\ R_{mit} \end{pmatrix} = \begin{pmatrix} f(Y_{it-1}, R_{1it-1}, R_{2it-1}, ..., R_{mit-1}, X_{it}) \\ g_1(Y_{it-1}, R_{1it-1}, R_{2it-1}, ..., R_{mit-1}, X_{it}) \\ g_2(Y_{it-1}, R_{1it-1}, R_{2it-1}, ..., R_{mit-1}, X_{it}) \\ \vdots \\ g_m(Y_{it-1}, R_{1it-1}, R_{2it-1}, ..., R_{mit-1}, X_{it}) \end{pmatrix}, \tag{1}$$

where Y_{it} is the household current income, R_{jit} is amount level of current resources, $j = 1, 2, ..., m$, of each household, $i = 1, 2, ..., n$. Resources and household income level at $t-1$ determine both current income level (Y_{it}) and current level of each resource (R_{jit}). X_{it} includes exogenous characteristics. If households' income only fulfills their poverty level of consumption, the households are more likely to be trapped in income and resources, since the households cannot save sufficiently to invest for future resources. As a result, there are inadequate resources to increase nutrition, education, and so on. Hence, $m + 1$ dimensional poverty traps could appear. If two or more traps are present simultaneously, we term this a multidimensional poverty trap. If they are also mutually reinforcing through complementarity, we term them "interlocking" poverty traps. This method can help determine the larger or smaller sets of combinations of deprivations that have a large functional impact on poverty persistence and severity in a given region.

The presence of multiple human capital deprivations may function as a self-reinforcing mechanism which causes low human capital accumulation – "and hence poverty –" to persist. Under-nutrition (or very low health capital generally) may lower the return on investment in education: for example, under-nutrition reduces school attendance; and undernourished children perform poorly even if they are able to attend school; and undernourished individuals are less able to productively use education at any point in life. On the other hand, public health and nutrition programs are likely to be unsuccessful when intended beneficiaries are illiterate, and lack of schooling means children are not taught basic personal nutritional guidelines, hygiene, and sanitation. Chronic deprivation of one form of human capital therefore can lead to disincentives to invest in other forms of human capital; and this problem can be decisive at very low levels of consumption when any saving is challenging. Note that we are describing individual investment incentives and constraints - even before considering complementarities across individuals that could compound the difficulties. Moreover, the combination of human capital deprivations may reduce the potential benefits of other forms of asset accumulation, even if some savings resources were available.

Our empirical approach allows for the possibility that lack of one type of asset or capability can be made up for (substituted) by other assets - but only to a degree, as a sufficiently large set of missing assets together function as complementary inputs. For example, health and education to a degree might act as substitutes for each other in allowing the accumulation of assets, but when both are lacking this may prevent accumulation. For the very poor, the lack of a resource such as health or education can through strong complementarity change the household asset growth function. This reflects that the very poor are more likely to own few resources that can function as substitutes after some point. In the extreme, lack of one resource even prevents the resources that the poor household have from providing more than negligible productivity.

In this paper, then, we also investigate the existence of interlocking poverty traps by exploring the existence of such complementarities. In the range of extreme poverty, household assets such as health, nutrition, education, and farm capital, may function as strong complements in equation (1).

3 Empirical Literature Review

Empirical research into multiple equilibria even with a single indicator of interest has begun fairly recently (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 semi/nonparametric estimation methods have been used to estimate poverty dynamics but almost exclusively only in either income or asset space. However, poverty traps could appear in other dimensions. Hoff and Stiglitz (2001) point out that 'low-level equilibrium traps' can occur due to lack of other indicators of welfare (for example, lack of political freedom or institutions).

Just a few studies have investigated whether a single dimensional poverty trap exists in other dimensions beyond income and assets.

For example, Emerson and Souza (2003) present empirical evidence on the intergenerational persistence of child labor using the 1996 Brazilian Household Survey. They find that parental child labor significantly increases the probability that their child will work in the labor market, and that the more years that parents worked as children, the greater their own children's likelihood of entering the labor force. In addition, they find that past child labor significantly reduces current income (which increases the incentive, or the necessity, for child labor also from the following generation).

Mayer-Foulkes (2008) presents existence of a human capital accumulation trap in Mexico using the 2000 National Health Survey (ENSA 2000); he finds that schooling is an important factor for adult income; that the schooling experience of parents significantly affects the schooling decision of adolescents; and that the shapes of schooling year distributions over time have double-peaks. He proposes that the composition of all three findings support the existence of multiple equilibria in human capital space.

Jha et al. (2009) use the data from the National Council for Applied Economic Research (NCAER) and test for the existence of an undernutrition trap in rural India. They focus on agro-climatic zones to acquire homogeneity (i.e. agricultural activity). Using Heckman's (1976) sample selection model, they estimate the impact of micronutrient consumption on wage rates over various categories of work, and find some evidence of undernutrition traps.

As proposed in section 2, however, the extremely poor could have two or more poverty traps simultaneously, which can interact complementarily to hinder the accumulation of household assets. Therefore, we introduce idea of multidimensional poverty traps to this literature, including the examination of complementarity across traps, which we call interlocking traps.

4 Data: The Ethiopia Rural Household Survey

This study uses Ethiopia Rural Household Survey (ERHS) data set[6]: First, per capita income in Ethiopia is one of the lowest in the world[7]; yet, rural Ethiopia has experienced "pro poor" growth.[8] We have opportunities to examine conditions under which the poor might be escaping from poverty traps. ERHS contains information that can be used to explore multiple traps beyond income and assets, including basic health and basic education. These might help us understand why some families and regions might fail to benefit even in a general national environment of pro poor growth.

ERHS is publicly available by International Food Policy Research Institute (IFPRI). ERHS studies 1,477 households residing 15 villages, stratified in three agro-ecological zones of Ethiopia.[9] Households are randomly selected within each village. In the data, population shares are broadly consistent with the population shares in the three main sedentary farming systems, which are the grain-plow complex highlands, the grain-plow/hoe complex, and the enset growing area. Figure 3 represents the survey sites and 3 categories according to farming systems in rural Ethiopia.[10]

Land is owned by the state in Ethiopia due to socialist backgrounds, though utilization

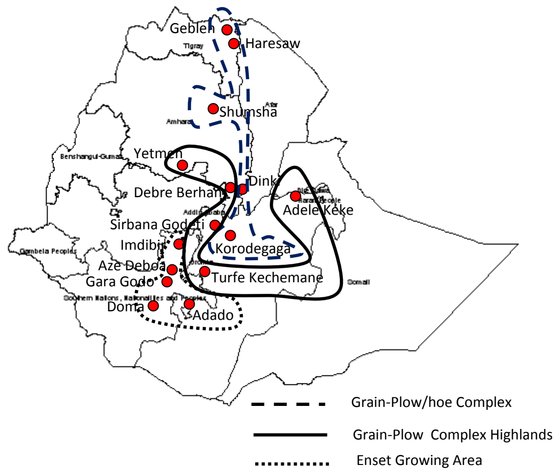


Figure 3: Ethiopia Rural Household Survey Villages

of land is a key to economic activity in Ethiopia. Thus, when households migrate to another region, they have a difficulty in acquiring land from an unfamiliar peasant association. Naturally mobility is highly restricted. Moreover, due to insecure land holding system farmers do not have an incentive to invest in lands. Thus, farmers have low productivity from land and perpetuating low growth. At the end they stay in poverty.[11]

We first investigate changes in poverty from 1994 to 2004 over the 3 agro-ecological regions. Table 1 presents the 1994 and 2004 poverty measure for the ERHS sample of 1,254 households.[12] Comparing the 1994 measures with the measures in 2004, we find that the expenditure based poverty measures decreased. The head count measure decreased from 56.8% to 41.0%. In addition, the FGT poverty severity measure decreases from 0.152 to 0.082 over time. Comparing the poverty measures across the 3 regions, we find that the enset area has the largest population suffering from poverty. The basic head count measure of the enset area is almost twice that of the highlands area in both 1994 and 2004. Even though rural Ethiopia experienced the pro poor growth, Table 1 suggests that the poor in the enset area have tended to stay poor. That is, the poor fail to escape from poverty over time even with pro poor growth.

To date, the econometric literature on poverty traps has focused on the presence of one dimensional trap, indexed by a single variable, generally an asset index or consumption. Barrett et al. (2006) present that current income and consumption is not sufficient to identify chronic poverty since this flow includes both structural and stochastic components of income simultane-

Table 1: Poverty Measures from 1994 to 2004

Areas	Head Count 1994	Head Count 2004	Poverty Severity (FGT P_2) 1994	Poverty Severity (FGT P_2) 2004	Rate of Pro poor Growth 1994-2004
Highlands	38.6(%)	27.6(%)	0.067	0.046	1.88
Hoe	65.4(%)	41.4(%)	0.179	0.071	4.95
Enset	70.4(%)	58.1(%)	0.231	0.142	3.56
Population	56.8(%)	41.0(%)	0.152	0.082	3.62
Number of Households	1254	1254	1254	1254	

[a] Poverty lines are set by real consumption of 72 Birr per adult equivalent per month, which is equivalent to $1 per day in 1994.
[b] Rate of pro poor growth is the mean of growth rate at each percentile of the expenditure distribution up to the headcount poverty measure. The numbers are estimated, following Ravallion and Chen (2003). The numbers measure how much the poor is benefiting from growth.
[c] The poverty severity measure, $\frac{1}{N}\sum_{i=1}^{M}(\frac{z-y_i}{z})^2$, was developed and axiomatically justified by Foster et al. (1984).

ously. Using the structural part of income, (i.e. assets), has an advantage for analyzing chronic poverty and poverty traps. Therefore, we estimate an asset index, which provides a proxy for household structural income.[13]

For present purposes, we have defined an illiteracy trap as remaining illiterate throughout the five periods.[14] In addition, we construct an undernutrition trap variable using anthropometric data.[15] After comparing the indicators, we adapt the z-scores of BMI-for-age from the widely used 1990 British Growth Charts to generate an undernutrition trap status variable.[16] The z-score of BMI-for-age is represented as

$$\texttt{z-score(BMI/Age)} = \frac{\texttt{BMI}_{ijk} - \texttt{Median BMI}_{jk}^{\texttt{reference population}}}{\texttt{S.D.}_{jk}^{\texttt{reference population}}}, \tag{2}$$

where BMI_{ijk} represents the BMI of an individual i, $i = 1, 2, ..., n$ whose age is k and whose gender(male/female) is j. We define a household as trapped if any members have BMI-for-age z-scores < -2 throughout the sample.[17] Using this simple definition, we find that 17.9% of the full sample are trapped.[18]

Based on poverty trap status, we examined whether households have different patterns of structural income levels. We use a simple t-test and the Epps-Singleton test for whether both trapped groups have the same mean and the same distribution, respectively. (See Tables A-4 and A-5 in the Appendix for detailed estimates.) We find that in the highlands area a household in an illiteracy trap does not have lower structural income (p-value is 0.7921) than those not trapped, while structural incomes in the other areas differ significantly depending on trap status. The difference of average asset index in the highlands area is 0.05, while other areas has

Table 2: Average Asset Index with Status of Poverty Traps

	(1) Undernutrition trap		(2) Illiteracy trap		(3) Non-Trapped	(4) Single trap[c]	(5) Double traps[c]
	Non-Trapped	Trapped	Non-Trapped	Trapped			
Full sample	2.322 (82.1%)	1.672 (17.9%)	2.252 (49.5%)	2.040 (50.5%)	2.363 (45.6%)	2.104 (54.6%)	1.588 (12.1%)
The Highlands	3.009 (89.9%)	2.644 (10.1%)	2.903 (54.4%)	2.951 (45.6%)	2.964 (50.6%)	2.914 (49.4%)	2.717 (6.4%)
The Hoe	2.072 (84.0%)	1.724 (16.0%)	2.120 (43.9%)	1.977 (56.1%)	2.229 (39.4%)	1.979 (60.6%)	1.747 (11.4%)
The Enset	1.544 (70.8%)	1.229 (29.2%)	1.631 (49.5%)	1.268 (50.5%)	1.701 (44.0%)	1.379 (56.0%)	1.103 (18.6%)
Observations	4,817	1,048	2,255	2,303	1,826	2,179	553

[a]The proportion of the households having each trap status is in parenthesis.
[b]We only use the observations that we can identify both undernutrition and illiteracy trap status to define a single trap and double trap (n=4,558). The reason is that if we know the information of only a single trap, the trapped households may have another trap that we fail to identify. Hence, we only use the cases that both trap status are identified. As a robustness check, we include all the cases that we fail to identify either illiteracy or undernutrition trap in Table A-6.
[c]Single trapped households in the fourth column represent the households that have only one trap regardless of undernutrition and illiteracy. Double trapped households have both illiteracy and undernutrition trap simultaneously.

larger difference: 0.15 and 0.37 for the hoe and the enset areas, respectively. We note, however, that the distribution of structural income in the highlands area varies significantly depending on illiteracy trap status at any conventional level. Moreover, a household in an undernutrition trap has lower structural income regardless of the region. In addition, we find that the distributions of the trapped and non-trapped household incomes are significantly different within each region, and across the traps. Moreover, we find that the illiteracy and undernutrition traps are significantly positively correlated.[19]

Table 2 shows the average structural income according to trap status. Trapped households have lower structural income levels than non-trapped households. In particular, comparing the difference of the average structural income between the illiteracy trapped group and the non-illiteracy trapped group across regions, we find that the difference is largest in the enset area; the difference is the smallest in the highland area. These findings suggest that an illiteracy trap affects the asset level heterogeneously over the income (or regional) distribution. In contrast, comparing the difference of the average structural income between the undernutrition trapped group and the non-undernutrition trapped group across regions, we find that the difference is around 0.35 over the three regions. This implies that an undernutrition trap affects the asset level uniformly.

In addition, comparing the proportion of trapped households within each region, we find that the highlands area has the smallest proportion in each trap. The enset growing area has largest proportion in undernutrition and double traps relative to two other areas.[20] Given that households may have an incentive to invest more in education if access to and accumulation of other assets is difficult, the smaller differences in the proportion of households in an illiteracy trap across regions can be explained. Households in the most deprived area may have more incentive to invest in education if the rate of return on schooling is high under the assumption that assets are substitutes. Therefore, the illiteracy trapped households seem to have a somewhat different set of characteristics from those in an undernutrition trap.

The column (3) provides the average asset index level of non-trapped households. The highlands area has the highest asset holding level, while the enset area records the lowest level. The column (4) in Table 2 represents the average structural income (asset index) of households with a single trap, regardless of what kind of traps households have. First, note that the difference between asset levels of single-trapped (column (4)) and non-trapped (column (5)) households in the full sample (that is, treating regions as homogeneous) is small, about 10.96%. Comparing the asset level of double trapped households in column (5) with non-trapped households in column (3), however, the gap is triple (32.80%) that of the difference between the non-trap and single trap. This finding may support our argument in section 2; when one resource is missing in the household asset accumulation function, other resources can make up for it. When both resources are missing simultaneously, however, trapped households could be prevented from household asset accumulation by complementarity of resources since the very poor are more likely to have only a small amount of other resources.

As we have already, however, poverty conditions differ across the three agro-ecological regions. Considering the regional levels, the difference of the average asset index between column (3) and (4) is negligible in the richest area, the highlands area. (t-test statistics= 0.8227, p-value=0.4108 for a two-sided test.) However, the more deprived the area is, the larger the difference is. The enset area, the most deprived area, has the largest difference of asset levels. This finding is more obvious in the case of double trapped households, as seen in column (5). Therefore, this finding provides a hint that the very poor and/or the very poor regions have a higher likelihood that the complementarity of inputs appears in household asset accumulation.

5 Asset Dynamics in the Presence of Undernutrition or Illiteracy Trap

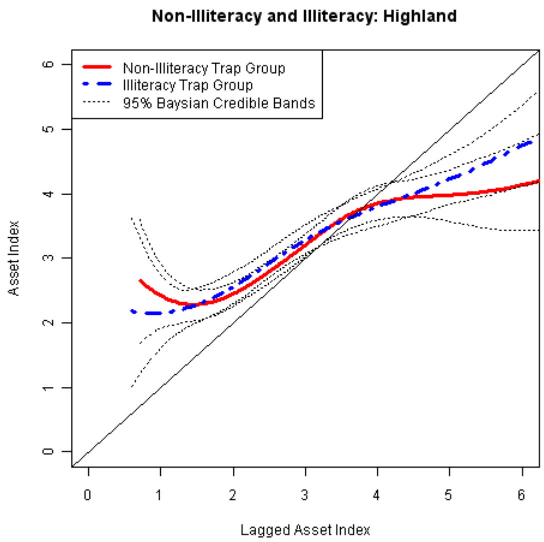
We first consider asset dynamics of the full sample treating all regions as homogeneous according to trap status; then we explore further the dynamics of the three regions, according to trap status, using penalized splines with Bayesian inference proposed by Krivobokova et al. (2009). We first consider asset dynamics of the full sample treating all regions as homogeneous according to trap status; we then explore further the dynamics of the three regions, according to trap status, using penalized splines with Bayesian inference as proposed by Krivobokova et al. (2009). Our indicators for an illiteracy trap and an undernutrition trap are both binary variables, so we cannot estimate the dynamics of these indicators. Instead, we estimate asset dynamics conditional on the illiteracy-trapped and/or undernutrition-trapped status of the households. Comparing the asset dynamics given these traps, we gain insight into how these deprivations impact the household asset growth functions (in equation (1)) which in turn would affect other long-term household outcomes. For example, if other household inputs do not sufficiently substitute for literacy deprivations in the household asset growth functions, long-term asset dynamics of illiteracy-trapped households should converge to a statistically lower implied equilibrium than that of non-illiteracy trapped households. The same may be true for undernutrition-trapped households; and when illiteracy and undernutrtion are present simultaneously their combined effects may be more than additive. Figure A-2(a) represents the asset dynamics of illiteracy trapped and non-illiteracy trapped households. Intriguingly, both dynamics converge to the same equilibrium statistically regardless of trap status. The dynamics of undernutrition trap in Figure A-3(a) also converge to statistically the same equilibrium regardless of trap status. In these data, when we combine households from all the agro-ecological regions, we do not identify differences in implied equilibria for those in either illiteracy or undernutrition (single) traps.[21] We examine three hypothetical explanations of these findings: First, neither trap status determines the asset dynamics of rural Ethiopia; second, the non-illiteracy (Non-undernutrition) trapped households are also severely affected by undernutrition (illiteracy) traps; third, the household conditions in the three regions are so different that pooling them in this analysis could be misleading.

If the dynamic path of households having no trap is located above the dynamic path of non-illiteracy or non-undernutrition households, we may conclude that other types of trap hinder (or constraints more generally) households from accumulating assets and the trap status determines the asset dynamics. The implied equilibrium of the non-trapped households should be greater than that of the trapped households. On the contrary, if the dynamic path of households having no trap is similar to the dynamic path of illiteracy or undernutrition trapped households; and if both paths converge to the same equilibrium; we conclude that the each trap does not have effect on the asset dynamics on average.

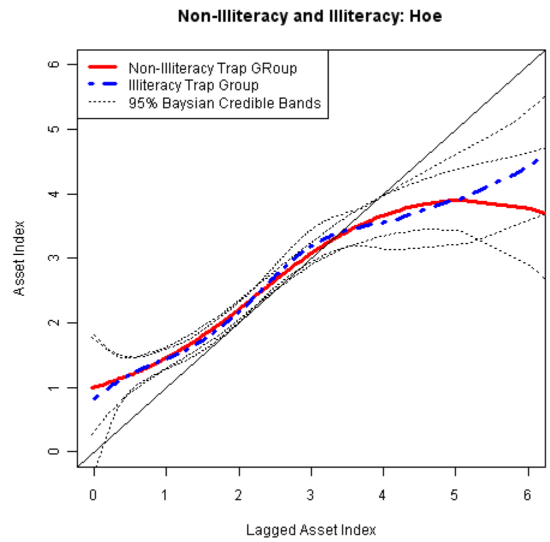
To test these alternative hypotheses, we estimate the asset dynamics of the households having no trap. From the full sample (that is, treating regions as homogeneous), we find that the dynamics overlap and converge to statistically the same equilibrium.[22] Hence, we conclude that the one dimensional traps (i.e., either illiteracy or undernutrition trap), on average, may not determine the long run asst dynamics. However, the traditional mean regression approaches, including both parametric and nonparametric regressions, may be misleading because the analysis does not fully represent the lower tail of income distribution.

Hence, we next consider the asset dynamics of the three regions according to illiteracy trap status since the three regions have different income distributions.[23] We find that the enset area is poorest and the highlands area is richest among the three regions in our data set. Figure 4 presents the equilibria of the illiteracy trap group and the non-illiteracy group across farming system regions, respectively. Across all regions, the equilibrium of the illiteracy and non-illiteracy trap group are not significantly different. When households are merged in the data set across regions, they show some differences in structural income on average depending on the trap status as in Table 2. However, they converge to the statistically same equilibrium of structural income in the long run, regardless of trap status in the highlands and the hoe areas. Moreover, the dynamic paths of the highlands and the hoe areas are almost identical regardless of the trap status. However, the dynamic paths in the enset growing area represent different patterns depending on the trap status when we compare them with those in other regions: First, the equilibrium is much lower than in two other regions; furthermore, the dynamic path of non-illiteracy group is located above that of illiteracy trap group.

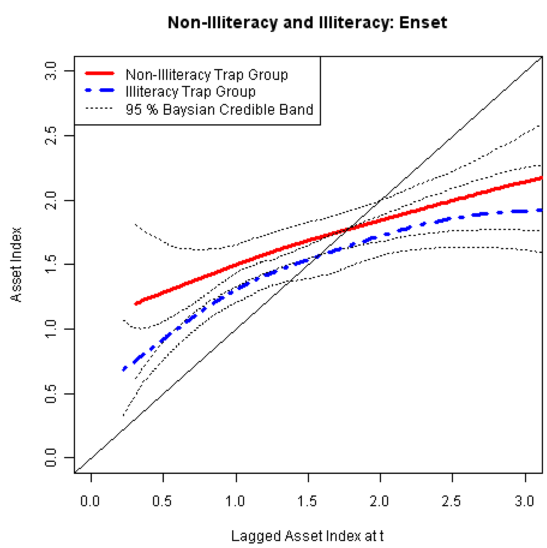
Therefore, we proceed to examine the enset growing area in more detail. First we consider



(a) Highlands Area



(b) Hoe Area



(c) Enset Area

Figure 4: Bayesian Penalized Spline: Comparison between Illiteracy Trap Group and Non-Illiteracy Group across Farming System Regions

separately illiteracy and undernutrition traps in the enset area. We find the same patterns of the dynamics as in Figure 4(c). (That is, we compare with the asset dynamics of households having no traps; for details see Figure A-4(a) and A-5(a); Figure A-4(b) and A-5(b) represent the dynamics of households residing in the enset area who suffer from the illiteracy trap and the undernutrition trap, respectively.) We also find that the dynamic paths of households having no trap are located above the paths of both the illiteracy and the non-illiteracy trapped groups, though the difference is not statistically significant. These findings provide at least suggestive evidence that the poverty trap status determines the asset dynamics in the most deprived area.[24]

In addition, it is still questionable that each asset dynamics converges to the same equilibrium regardless of trap status in the full sample (that is, treating regions as homogeneous), since the the dynamics at the lower extreme percentile of income distribution are apparently different from that of median or higher percentile of income distribution. To address this important concern systematically, it is insightful to utilize a nonparametric quantile regression known as the quantile smoothing spline. We estimate the relationship, $\ln y_{i,t} - \ln y_{i,0} = m(\ln y_{i,0}) + e_i$, using the full sample.[25] That is, we estimate the unconditional growth regression for each trap status. We use the B-spline regression quantiles proposed by Ng and Maechler (2007). The smoothing parameter λ is selected by minimizing the Schwarz information criterion.[26]

Illiteracy trap status affects the dynamics of the structural income. (For details see Figure A-6 in the Appendix.) We find evidence of poverty traps in the dynamics of both non-illiteracy and illiteracy trapped households from the 20th percentile quantile regression. Excepting the 20th percentile quantile regression, all dynamics from other percentiles have a single stable equilibrium. Interestingly, the dynamics of the illiteracy trapped households converge to a lower equilibrium than that of the non-illiteracy trapped households up to 40th percentile quantile regressions. In above median quantile regressions, however, the dynamics from each quantile regressions have statistically the same equilibrium regardless of the trap status. These findings suggest that the illiteracy trap status is only correlated with the long term dynamics of the households in lower percentiles of the income distribution, not those in higher percentiles. In order to further test this finding, we compute the average education years of both sons and daughters according to the illiteracy trap status of the households, as seen in Table 3.

Table 3: Average Education Attainment Years of Sons and Daughters based on Household Illiteracy Trap Status

Asset Index Percentiles	Nonilliteracy Trapped Household	Illiteracy Trapped Household	t-value	Two-sided Test $\Pr(\|T\| > \|t\|)$	One-sided Test $\Pr(T > t)$
Below 60th percentiles	5.911	4.246	1.955	0.052	0.026
Above 60th percentiles	4.085	4.045	0.042	0.967	0.484
Total	5.031	4.176	1.338	0.182	0.091

[a]Source: ERHS 1994a.
[b]The numbers are average education years of sons and daughters within a household according to the illiteracy trap status of the household.
[c]The alternative hypothesis of the one-sided test is that the education years of children in a non-illiteracy trapped household are greater than that in the counterpart.
[d]60th percentiles of asset index is used to identify poor households since we identifies about 60% of households as the poor households in Table 1.
[e]Education years of children are computed by following: aggregating education years of both sons and daughters greater than 13 years old, and then the aggregated number is divided by the total number of the sons and daughters.

As Table 3 reveals, the average educational attainment year of sons and daughters born into non-illiteracy trapped households is significantly greater than the counterparts within households having relatively low asset levels (below 60th percentile of the asset index distribution). However, we fail to find evidence of differences in sons and daughters' educational attainment between the two groups within households above the 60th percentile of the asset index distribution. These findings suggest that the lowest (permanent) income households (as identified by asset levels) can have differing long-term outcomes, such as the human capital level of descendants, according to the illiteracy trap status of the current generation. Hence, the long term asset dynamics of future generations within relatively asset poor households may also depend on the illiteracy trap status of the current generation; this could be an explanation of heterogeneous asset dynamics in Figure A-6 in the Appendix. In other words, such households with sufficient assets and consumption may be able to send their children to school and escape intergenerational poverty traps in the longer-run.

The nonparametric quantile smoothing splines of both undernutrition and nonundernutrition trapped groups are presented in Figure A-7 in the Appendix: the asset dynamics of both undernutrition and nonundernutrition trapped groups along the structural income distribution. All dynamics converge to the same single stable equilibrium regardless of the trap status, which is consistent with the mean regression estimation results.[27] A plausible explanation of this result for households suffering from an undernutrition trap is "asset smoothing." For example, the short term response of undernutrition trapped households is not to sell an animal to buy food, instead they eat less, if they expect that assets' future rate of returns is greater than their current rate of returns. In the long run, there is no difference between the dynamics of the trapped households and those of the non-trapped households, since the trapped households still have their own assets to utilize in the future.[28]

The Ethiopian evidence examined here suggests a wider implication that in general it will be important for practitioners and policymakers to determine the types of poverty traps (if any) that affect households located in the lower quantiles of the income distribution, since the structural income dynamics of households must evolve in the long run according to which trap is prominent.

6 Analysis of Interlocking Poverty Traps

Thus far we have presented long term evidence that undernutrition and illiteracy traps decrease households' asset holding levels in the most deprived region and in households in the lower percentiles of the income distribution. In equation (1), we present that a deprived input in household asset growth functions determines long-term household outcomes with other household resources. We now investigate further whether illiteracy and undernutrition traps work together through complementarity to worsen asset poverty. For example, either undernutrition or illiteracy may impair the ability of the household to accumulate assets, but when both are present their combined or interaction effects may be more than additive.

Since only households that remain in illiteracy (or undernourishment) in all periods are defined as trapped, we cannot simply transform the data to remove the household specific effect. Hence, utilizing the Mundlak device within the random effect model,[29] we construct a pseudo-fixed effect model. (Mundlak, 1978) This estimation approach allows us to analyze whether or not the illiteracy trap status significantly interacts with the undernutrition trap to worsen asset conditions in the short term, controlling for unobservable heterogeneity. To test this, we include an interaction term between an undernutrition and an illiteracy indicator within our equation (3) estimated.

$$\ln A_i = \beta_0 + \beta_1 P_{1i} + \beta_2 P_{2i} + \beta_3 P_{1i} P_{2i} + \mathbf{X}_i \alpha + \bar{\mathbf{X}}_i \theta + e_i, \quad i = 1, 2, ..., n, \tag{3}$$

where A_i is the asset index (structural income) of each household i, P_{ji}, $j = 1, 2$ represents the

Table 4: Interlocking Poverty Trap Analysis across Regions

Dependent Variable ln Asset Index	(1) Full Sample	(2) Highlands Area	(3) Hoe Area	(4) Enset Area
Undernutrition Trap(=1)	-0.161***	-0.0854*	-0.310***	-0.0948**
	(0.0363)	(0.0447)	(0.0774)	(0.0428)
Illiteracy Trap(=1)	-0.0784***	0.0204	-0.130**	-0.162***
	(0.0255)	(0.0245)	(0.0565)	(0.0367)
Undernutrition×	-0.0576	0.0447	0.145	-0.122**
Illiteracy	(0.0494)	(0.0634)	(0.101)	(0.0576)
Age of Household Head	-0.0175***	-0.0172**	-0.0151**	-0.0183**
	(0.00457)	(0.00834)	(0.00613)	(0.00745)
Age squared	0.0000817*	0.0000894	0.0000817	0.0000589
	(0.0000426)	(0.0000764)	(0.0000613)	(0.0000676)
Gender of Household Head	-0.0431	-0.0760	-0.0556	-0.0319
	(0.0339)	(0.0694)	(0.0409)	(0.0623)
Number of Children	-0.0608***	-0.0585***	-0.0860***	-0.0530***
	(0.00580)	(0.00934)	(0.00970)	(0.00971)
Land Holding Size	0.0952***	0.0701***	0.158***	0.120***
	(0.00854)	(0.00951)	(0.0241)	(0.0168)
Number of Livestock Units	0.0220***	0.0153***	0.0363***	0.0365***
	(0.00455)	(0.00393)	(0.00670)	(0.0101)
Round 3	0.0551***	0.0129	0.211***	-0.0337**
	(0.0119)	(0.0194)	(0.0244)	(0.0171)
Round 4	0.240***	0.215***	0.169***	0.314***
	(0.0146)	(0.0182)	(0.0367)	(0.0170)
Round 5	0.374***	0.317***	0.640***	0.180***
	(0.0185)	(0.0249)	(0.0355)	(0.0297)
Round 6	0.464***	0.385***	0.589***	0.403***
	(0.0169)	(0.0251)	(0.0314)	(0.0309)
the Hoe(=1)	-0.360***			
	(0.0265)			
the Enset(=1)	-0.555***			
	(0.0238)			
Constant	1.122***	1.295***	0.290	0.801***
	(0.109)	(0.115)	(0.241)	(0.170)
Mean Values of Time-varying Variables				
Mean of Head Age	0.00768	-0.00173	0.0292**	-0.00489
	(0.00639)	(0.00901)	(0.0122)	(0.0101)
Mean of head Age Squared	-0.0000222	0.0000457	-0.000244**	0.000125
	(0.0000609)	(0.0000831)	(0.000122)	(0.0000956)
Mean of Head Gender	0.0112	0.0112	0.0431	0.0232
	(0.0470)	(0.0749)	(0.0743)	(0.0833)
Mean of Number of Children	0.0181**	0.0184*	0.00689	0.0333***
	(0.00780)	(0.0110)	(0.0183)	(0.0113)
Mean of Holding Land	-0.0414***	0.0345***	-0.207***	0.0663***
	(0.0143)	(0.0120)	(0.0322)	(0.0178)
Mean of Livestock Units	-0.00730	-0.00807*	0.00890	-0.0313**
	(0.00548)	(0.00490)	(0.0126)	(0.0155)
Observations	4556	1586	1410	1560

[a] Standard errors are in parentheses.
[b] We use 5 rounds of ERHS. (1994a, 1995, 1997, 1999, 2004) We also use 3 rounds of ERHS (1994a, 1999, and 2004) as a robustness check. The significance of variables do not change.
[c] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
[d] Column (2) includes interaction terms between regional dummy and trap indicators.

illiteracy trap status and undernutrition trap status, respectively, and $\mathbf{X}_i$ represent time-varying explanatory variables including age of household head, squared age of household head, gender of household head, number of children, land holding size, and number of tropical livestock units. We also include time dummies to control for the time specific effect. The first column in Table 4 includes regional fixed effect dummies. In column (2) to (4), we estimate equation (3) across farming system regions to explore whether or not both the illiteracy trap and the undernutrition trap negatively affect household structural income level, and whether the traps interact to lower the asset level significantly.

Table 4 provides the estimates from pseudo-fixed effect estimations. The appropriate F-test for the fixed effect model, in which the null hypothesis is that all coefficients of group mean values are equal to zero, (that is, θ=0) is rejected at any conventional level.[30] With specification (1), the interlocking poverty trap status does not have a significant effect on the percentage change in structural income, while undernutrition and illiteracy traps affect it significantly at any conventional level.[31] From specifications (2) through (4), the significantly negative coefficient of the interaction term at 5% level in the enset area implies that the simultaneous presence of traps effectively reduces household structural income, that is, significantly reinforce each other, while the coefficients from the highlands and the hoe regions do not. These findings support that the chronic poverty conditions are working together to reduce household structural income level particularly in the most deprived area.

Depending on current asset holding levels of households, the short term relationship of each trap indicator and current asset levels can differ significantly. Among other things very low-asset households may be more likely affected by interlocking poverty traps. We estimate quantile regressions over the structural income distributions in each agro-ecological region using pooled data. Conditional mean regression is (as the name suggest) evaluated at the mean. Thus, its results are not sufficient for fully representing the behaviors of the poor located in the extreme quantiles of the income distribution.[32] The estimating equation is given by,

$$\ln A_i = \beta_0 + \beta_1 P_{1i} + \beta_2 P_{2i} + \beta_3 P_{1i} P_{2i} + \mathbf{X}\alpha + e_i, \quad i = 1, 2, ..., n. \tag{4}$$

We note that poverty conditions could appear differently at regional levels, and only the

Figure 5: Quantile Regression: the Highlands Area

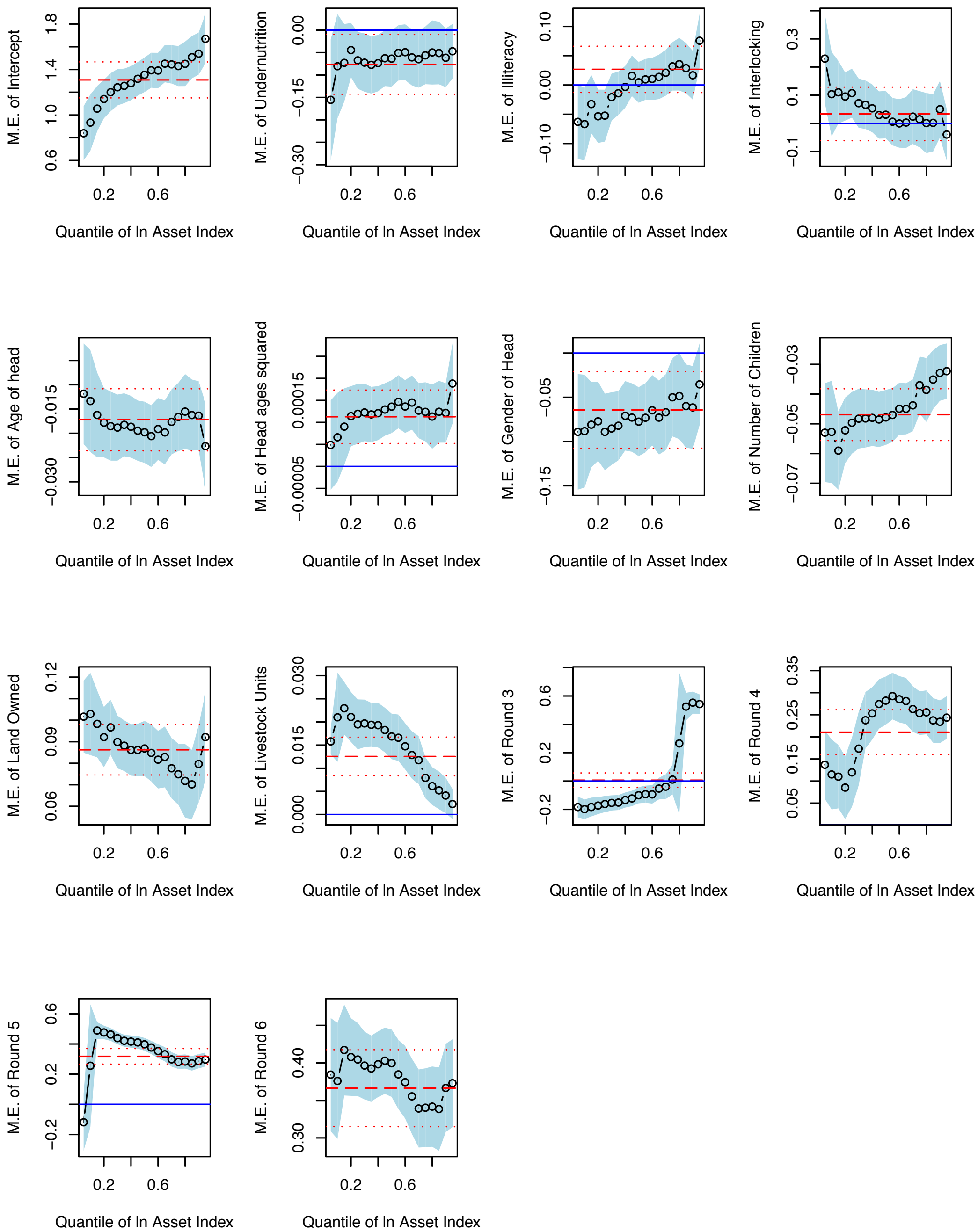
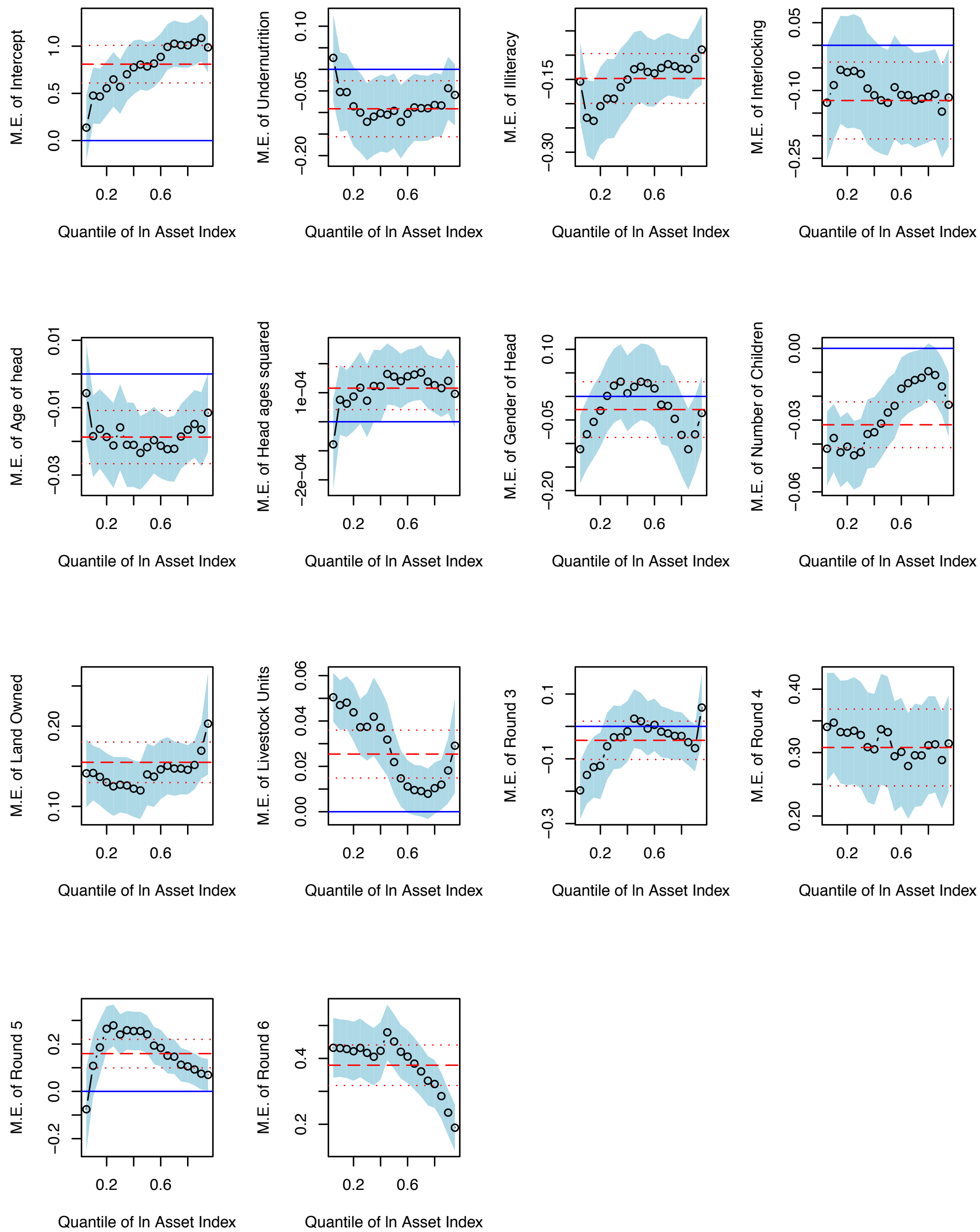


Figure 6: Quantile Regression:the Enset Area



most deprived region (the enset area) has evidence of interlocking poverty traps. Hence, we first focus on local levels. Figure 5 and Figure 6 represent distributions of marginal effects on the log of structural income in the highlands region and the enset region, respectively.[33] We find that livestock units have a significantly positive and very heterogenous effects, while land owned has a significantly positive and relatively uniform effect over the whole range of the structural income distribution. The number of children within a household significantly worsens the household asset condition. Age of household heads has a negative and relatively unform effect. The effect of gender of the household head represents a different pattern between the highlands area and the enset area. The gender effect is negative and relatively uniform over the whole distribution in the highlands area, while the effect is significantly negative only in the lower percentile of the distribution in the enset area. The illiteracy trap has a significantly negative and very heterogeneous effect on the percentage change in the structural income in the enset area, but in the highlands area, it is insignificant for nearly all quantiles. An undernutrition trap has a relatively uniform effect on the structural income. Moreover, the impact of an undernutrition trap is marginally significant at 0.1 level over the whole range of the distribution in the highlands area; but it is significant in the enset area except at the highest and lowest percentiles of the income distribution.

In the highlands area, the interlocking poverty trap has an insignificant effect on log of asset index except among the lower percentiles of the distribution. Even though the differences between the percentage change in the structural income of the trapped and that of the non-trapped households are significant in the lower percentiles of the income distribution, the differences between the absolute income levels of the trapped and those of the non-trapped households are negligible.[34] We conclude that an interlocking trap does not have significant effects on the structural income of the households in the highlands area. In the enset area, however, an interlocking trap has heterogeneous effects on the percentage change in the structural income over the income distribution. The percentage change in the income of the trapped households is not significantly different from that of the non-trapped households in the lower percentiles (i.e., below about 50th percentile), while the percentage change in the income of the trapped households is significantly less than that of the non-trapped households in the upper percentiles. This finding implies that there is household heterogeneity in the enset area in the impact of interlocking poverty traps over the income distribution.[35]

We estimate the equation (4) again to compare the effects of each poverty trap indicator on household structural income at local levels with those in combined samples, treating all regions as homogeneous. (See Figure A-8 in the Appendix to see the estimation results.[36]) We also find heterogeneous effect of an illiteracy trap. It uniformly reduces about 15% of the structural income for the poor.[37]

From the pseudo-fixed effect model and the quantile regressions, we have found that multidimensional, or interlocking poverty traps are likely to affect more severely households in the lower income distribution residing in the more deprived region. For additional evidence on the existence of multidimensional, and interlocking poverty traps, we revisited the estimation of the asset dynamics using nonparametric local linear regressions using ERHS round 1, 3, 4, 5, and 6 data, which are used in Table 2.[38] We estimate three asset dynamics according to trap status: No-trap, single trap, and double trap.[39]

Table 2 gives a hint that there is complementarity of household resources in asset accumulation. Based on the findings in that table, we construct the following working hypothesis: First, if the dynamics of the single trapped group and the no-trapped group converge to the same equilibria, other resources in households work as substitutes for the trapped resource. Similarly, if the dynamics of the double trapped and the no-trapped groups converge to the same equilibrium, other resources in households work as substitutes for the trapped resource. However, if the dynamics of the non-trap group and single trap group converge to different equilibria; or if the dynamics of the non-trap group and double trap group converge to different equilibria; the significant difference of equilibria suggests that the lacked resources (trapped capacities or other assets) work with complementarity to hinder household asset accumulation. We hypothesize that this complementarity is more likely to appear in the most impoverished area. If the dynamics of the single or double trapped group converge to a very low equilibrium distinguished from the equilibrium of non-trapped group's dynamics, we may conclude that multidimensional and interlocking traps exist since this complementarity involves the existence of interlocking traps.

Figure 7 represents the asset dynamics of each trap status estimated with a local linear regression.[40] It is not clear that the three dynamics in general are significantly different, par-

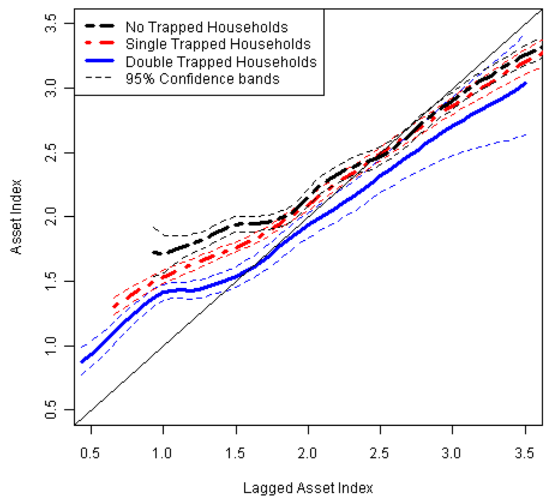


Figure 7: Asset Dynamics across Trap Status: All Areas

ticularly around their own equilibria. The clearest difference is observed in the dynamics of the most-asset poor (with a lagged asset index of approximately 0 to 1.7). This difference implies that trap status tends to affect only the very asset-poor, which conforms with our interpretation of Figure A-6, as well as Table 4. This finding may suggest that missing resources in a household asset growth function only determine the asset accumulation of the very poor.

Poverty could appear differently at local levels. As Table 2 suggests, the poor area has a much higher likelihood of complementarity of inputs in a household asset growth function. Hence, we investigate how trap status (or chronically lacking resources) hinders poor households from asset accumulation. We do so by estimating nonparametric local linear regressions according to trap status (no, single, and double trap). Particularly, we focus on the enset and the highlands areas.

Figure 8 presents the asset dynamics across trap status in the enset area. We find that the dynamics of no-trapped household converge to the highest equilibrium, while the dynamics of the double trapped households converge to the lowest equilibrium.[41] Moreover, the dynamics of single trapped households also converge to a significantly lower equilibrium than that of no-trapped households. However, we fail to observe these changes of dynamics depending on trap status for the highlands region as seen in Figure 9.[42] All dynamics in Figure 9 converge to the statistically same equilibrium. The interpretation of this finding is that in richer region,

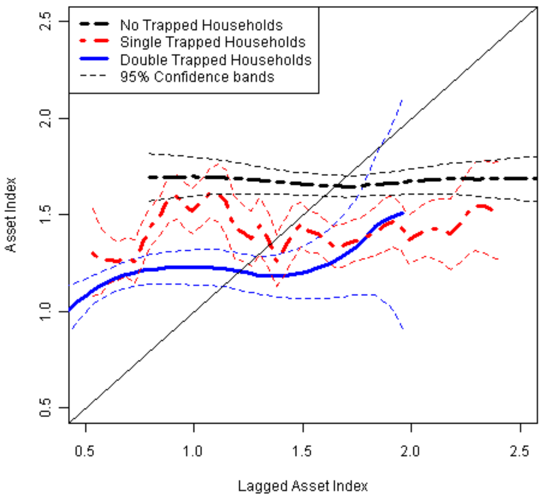


Figure 8: Asset Dynamics across Trap Status in the Enset Area

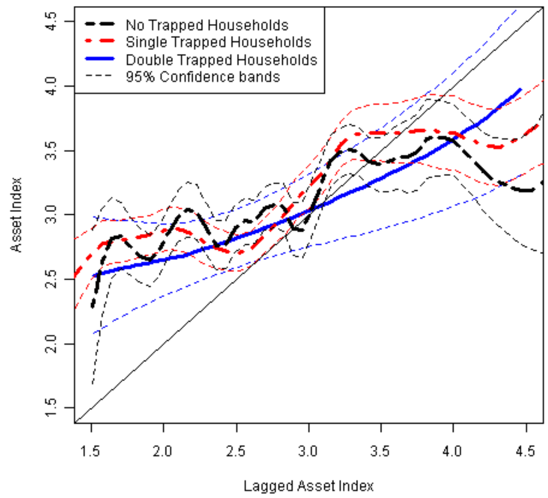


Figure 9: Asset Dynamics across Trap Status in the Highlands Area

lack of one resource or even two resources, does not necessarily prevent households from asset accumulation since other surplus resources can make up for it in the long run. In the most impoverished area, however, the dynamics are clearly distinguished from each other. The interpretation in this case is that the lack of one resource makes the asset dynamics converge to the lower equilibrium. The households in the poorest area may have little surplus resources to make up for the missing resource. Lack of one resource in the end makes other resources unproductive so that the asset dynamics converges to a lower equilibrium than no-trapped households. This complementarity suggests the existence of multidimensional and interlocking poverty traps. Moreover, the stable equilibrium of the double trapped households is identified at about 1.3. The implied equilibrium is less than \$1 per day, which may be readily interpreted as an asset poverty trap.[43]

Therefore, we conclude that the interlocking effect of the traps is likely to appear in the most deprived area. We find that it is hard to distinguish the effect of each poverty trap on the dynamics of the non-poor area or the non-poor. This implies that the surplus resources that they have work as substitutes in the household asset growth function. From these results it may be inferred that the dynamics of the poor are not likely to converge with those of the non-poor in the long run when multidimensional and interlocking poverty traps exist. Hence, the hypothetical explanation could be rejected that neither trap status determines the asset dynamics of rural Ethiopia. In addition, we may interpret the lowest stable equilibrium of the double trapped households as a form of multidimensional poverty trap. Since the multidimensional poverty traps affect the asset dynamics in the most deprived region, and hinder households from the accumulation of assets, we finally conclude that interlocking poverty traps do exist in the most impoverished region of Ethiopia.

7 Concluding Remarks

In this paper, we have considered the presence of multiple poverty dimensions. In addition to low-consumption (assets), we considered health traps as proxied by continued low BMI-for-age z scores, and education traps as proxied by continued illiteracy.

Estimating long term asset dynamics with the full sample, we fail to find evidence that the asset dynamics of the single trap households (i.e. either in an illiteracy or an undernutrition trap but not both), on average, differ from those of the non-trapped households. Considering differences at the regional level, however, we find evidence that the dynamic paths in the poorest region (enset growing area) represent different patterns depending on the trap status: First, the equilibrium is much lower than in two other regions; furthermore, the dynamics of the non-illiteracy group is located above that of illiteracy trap group.

However, the results from conditional mean regressions do not fully represent the behavior of the poor located in left tails of the structural income distribution. Considering long term differences across the structural income distribution, we adapt nonparametric quantile regression. We first examine the full sample according to the trap status. The patterns of asset dynamics are significantly different according to the presence of an illiteracy trap only below the 40th percentiles of the income distribution. That is, the dynamics of the households in lower income fractiles (above the 50th percentile of the income distribution) converge to the same equilibrium regardless of illiteracy trap status, but the dynamics of the households in the lower income fractiles in an illiteracy trap converge to a lower equilibrium than households in similarly low parts of the income distribution not having an illiteracy trap.

We adapted a pseudo-fixed effect model to consider short term differences at the regional level. We further examined the possibility that there are interlocking traps, in the sense that low levels of health and education have a negative interaction effect on assets. We find this effect in the most deprived region: both illiteracy and undernutrition trapped households have significantly less assets than the counterparts; and there is a statistically significant negative interaction effect of illiteracy and undernutrition on assets. In highlands area, only the undernutrition trap status variable has a marginally significant negative effect on assets, but there is no significant interaction effect. In the hoe area, we also fail to find evidence of a significant negative interaction effect.

Considering short term differences across the structural income distribution at the regional level, results from quantile regressions show that the significance of each trap differs across regions over the income distribution. In particular, in the highlands (the region with the best technology and resources) an illiteracy trap has no significant impact on asset change across the asset distribution. However, in the enset (most deprived) region, an illiteracy trap has a significantly negative effect on asset change, and the effects are very heterogeneous over the asset distribution. These results are suggestive that policy and programs should be attuned to whether the poor are trapped and in what ways.

In section 2, we argue that health and education, for example, to a degree might act as substitutes for each other in allowing the accumulation of assets, but when both are lacking this may prevent accumulation since the very poor have only very small amount of other assets that might otherwise work as substitutes for the lacking resources. That is, with high deprivations, all resources turn out to be complementary inputs for asset production. The existence of this complementarity is itself further evidence of interlocking poverty traps.

Therefore, we re-examined the long term asset dynamics, to further investigate the presence of interlocking poverty traps at the regional level. We find that asset dynamics in the most deprived region is distinguished from those of other areas: the estimated dynamics in the most impoverished area are separated out according to the trap status (no, single, and double trap), while all the asset dynamics estimated in other areas converge to statistically the same equilibrium. Only in the enset area are the dynamics of no-trapped, single-trapped, and double trapped households all statistically different: the equilibrium of the double trapped group is statistically below that of the single-trapped groups, which in turn are below the equilibrium of the non-trapped group. This finding supports that household inputs turn out to be complements in the most impoverished area, when a set of household resources is lacking. Therefore, the most impoverished area has the highest likelihood that the multidimensional, and interlocking poverty traps are found.

Notes

[1]We utilize the GNU Software R for statistical computing and graphics with ConfBands (Krivobokova et al., 2009), np (Hayfield and Racine, 2010), plm (Croissant, 2010), quantreg (Koenker, 2009), and SemiPar (Wand et al., 2005) packages.

[2]Plausibly, such traps result from credit constraints; and credit has been emphasized as a binding constraint by practitioners advocating microfinance. However, other practitioners argue that the poorest are too deprived in multiple dimensions to benefit from credit without first establishing some preconditions.

[3]For example, BRAC, formerly known as the Bangladesh Rural Advancement Committee, pioneered the "ultra-poor" program, targeting the poorest women living in villages in widely impoverished regions. This program includes large asset transfers (livestock or trees), enterprise training, health services, and legal services.

[4]See Smith (2002).

[5]See e.g. Antman and McKenzie (2007).

[6]We exclude Round 2 because Round 2 is surveyed 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). 6 villages of Round 4 were also surveyed during the Bega season.

[7]According to the International Monetary Fund's *World Economic Outlook Database*, purchasing power parity per capita of Ethiopia was $360 in 1994. In 2004, (i.e., the last year of the panel), the purchasing power parity per capita was $560.

[8]Dercon (2000, pp. 18-19) and Geda et al. (2009, pp. 964-966) find evidence of the pro poor growth in rural Ethiopia.

[9]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.

[10]Using the data of Global Administrative Areas from "http://www.gadm.org," we draw the map by package "*maptools*" in R. The characteristics of 3 regions are found in Dercon and Hoddinott (2009, p.9). Table A-2 in the Appendix presents large differences in the consumption level based on the farming system regions.

[11]Dercon and Ayalew (2007) use the Ethiopia Rural Household Survey (ERHS) from 1994 to 2004 to examine whether land rights affect household investment decisions. Dercon and Ayalew's (2007) findings also support this prediction.

[12]Among 1,477 households at the round 1 (1994), 223 households were not reinterviewed in 2004.

[13]We estimate the following equation:

$$\Lambda_{ivt} = \sum_{j} \beta_j (A_{ijvt}) + \sum_{j,k} \beta_k (A_{ijvt})(A_{ikvt}) + \sum_{j} \alpha_j H_{ijt} + \sum_{v,t} \delta_v (\Psi_v)(\Upsilon_t) + \sum_{v} \phi_v \Psi_v + \sum_{t} \gamma_t \Upsilon_t, \tag{5}$$

where 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. 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 (Ψ_v and Υ_t) are included. In addition, the interacted terms of time dummies and village dummies are included to control for village specific transitory effects.

[14]Based on this definition, we here construct illiteracy status of round 6 using round 5 information, since there exist households having new heads in round 6–about 160 households install their new household heads. If the household head is not changed, we treat their illiteracy status is the same as round 5. If the household head is changed in round 6, we use round 5 information on illiteracy status of the new household head. We then see whether those in such traps exhibit fundamentally different income and asset dynamics, that can be interpreted as an income or asset trap.

[15]Various anthropometric indicators exist: weight-for-height, height-for-age, weight-for-age, body mass index (BMI) and so on. Weight-for-height indicates current nutritional status. That is, it measures short-term changes in nutritional status. On the other hand, height-for-age represents chronic inadequacies of nutritional status. Weight-for-age is a mixture of height-for-age and Weight-for-height. In addition, BMI is another important indicator of chronic energy deficiencies (or obesity).

[16]We use Vidmar, Carlin, Hesketh, and Cole's (2004) "zanthro" in Stata to compute z-scores under the assumption that household members over 23 years old are not getting old. Thus, the numbers of households with the chronic energy deficiency may be an upper bound due to the aged.

[17]Round 5 has no anthropometric information, so in effect we are assuming that if undernutrition is observed in all other periods then it would have occurred in period 5 as well.

[18]The most common cutoff value is -2 to identify abnormal anthropometry. World Health Organization (WHO) has more general undernutrition classification. (Details are in WHO (1995).) As a robustness check, we construct another undernutrition trap status variable using only the information of round 1, 4, and 6. The proportion of trapped households from the full sample increases to 22.0 %.

[19]The Chi-Square statistic is $\chi^2_{(1)} = 16.769$ with p-value=0.000; and the phi-squared value is 0.0037.

[20]As a robustness check, we also compute the trapped household ratios including all observations for which we have missing information on illiteracy trap or undernutrition trap status, assuming that no trap is present in these cases. We find statistically the same results.

[21]Krivobokova et al. (2009) propose "simultaneous Bayesian credible bands" derived from Markov Chain Monte Carlo (MCMC) simulation output. In this framework, we use truncated line basis with degree 2. Higher orders of degree lead to smoother spline function. Consider the regression model

$$A_{it} = \beta_0 + \beta_1 A_{it-1} + \sum_{k=1}^{K} u_k (A_{it-1} - \kappa)_+^2 + \varepsilon_i, \tag{6}$$

where A is the asset index, 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 $\sigma_\theta^2 \sim IG(0.001, 0.001)$. One advantage of Bayesian inference is that the bias from measurement error can be automatically adjusted from the Bayesian framework (Berry et al., 2002).

[22]This can be seen simply by noting the addition of the estimated lines into Figure A-2(a) and A-3(a), which then produce Figure A-2(b) and A-3(b) in the Appendix.

[23]As reported in Table A-4 and A-5 in the Appendix, we find that the income distributions differ according to trap status. Figure A-1 in the Appendix provides additional evidence that each region has a different income distribution.

[24]Hence, we conclude that the first explanation in section 5 is likely to be rejected, while the second is not conclusive thus far. More conclusive estimation is reported in the next section using no, single, and double trap definition.

[25]To our knowledge, there is still no known method to generate meaningful data driven smoothing parameters in the multivariate case by minimizing Schwarz Information Criterion (SIC) (Koenker, 2010, p.15). The spline estimator of $m(\cdot)$ is found from the function $f(X)$ that minimizes

$$\min \sum_{i=1}^{n} (Y_i - f(X_i))^2 + \lambda \int (f''(X_i))^2 dx, , \tag{7}$$

where X_i is an explanatory variable, and $\lambda > 0$ is a smoothness parameter for the adjustment. In extreme cases, when λ goes to infinity, the function is linear over the whole range of x. That is, larger λ indicates that we have a much smoother curve, but also a larger mean squared error. To determine whether rural Ethiopia may be characterized as being in a trap-like stagnation, with respect to illiteracy or undernutrition, we begin by considering that income growth may depend on the log of income y and other factors, X.

$$\ln y_{i,t} - \ln y_{i,0} = \beta \ln y_{i,0} + \gamma X_i + e_i, \tag{8}$$

where $y_{i,0}$ is initial income of i and X_i contains explanatory variables related to income growth in a household. In this regression, a negative β means a negative relationship between initial household income and the household income growth rate, since a household with higher initial incomes would have smaller rates of growth rate than those with lower initial income under the decreasing returns to factors of production. This may be understood at the local level as decreasing inequality among households. We find a decrease in inequality in the evidence from Table A-3. This household level analysis may be compare to country growth regression studies. (Barro, 1991)

[26]20 knots are equally spaced in percentile levels. The estimation results are shown in Figure A-6 and A-7 in the Appendix.

[27]See Figure A-3.

[28]For more on "asset smoothing" research see Zimmerman and Carter (2003). Another possible explanation is that households in a non-undernutrition trap could be in an illiteracy trap. The ratio of the illiteracy trapped households to the non-undernutrition trapped households is about 0.51, while the ratio of the undernutrition trapped households to the non-illiteracy trapped households is 0.18.

[29]The Mundlak devices are each household' mean values of time varying explanatory variables over time. That is, in equation (3) each $\bar{X}_i$ is computed by $(\sum_{t=1}^{T} X_{it})/T$, where t represents data period, i indicates each household, and T is the total number of surveyed periods. Mundlak's (1978) approach depends on the

assumption that unobserved effects are correlated with explanatory variables. The details are in Mundlak (1978) and Wooldridge (2002). By this approach, we can also justify adapting the fixed effect rather than the random effect model by testing whether the all coefficients of group mean variables are equal to zero.

[30]From the first column in Table 4, we find that the null hypothesis of θ=0 is rejected at any conventional level. The χ^2_5=24.75 and p-value ($Prob > \chi^2_5$) is 0.0002. Hence, the pseudo-fixed effect model is justified rather than the random-effect model.

[31]The Breusch and Pagan Lagrangian multiplier test rejects random effects ($\chi^2_{(1)}$ =1096.40). Also a test for autocorrelation proposed by Wooldridge (2002, 282-283) marginally rejects the null hypothesis of no first-order autocorrelation. In addition, the quantile regression results support the existence of heteroskedasticity. Hence, we report robust standard errors in Table 4.

[32]ERHS round 1, 3, 4, 5, and 6. We compute the fit using the Frisch-Newton interior point algorithmic method, which is described in detail in Portnoy and Koenker (1997). Standard errors are computed by nonparametric estimates of the covariance.

[33]The dark area represents the 95% confidence bands. The dashed line and the dotted line are the coefficient and 95% confidence intervals from OLS.

[34]We estimate the following specification.; $A_i = \beta_0 + \beta_1 P_{1i} + \beta_2 P_{2i} + \beta_3 P_{1i} P_{2i} + \mathbf{X}\alpha + e_i$. We find that the interlocking trap has no significant effect on the level of the structural income over the whole range of the distribution.

[35]We also estimate the effect of the trap variables on the level of the asset index. The significant differences of the absolute asset index level between the trapped and the non-trapped households are detected in the upper percentiles as well.

[36]The dark area represents the 95% confidence bands. The dashed line and the dotted line are the coefficient and 95% confidence intervals from OLS. Undernutrition trap is significantly negative effect on the income. In rural Ethiopia, about 60% of total households are identified as poor. However, the illiteracy trap heterogeneously reduce about 5% to 10% of the income for the poor. The cultivated land increases about 6% of the structural income for the poor, while it increases about 7.5% of the income for the non-poor. Livestock increases the structural income very heterogeneously.

[37]Here, the poor are identified based on the findings in Table 1. Here, we find that about 60% of total households are below the poverty line in 1994.

[38]We estimate a bivariate local linear regression: $A_{it} = f(A_{it-1})$, using Epanechnikov kernel. Optimal bandwidth is selected by likelihood cross-validation. In some cases, a fixed type bandwidth reports an over-smoothed fit. In these cases, we adapt an kth nearest neighbors for the continuous variables. In this case, the bandwidth is a function of the number of the nearest neighbors. Moreover, to avoid the high variability generated from sparse data points at lowest and highest tails, we remove the points located below 5 percentiles and above 95 percentiles of asset index. As a robustness check, we use all samples to estimate asset dynamics in the enset area in Figure A-9 in Appendix.

[39]Single trapped households are defined as households suffering from only one dimensional poverty trap, either illiteracy or undernutrition trap. Double trapped households represent households having two or more poverty traps simultaneously.

[40]All estimations use a local linear regression with Epanechnikov kernel. The optimal adaptive bandwidth are selected by cross validation. The kth nearest neighbors are 142, 289, and 62 for no-trapped, single trapped, and double trapped households, respectively. Confidence bands are estimated by 500 replications of bootstraps.

[41]A local linear regression is used. Confidence bands are estimated by 500 replications of bootstraps. The optimal kth nearest neighbors are 117 and 18 for no-trapped and single trapped households, respectively. We utilizes a fixed type bandwidth to estimate the dynamics of the double trapped households in the enset area due to the small number of observations.(Optimal bandwidth=0.2462) As a robustness check, we provide the double trapped households' asset dynamics in the enset area changing the bandwidth types in Figure A-10. The equilibrium does not depend on the bandwidth types. Moreover, we estimate asset dynamics using the sample without trimming as a robustness check. Figure A-9(a) in Appendix presents over-smoothed fits of asset dynamics across trap status in the enset area. This figure also supports that asset dynamics converge to different equilibria according to trap status.

[42]We use a local linear regression with an Epanechnikov kernel. All bandwidths are optimally selected by the cross-validation. The kth nearest neighbors are 21 and 36 for no trapped and single trapped households, respectively. For the double trapped households, a fixed type bandwidth (1.1357) and kth nearest neighbors, 34 are estimated optimally by minimizing Asymptotic Mean Integrated Square Error (AMISE).

[43]We use the conversion factor from World Bank (http://www.worldbank.org/data).

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Appendix A

A.1 Descriptive Statistics

Table A-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]Source: ERHS 1994a, 1995, 1997, 1999, 2004.

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

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

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

Table A-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.

Table A-3: 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.

Table A-4: Asset Index with the Status of Undernutrition Traps

Area	Undernutrition trap Non-Trapped	Trapped	t-values* (Pr(T>t))	Epps-Singleton Test** (Pr(T<t))
Full sample	2.322 (82.1 %)	1.672 (17.9 %)	18.3505 (0.0000)	(0.00000)
Highlands Area	3.009 (89.9 %)	2.644 (10.1 %)	4.5457 (0.0000)	(0.00001)
Hoe Area	2.072 (84.0 %)	1.724 (16.0 %)	6.0001 (0.0000)	(0.00000)
Enset Area	1.544 (70.8 %)	1.229 (29.2 %)	9.2550 (0.0000)	(0.00000)
Observations	4817	1048		

[a]The proportion of trapped households in each region is in parenthesis.

*The null hypothesis is that the mean of non-trapped income is equal to that of the trapped. P-values in parenthesis are for the one-sided test.

**The Kolmogorov-Smirnov test can be used, but usually it has a lower power. The Epps-Singleton test is a nonparametric test proposed by Epps and Singleton (1986). It tests whether the distribution functions coming from two independent samples are identical.

Table A-5: Asset Index with the Status of Illiteracy Traps

Area	Illiteracy trap Non-Trapped	Trapped	t-values* (Pr(T>t))	Epps-Singleton Test** (Pr(T<t))
Full sample	2.252 (49.5 %)	2.040 (50.5 %)	6.1343 (0.0000)	(0.00000)
Highlands Area	2.903 (54.4 %)	2.951 (45.6 %)	-0.8139 (0.7921)	(0.00130)
Hoe Area	2.120 (43.9 %)	1.977 (56.1 %)	2.6405 (0.0042)	(0.02236)
Enset Area	1.631 (49.5 %)	1.268 (50.5 %)	9.4841 (0.0000)	(0.00000)
Observations	2255	2303		

[a]The proportion of trapped households in each region is in parentheses.

*The null hypothesis is that the mean of non-trapped income is equal to that of the trapped. P-values in parenthesis are for the one-sided test.

**The Kolmogorov-Smirnov test can be used, but usually it has a lower power. The Epps-Singleton test is a nonparametric test proposed by Epps and Singleton (1986). It tests whether the distribution functions coming from two independent samples are identical.

Table A-6: Asset Index with the Status of Poverty Traps: Robustness Check

	Non Single Trapped	Single trap*	Double trap*	Population (n)
Full sample	2.392 (52.6%)	1.991 (47.4%)	1.588 (9.4%)	2.202 (5,909)
Highlands Area	3.002 (62.5%)	2.897 (37.5%)	2.717 (4.5%)	2.963 (2,261)
Hoe Area	2.093 (49.3%)	1.938 (50.7%)	1.747 (8.9%)	2.014 (1,814)
Enset Area	1.652 (43.8%)	1.294 (56.2%)	1.103 (15.8%)	1.451 (1,834)
Observations	3,111	2,798	553	5,909

[a]The proportion of trapped households in each region is in parentheses.

[b]We include all observations for which we lack information of either illiteracy or undernutrition status as a robustness check.

*Alkire and Foster (2011) examine three identification methods for a poverty status. The 'intersection' method identifies the poor in a too constricted way (e.g. as dimension increases, the identified number of the poor decreases), while 'union' method identifies the poor in an exaggerated way (e.g. Non-poor in too few outcomes could be considered as poor). They propose 'dual cutoff' method of identification to identify a poor person. Here, single trap is defined by the union method while double trap is defined by the intersection method. As we only have two dimensions in this study, the intersection identification method is not harmful and it successfully identify as poor a group which is most deprived.

A.2 Land Weight

Land weights are computed based on the revenue per hectare per work time at each plot using 1999 data set. Only 1999 data allows us to identify the outputs, revenues, and inputs including labor use per plot. There exist information on 6,267 plots, but after removing missing variables of work hours and revenues we have 5,320 observations of revenue per hectare per work time at each plot. Data also allow us to identify harvesting season, Meher(observations=4,850) and Belg(observations=470). We use all observations to compute the weights. The specific summary statistics are in Table A-7.

Table A-7: Summary of Lands Cultivated: Round 5

Land quality	Statistics	Medda(Flat)	Slope Dagathama	Geddel(Steep)
Lem	Frequency of plot	2630	510	41
(Best)	Total hectare of land (H)	789.61	100.71	6.07
	Total revenue (R)	19,757,71	12,691,589	935,825.51
	Total work hours (WH)	399,452.01	190,014.2	34,964.93
	Revenue per hectare per work hour	1,054,472	541,223.26	34,005.84
Lem-Teuf	Frequency	1,096	451	25
	Total hectare of land (H)	393.40	130.61	5.91
	Total revenue (R)	4,108,76	3,246,785.6	54714.76
	Total work hours (WH)	257,909.53	54,678.60	651.15
	Revenue per hectare per work hour	220,083.48	146,361.03	1,379.33
Teuf	Frequency	427	131	9
(Worst)	Total hectare of land (H)	133.091	38.937	2.75
	Total revenue (R)	1,266,906.2	367,696.25	40629.70
	Total work hours (WH)	321,315.44	6,095.67	180.89
	Revenue per hectare per work hour	157,060.02	13,664.37	674.29

[a] All numbers are authors' computation using ERHS 1999.
[b] Total Revenues are computed by $R = \sum_i output_i \times price_i$.
[c] Total work hours are computed by $WH = \sum$ (Clearing, Land prep, Trampling, Drainage,Fertilizer/Pesticide application, Weeding, Shilshalo, Pruning, Transporting, Threshing/Shelling, Guarding).
[d] Revenue per hectare per work hour=$(R/H)/WH$

Most lands are Lem or lem-teuf quality and flat. Only a small portion of land has steep slope and poor fertility. Land weight are computed by setting revenue per hectare per work hour of the best flat plot as 1. For example, the weight of Lem-teuf and Medda plot is $220,083.48/1,054,47 = 0.209$.

Table A-8: Plot Weight

	Medda (Flat)	Dagath-Ama	Geddel(Steep Incline)
Lem (Best)	1	0.513	0.032
Lem-Teuf	0.209	0.139	0.001
Teuf (Poor)	0.149	0.013	0.001

Table A-9 shows the mean values of asset indices, weighted land, and non-weighted land across farming system regions. The asset index is not much different while weighted lands are much smaller than non-weighted except for the enset growing area, in which weighted land are a little larger. Considering that land is less important than livestock in the enset growing area, the unchanged asset index can be explained. If land is an important asset in the enset area, we can expect the asset index to increase. However, the asset index does not change.

Table A-9: Asset Index using Weighted Land

Farming System Regions	Asset Index with Weighted land	Asset Index with Non-Weighted land	Weighted land per Adult	Land per Adult
Highlands Area	2.967	[2.963]	.3685	.4875
	(1.237)	[(1.284)]	(.8482)	(.4809)
	2212	[2261]	2212	2261
Plow/Hoe Area	2.01	[2.014]	.2406	.4066
	(.9928)	[(.9863)]	(.3563)	(.3694)
	1809	[1814]	1809	1814
Enset Growing Area	1.441	[1.451]	.2094	.1634
	(.6629)	[(.7523)]	(.9127)	(.2797)
	1816	[1834]	1816	1834
Total	2.195	[2.202]	.2794	.3621
S.D.	(1.198)	[(1.23)]	(.7589)	(.4165)
N	5837	[5909]	5837	5909

[a] Asset index are estimated by the same method in equation (5).

[b] Mean of asset indices using non-weighted land is in square bracket.

[c] Standard deviations are in parentheses.

A.3 Figures

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

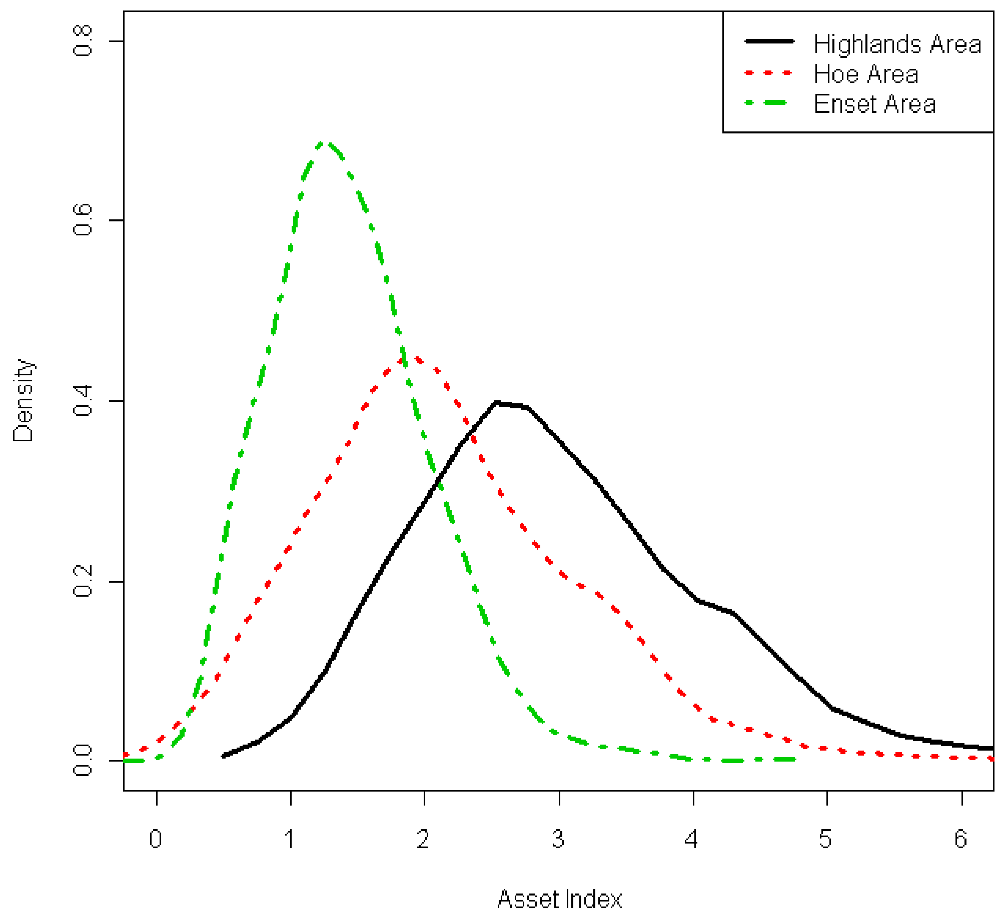
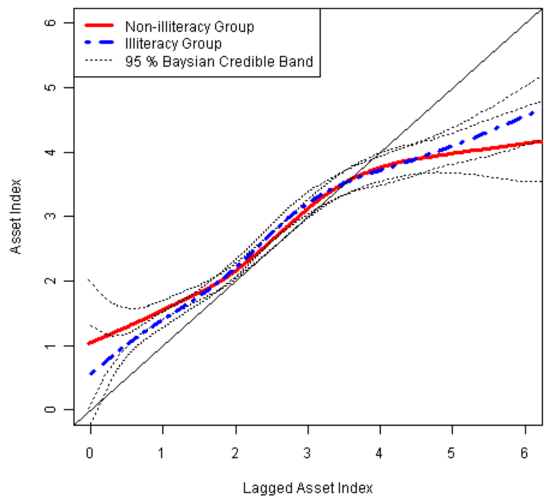
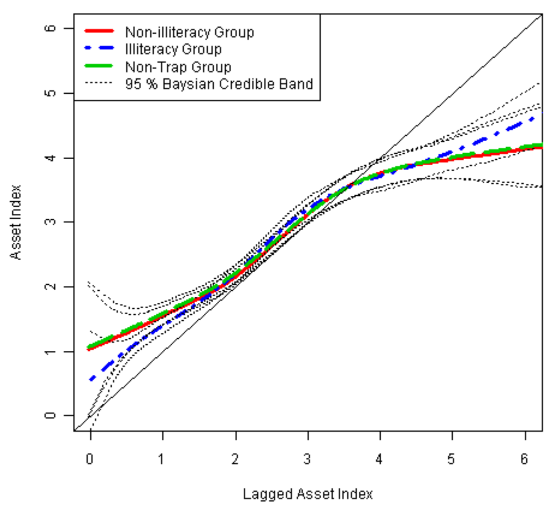


Figure A-2: Illiteracy, Non-illiteracy, and Non-Trap: Full Sample

(a) Illiteracy and Non-illiteracy[a]



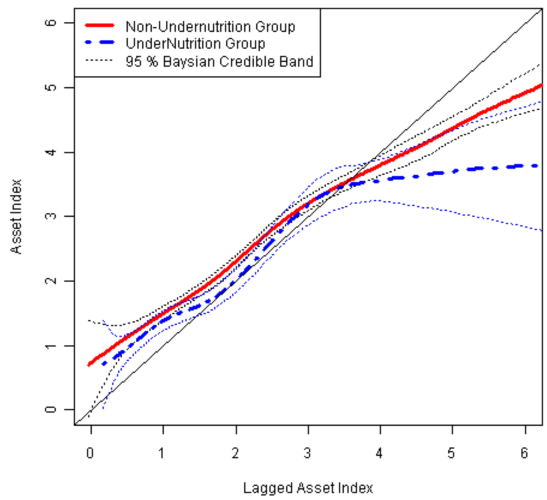
(b) Adding No-Trap[b]



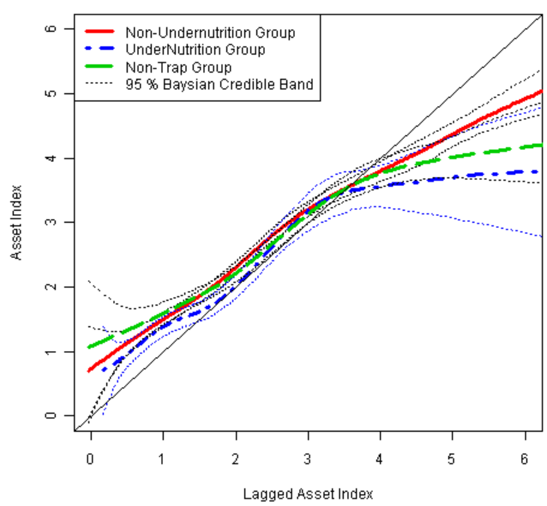
[a]ERHS 1994a, 1995,1997, 1999, and 2004 are used. Bayesian Penalized spline with 95% credible bands estimated using 20,000 sampling and 2,000 burn-in.
[b]The same data and estimation method as in figure A-2(a).

Figure A-3: Undernutrition and Non-undernutrition: Full Sample

(a) Undernutrition and Non-undernutrition[a]



(b) Adding No-Trap[b]

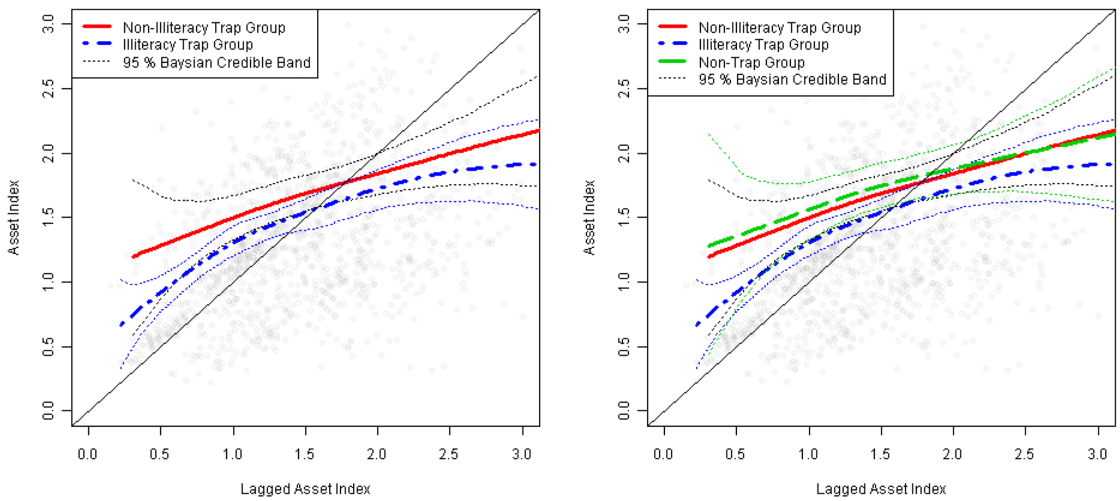


[a]ERHS 1994a, 1995,1997, 1999, and 2004 are used. Bayesian Penalized spline with 95% credible bands estimated using 20,000 sampling and 2,000 burn-in.
[b]The same data and estimation method as in figure A-3(a).

Figure A-4: Illiteracy Trap: the Enset Area

(a) Non-illiteracy and Illiteracy[a]

(b) Adding No-Trap[b]



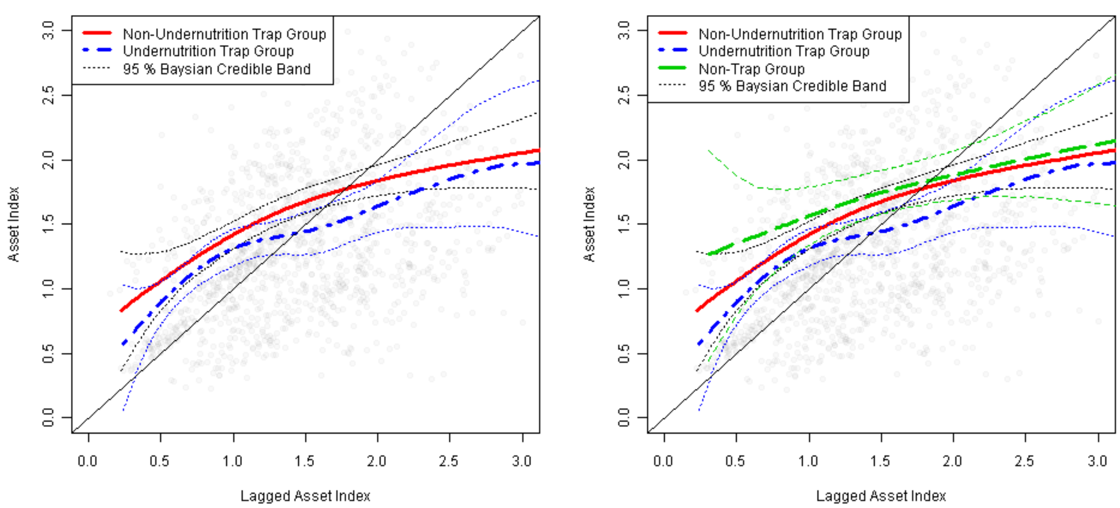
[a]ERHS 1994a, 1995,1997, 1999, and 2004 are used. Bayesian Penalized spline with 95% credible bands estimated using 20,000 sampling and 2,000 burn-in.

[b]The same data and estimation method as in figure A-4(a).

Figure A-5: Undernutrition Trap: the Enset Area

(a) Non-undernutrition and Undernutrition[a]

(b) Adding No-Trap[b]

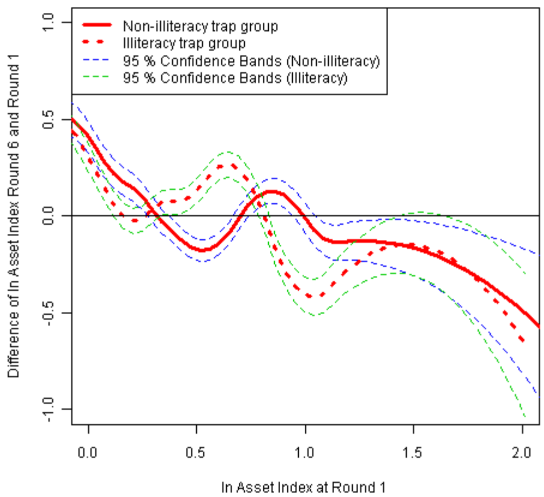


[a]ERHS 1994a, 1995,1997, 1999, and 2004 are used. Bayesian Penalized spline with 95% credible bands estimated using 20,000 sampling and 2,000 burn-in.

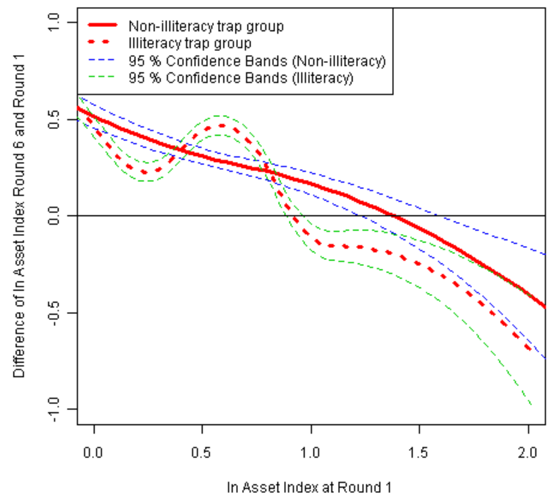
[b]The same data and estimation method as in figure A-5(a).

Figure A-6: Nonparametric Quantile Regression: Illiteracy trap[a]

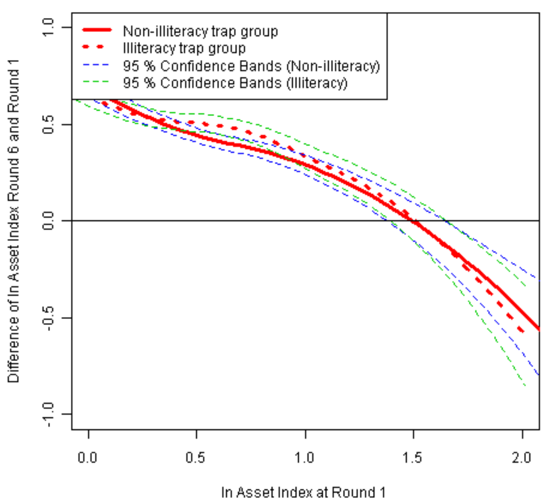
(a) 20% Quantile[b]



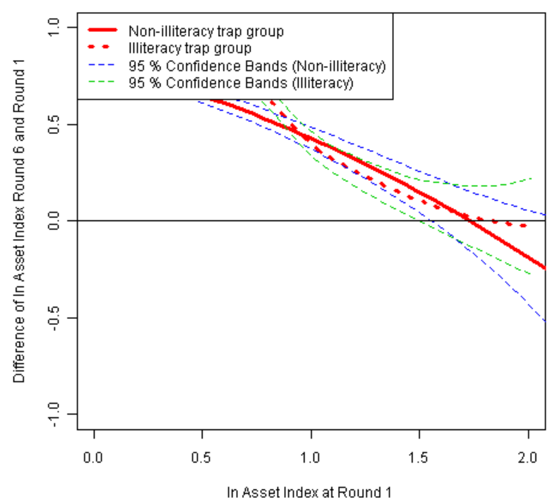
(b) 40% Quantile[c]



(c) 60% Quantile[d]



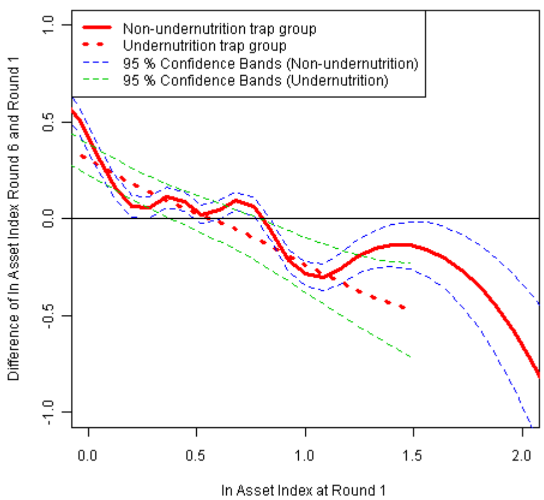
(d) 80% Quantile[e]



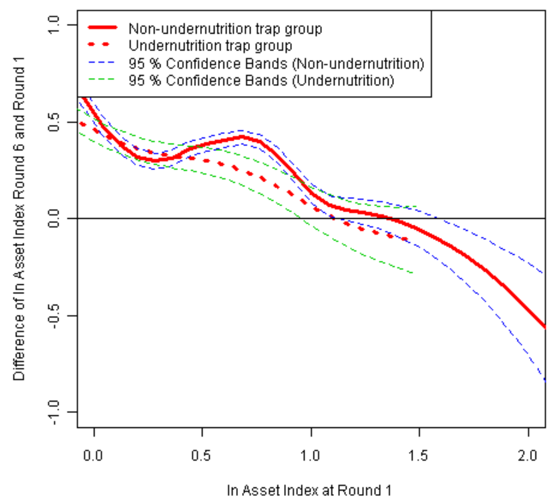
[a]Quantile smoothing spline is utilized with ERHS round 1 (1994a) and round 6 (2004) for all combined regions.
[b]Optimal λ is estimated: 0.1544 and 0.0725 for non-illiteracy and illiteracy trap households, respectively.
[c]Optimal λ is estimated: 4.4353 and 0.2777 for non-illiteracy and illiteracy trap households, respectively.
[d]Optimal λ is estimated: 2.4941 and 1.6724 for non-illiteracy and illiteracy trap households, respectively.
[e]Optimal λ is estimated: 2.2660 and 0.2777 for non-illiteracy and illiteracy trap households, respectively.

Figure A-7: Nonparametric Quantile Regression: Undernutrition trap[a]

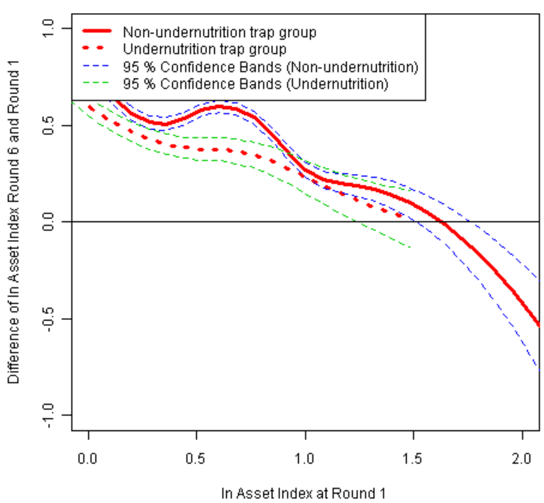
(a) 20% Quantile[b]



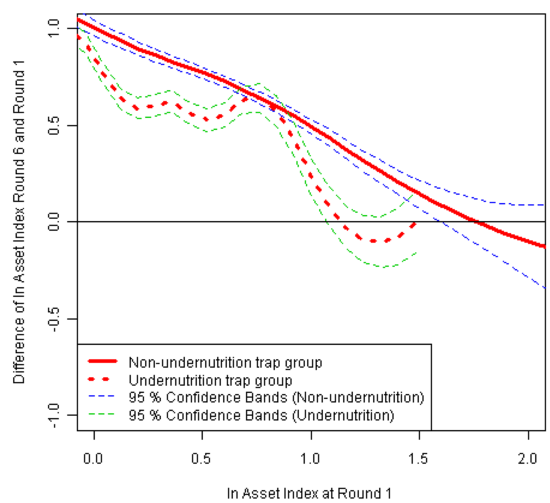
(b) 40% Quantile[c]



(c) 60% Quantile[d]



(d) 80% Quantile[e]



[a]Quantile smoothing spline is utilized with ERHS round 1 (1994a) and round 6 (2004) for all combined regions.

[b]Optimal λ is selected by minimizing SIC: 0.1943 and 0.8481 for non-undernutrition and undernutrition trap households, respectively.

[c]Optimal λ is selected by minimizing SIC: 0.3802 and 0.8481 for non-undernutrition and undernutrition trap households, respectively.

[d]Optimal λ is selected by minimizing SIC: 0.6059 and 0.3576 for non-undernutrition and undernutrition trap households, respectively.

[e]Optimal λ is selected by minimizing SIC: 2.8513 and 0.1131 for non-undernutrition and undernutrition trap households, respectively.

Figure A-8: Quantile Regression (ERHS 1994a, 1995, 1997, 1999, 2004)

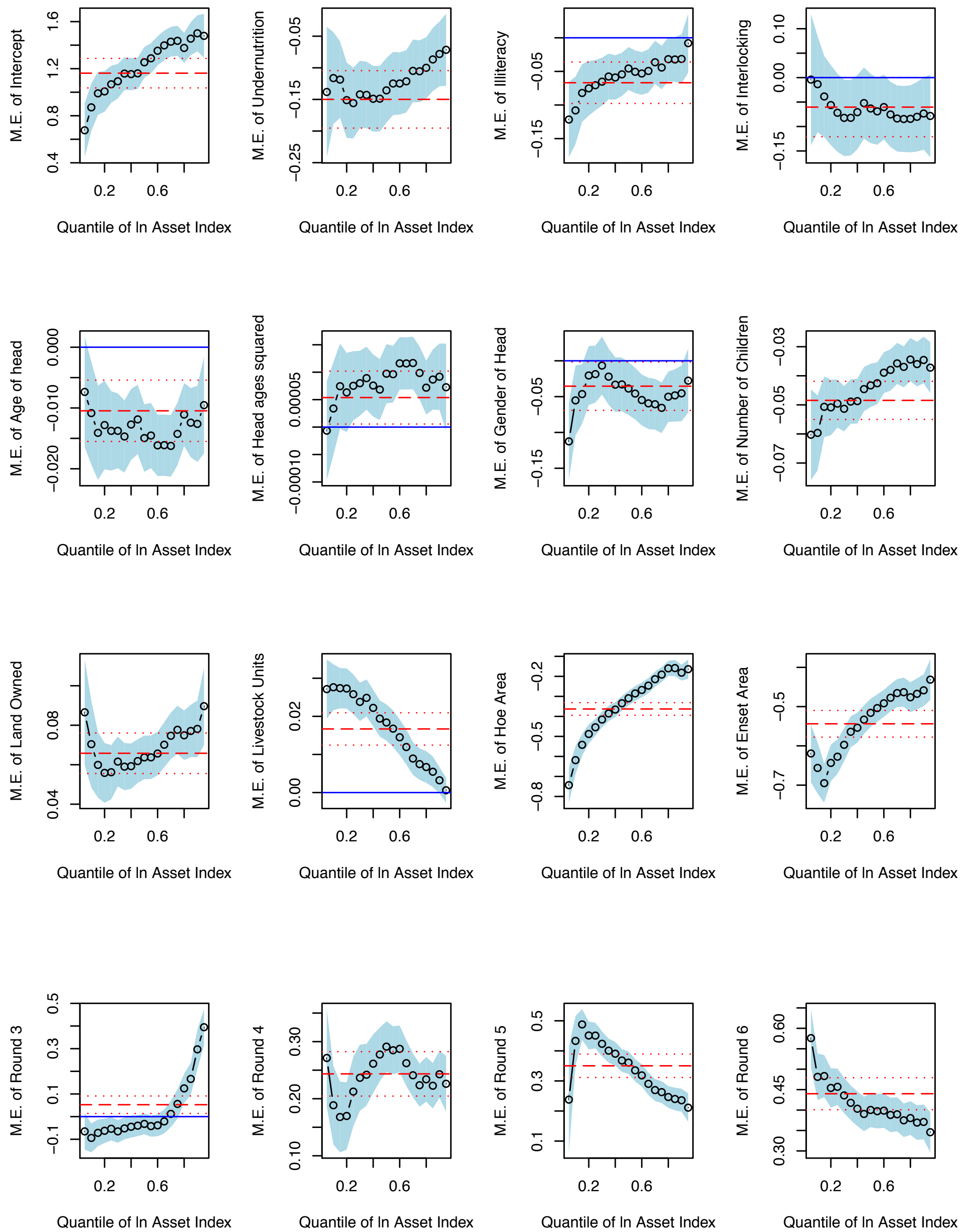
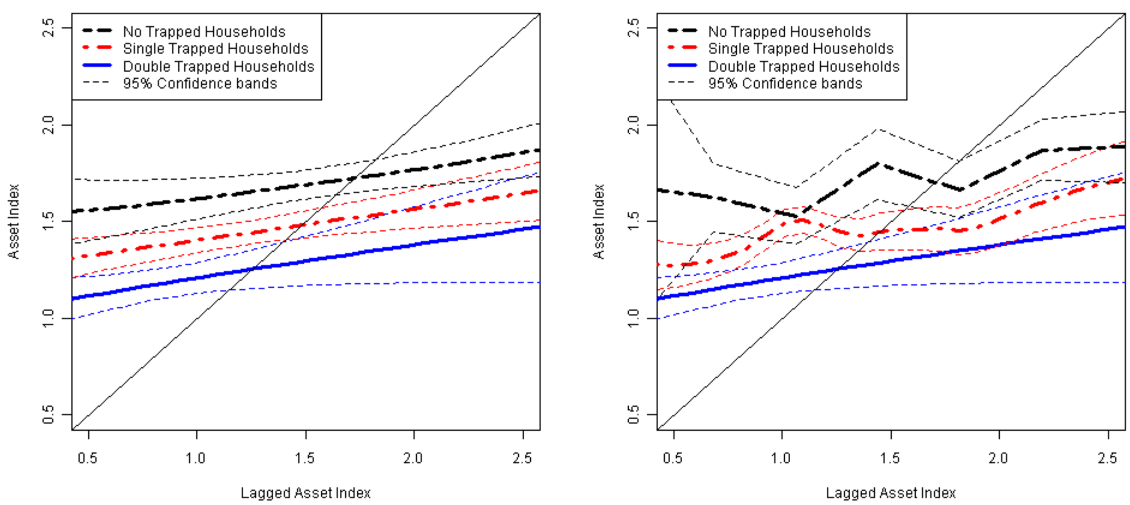


Figure A-9: Robustness Check: Asset Dynamics in the Enset Area

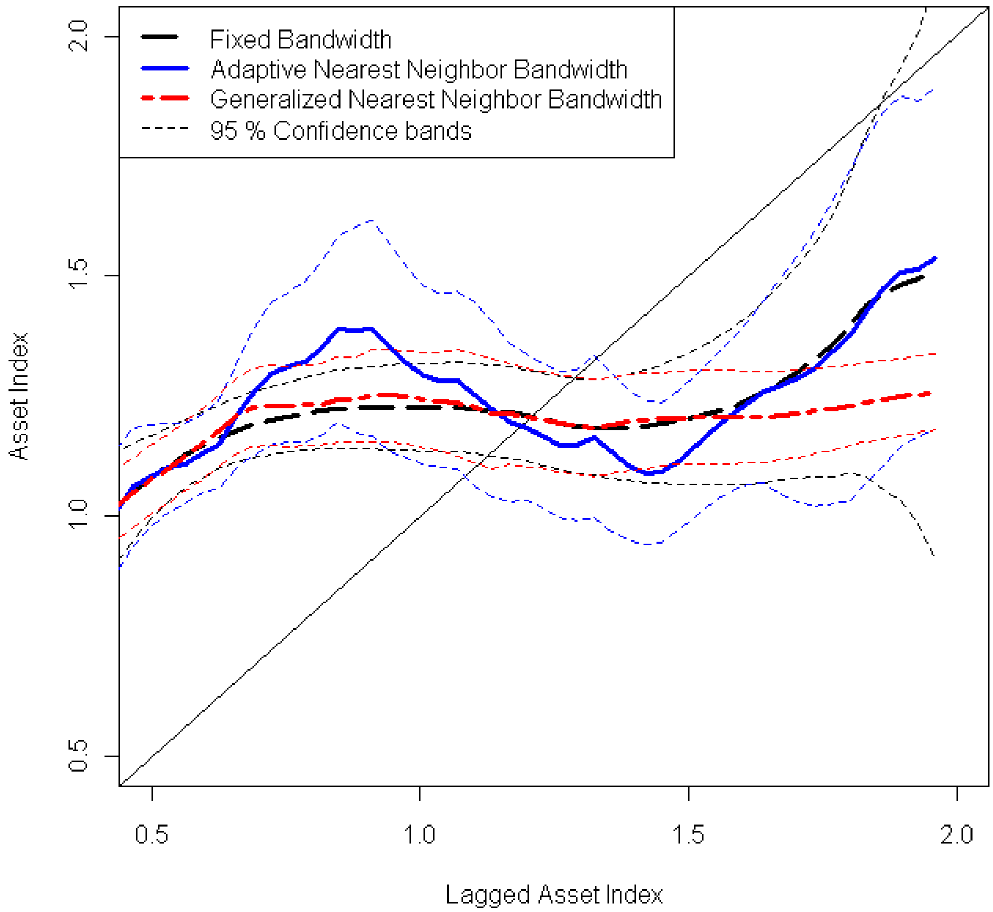
(a) Fixed Type Bandwidth[a] **(b)** Adaptive Type Bandwidth[b]



[a]Using ERHS 1, 3, 4, 5,and 6, the dynamics in the enset area are estimated by local linear regression with Epanechnikov kernel. Fixed type optimal bandwidth are selected by cross-validation. The fit is over-smoothed since the optimal bandwidths are too large (1.5142, 1721918, and 2.6153 for the no-trapped, the single trapped, and the double trapped households, respectively). We believe that this is due to the sparse points at the tails of asset index distribution.

[b]Using ERHS 1, 3, 4, 5,and 6, the dynamics in the enset area are estimated by local linear regression with Epanechnikov kernel. The kth nearest neighbors are 19 and 60 for the no-trapped and the single trapped groups, respectively. A fixed bandwidth for the double trap group is 2.6153. From an adaptive type bandwidth selection for the double trapped group, we do not gain anything for the fit since the number of observation (n=290) is too small and the optimal kth nearest neighbor is too large (163).

Figure A-10: Double Trap Groups's Asset Dynamics: the Enset Area (Bandwidth Types)[a]



[a]Using ERHS 1, 3, 4, 5,and 6, the double trap groups' dynamics in the enset area are estimated to find how bandwidth types affect the shape of dynamics. The kth nearest neighbors are 41 and 13 for a generalized and an adaptive nearest neighbor bandwidth types respectively. A fixed bandwidth is 0.2462. Generalized nearest neighbor type generates the most smoothing fit. The equilibrium does not depend on the bandwidth type.