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Assets, Shocks, and Poverty Traps in Rural Mozambique

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Abstract

Using a micro-level approach to poverty traps, this paper explores welfare dynamics among households in post-war rural Mozambique. Conceptually, the paper builds on an asset-based approach to poverty and tests empirically, with household panel data, for the existence of a poverty trap. Findings indicate that there is little differentiation in productive asset endowments over time and that rural households gravitate towards a single equilibrium, which is at a surprisingly low level. The analysis shows that shocks and household coping behavior help to explain the observed poverty dynamics. The single low-level equilibrium points to an overall development trap in the rural farm-based economy. This is attributed to the long-term impact of the civil war, which has consolidated unfavorable economic conditions in rural areas and limited new economic opportunities outside of the agricultural sector.

Keywords: Asset-based approach, Mozambique, poverty trap, shocks, violent conflict

JEL Codes: D31, I32, O12, O18

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1 Introduction

Research on poverty has recently focused on structural constraints that prevent the poor from moving out of poverty. The ideas of differentiated paths of wealth accumulation and of multiple equilibria, originally stemming from the macroeconomic literature, have also been applied to the micro-level. In what has been termed the asset-based approach to poverty (for example, Carter and Barrett 2006), which builds on the work of Deaton (1992) and others, assets are considered to determine a household's income-earning potential and future welfare. Households below a certain asset level are predicted to be trapped in poverty in the long term. The existence of a poverty trap may call for tailored policies to lift households above a critical threshold.

This paper applies the asset-based framework to poverty to rural Mozambique, and tests whether a poverty trap is present in the post-war period. The country underwent a long period of violent conflict that began with the war for independence in 1964, which then developed into a civil war between 1976 and 1992. Most acts of warfare took place in rural areas. RENAMO, the rebel army backed up by the white apartheid regimes of South Africa and (in the initial years of the war) Rhodesia, spread terror among the rural population as a means of discouraging people from supporting the FRELIMO government (Vines 1996; Wilson 1992). About one million individuals died in the course of the war (Hanlon 1996: 15f.), two million people took refuge in neighboring countries, and an estimated three million were internally displaced, with the majority of the latter seeking security in the periphery of cities (Synge 1997: 80f.). After the signing of the Peace Agreement in Rome in 1992, a large number of refugees and displaced people returned to the countryside and often to devastated areas. The war had destroyed most of the public infrastructure that was in place and many rural households also lost their productive asset base.

At the end of the war, GDP per capita was below its pre-independence level (Brück 2001: 59). With large inflows of donor assistance, investments in infrastructure, education, and the health sector were made and macroeconomic indicators improved steadily. Still, these improvements do not appear to have trickled down to rural households. Poverty remains high in Mozambique and about 64 percent of the rural population were below the poverty line in 2002, not least due to recurrent shocks, such as droughts, floods, cyclones, crop pests, diseases, and increasing mortality rates as a result of HIV/AIDS (Mather and Donovan 2008).

The analysis uses two waves (from 2002 and 2005) of a panel survey representative of smallholder farm households in rural Mozambique to explore household asset and welfare dynamics. The data set includes a large number of observations (about 4,000 households) and has detailed information on assets and income. Both non-parametric and parametric estimation techniques are used to investigate whether a poverty trap exists. Moreover, factors that determine households' asset accumulation in this fragile environment are examined, including time-invariant household characteristics, a drought, and coping strategies.

The ideal sample for testing the existence of poverty traps consists of a large number of households that are followed over their life cycles. Given that such data is virtually unavailable for developing countries, empirical studies have, for instance, drawn on a small sample of households (often less than 100) that have been followed over some 20 years (for example, Quisumbing and Baulch 2009). In this type of analysis, low rates of sample attrition and comparable price data over the years are crucial. Alternatively, a larger sample of households is followed for two periods, often only several years apart (for example, Adato et al. 2006). The time span observed in the Mozambican data of three years is too short to observe households' long-term accumulation paths. Rather, medium-term welfare dynamics will be explored. By the reliance on asset holdings, which are less prone to temporal fluctuations than flow-based measures such as income or expenditures, it is still possible to assess more than just stochastic trends in household welfare.

The paper contributes to the literature in three ways. First, few studies have tested the asset-based approach with empirical data. The context of rural Mozambique is particularly suitable for this endeavor, given that the post-war reconstruction period is characterized by low but variable asset endowments due to recent war and shocks. Thus, household asset endowments are expected to play a crucial role in determining household welfare outcomes in rural Mozambique. In other words, it indeed appears that "bicycles equal development," as Hanlon and Smart (2008) propose. In addition, some types of households may have been better able to take advantage of the new opportunities that emerged in the post-war period than others—for instance, peasants who are more open to adopting new farming techniques and to taking risks. Such inherent characteristics may help to explain the rising inequalities across households.

Second, the paper provides insights on how shocks and coping strategies relate back to welfare dynamics, which is seldom done in the empirical analyses of poverty traps. The way assets are used as a buffer to mitigate the impact of shocks is likely to shape a household's resilience against future shocks. The analysis thus reveals how factors other than initial conditions shape a household's accumulation dynamics.

Third, the findings are unusual. There appears to be no poverty trap in existence in rural Mozambique, while most other empirical studies based on data from sub-Saharan Africa do find evidence of poverty traps. We argue that this is rooted in the long-term impact of the civil war, which has made Mozambique different from other sub-Saharan Africa countries. Results are interpreted as a sectoral poverty trap of the rural farm-based economy. The civil war seems to have consolidated unfavorable economic conditions in rural areas and limited new economic opportunities outside of the agricultural sector.

The paper is structured as follows: the next section briefly summarizes the asset-based approach to poverty and provides an overview of current research. Section 3 introduces the *Trabalho de Inquérito Agrícola* (TIA) household panel data and discusses attrition. Section 4 outlines the estimation strategy. Empirical results are presented in Section 5, starting with descriptive evidence on income mobility and a poverty profile that highlights the relationship between asset endowments, exposure to shocks, and household well-being. Findings from non-parametric and parametric analyses are then discussed. Section 6 concludes.

2 Literature Review: Poverty Traps, Asset Dynamics, and Shocks

The concept of poverty traps has its origin in the macro-level growth literature. Cross-country studies on growth have introduced the concepts of conditional and club convergence and multiple equilibria that are associated with critical thresholds of capital.[1] These dynamics have been conceptualized at the micro-level by Carter, Barrett, and colleagues in the asset-based approach to poverty (for example, Carter and Barrett 2006; Carter et al. 2007; Carter and May 2001; Zimmerman and Carter 2003). In this framework, assets encompass "conventional, privately held productive and financial wealth, as well as social, geographic, and market access positions that confer economic advantage" (Carter and Barrett 2006: 179). Households' asset endowments are more accurately measured and less volatile than income or consumption expenditures. Moreover, assets to a large extent influence the range of income-

[1] Club convergence and conditional convergence refer to modifications of the unconditional convergence concept. Exogenous subgroups of countries are each assumed to follow a different dynamic path and equilibrium based on either initial conditions, which split countries into locally converging groups, or on heterogeneity in other, time-varying characteristics across the considered sample. Detailed surveys of the macroeconomic growth literature are provided by Barrett and Swallow (2006), Deardorff (2001), Durlauf et al. (2008), and Acemoglu (2009).

earning activities a household may engage in and are a better predictor of future welfare (Barrett et al. 2006a: 169).

The focus in the asset-based approach is on households' asset accumulation paths over time, as presented in Figure 1. The graph shows different asset recursion functions against the 45 degree line, as a reference, which represents a dynamic asset equilibrium at any point. If marginal returns to assets were not diminishing globally over the whole asset distribution as predicted by the classical Solow growth model (f1(At)), but were increasing locally instead (f2(At)), two (or more) stable equilibria may exist (Ap* and Ac*). The latter implies that there is an unstable equilibrium in between (Am), a "threshold at which accumulation dynamics bifurcate" (Carter and Barrett 2006: 190), also referred to in the literature as the Micawber threshold (Lipton 1994) or the dynamic asset poverty line. A household above this threshold is predicted to accumulate assets over time as more profitable activities and investments become accessible to the household. Eventually, the household reaches the stable upper asset equilibrium and moves out of poverty. In contrast, a household below the threshold is too poor to accumulate assets. If it also lacks the opportunity to borrow, the household remains trapped at a low welfare level.

Several circumstances may cause a locally positive relationship between asset level and marginal returns. For example, technology-intensive projects require a minimum investment that excludes poor households and risk avoidance may lead households to engage in activities with low but certain gains (Carter and Barrett 2006: 187f.). The aim of the asset-based approach is to detect in a given empirical context whether there are multiple equilibria towards which households converge in the long term. Hence, the dynamic asset-based approach identifies not only who is poor at a given moment in time, but also allows forward-looking projections of what types of households lack productive assets to escape poverty in the future.

Yet, few studies have applied the asset-based approach to empirical data, not least because household panel data with detailed information on well-being and assets are needed. Not all empirical studies examine poverty traps in asset space, but they also draw on consumption expenditures (for example, Jalan and Ravallion 2004) or income (for example, Lokshin and Ravallion 2002). The use of stock variables versus flow variables to test for poverty traps remains debated (Barrientos 2007). Moreover, different estimation techniques have been employed to test for poverty traps, including non-parametric (the most widely used methods), parametric, and semi-parametric methods. As Naschold (2005) points out, the choice of techniques implies a trade-off between flexibility with respect to the functional form (in non-parametric methods) and the ability to control for other factors that may influence a household's asset accumulation path (in parametric methods).

The different welfare measures, methodological approaches, and time spans used in empirical work make a comparison of findings across studies difficult. Still, some consistent geographical patterns are apparent. Studies on Asia, Europe, and Latin America do not find empirical support for the existence of a micro-level poverty trap.[2] In contrast, the majority of empirical studies using data from sub-Saharan Africa do indeed find evidence of poverty traps.[3] While each of those empirical studies offers local or country-specific interpretations for their respective findings, this could nevertheless suggest general underlying patterns driving the different results found in this region.

Poverty traps are more likely to be observed in volatile environments. On the one hand, more households may be observed out of their equilibrium, so that a poverty trap is more easily detected. For example, Lokshin and Ravallion (2002: 3) source their study on Hungary and Russia from the transition context "for which there must be a strong presumption that many households are being observed out-of-equilibrium." On the other hand, a shock may cast a household into a downward spiral in which the asset base is brought down to a level below which accumulation growth is not feasible, irrespective of a household's initial asset endowments. However, very few empirical studies on poverty traps explicitly take into account the role of shocks. Zimmerman and Carter (2003) and Carter et al. (2007) conceptually extend the asset-based framework by distinguishing the impact of short-term asset shocks (such as a hurricane) from more long-term income shocks (such as a drought). In their comparative study on Honduras and Ethiopia, Carter et al. (2007) find evidence that a hurricane in Honduras and a drought in Ethiopia trapped some households in poverty. Quisumbing and Baulch (2009) explore the impact of covariate and idiosyncratic shocks and positive events on household asset accumulation in Bangladesh. Both types of events are found to have significant effects on the accumulation of assets over time. Still, the signs of the

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[2] For instance, Naschold (2005) for Pakistan, Naschold (2009) and Dercon and Outes (2009) for India, Quisumbing and Baulch (2009) for Bangladesh, Lokshin and Ravallion (2002) for Hungary and Russia, Jalan and Ravallion (2004) for rural China and Antman and McKenzie (2007) for urban Mexico. One exception is a study by Carter et al. (2007) on the short-term effect of Hurricane Mitch in Honduras, which does find a poverty trap.

[3] For instance, Lybbert et al. (2004), Santos and Barrett (2006), and Carter et al. (2007) for Ethiopia, Barrett et al. (2006b) for Northern Kenya, and Adato et al. (2006) for South Africa. Two exceptions are a study by Naschold (2005) on Ethiopia and a study by Barrett et al. (2006b) on Madagascar, where no poverty trap is evident.

effects—for example, flood-affected Bangladeshi households experiencing higher asset growth—are at times surprising and difficult to interpret.

Besides the limited empirical evidence on the role of shocks in household welfare dynamics, there is even less evidence on the impact of household shock coping behavior on asset accumulation. One exception is the study conducted by Carter et al. (2007) that accounts for different household strategies to cope with drought. This way, findings are connected to an earlier field of research that explores whether households smooth consumption or assets when exposed to a shock.[4] A general conclusion from this literature is that better-off households typically sell assets in order to maintain their consumption stable when facing shocks. In contrast, poorer households sacrifice their consumption in order to secure their future livelihood. Carter et al. (2007) find that asset-poor households in Ethiopia sacrificed consumption during the long drought in order to protect their few, precious productive assets for future income generation.

The review of the literature has shown that there is: (a) an ongoing debate on the empirical validation of the poverty trap hypothesis at the micro level, and (b) limited evidence on how the experience of shocks and the adaptation of coping strategies relate back to household growth trajectories. Addressing these research gaps, two questions will be explored in the context of post-war rural Mozambique. First, we analyze the nature of household welfare dynamics in the medium term. Second, we examine the impact of shocks and shock coping strategies employed by households on asset accumulation.

3 Source of Data

The analysis employs the 2002 and 2005 panel waves of the *Trabalho de Inquérito Agrícola* (TIA) household survey collected in Mozambique by the country's Ministry of Agriculture, with technical support from Michigan State University (Ministério da Agricultura 2005; Ministério da Agricultura e Desenvolvimento Rural 2002). TIA is a rural household survey representative of small- and medium-sized[5] farm households across rural areas of all 10 provinces (except Maputo city) and agro-ecological zones. The TIA 2002 wave contains a

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[4] Influential studies in this field include: Asfaw and von Braun (2004), Dasgupta (1997), Dercon and Hoddinott (2005), Devereux (1993), Ersado et al. (2003), Fafchamps et al. (1998), and Rosenzweig and Wolpin (1993).

[5] Households cultivating more than 50 hectares of land, or owning more than 20,000 fruit trees, more than 100 heads of cattle, or more than 500 goats and pigs are classified as large-scale farmers and are not covered by the TIA survey.

sample of 4,908 rural households of which 4,104 could be re-interviewed in 2005 (in addition to a refresh sample). Taking potential attrition bias into account, the analysis focuses on the sample of 4,104 households that were interviewed in both years.

In both waves, the survey questionnaire covers household demography (including age, health, education, and exits and entries of members), income, assets, farming techniques, and access to services. Great care was taken particularly to measure land size, the most important physical asset in rural Mozambique.[6] TIA records household income in great detail but not consumption expenditures, which would have been our preferred measure for household well-being (for example, Deaton 1997).

Total income is calculated from crop production, sale of livestock and its by-products, wage work, self-employment, and remittances. Costs for seeds, fertilizers, and other inputs are deducted from revenues, and thus net income, rather than gross income, is considered. Crop income is by far the largest income component, and the bulk of it is the value of the harvest that a household retains for its own consumption. The median of self-reported producer prices at the district level was used to value the quantity of sold and retained harvest if at least 10 households reported price information for a given product. Otherwise, the median at the province level was used. To make income comparable across the survey years, all monetary measures from 2002 were adjusted to 2005 prices using province-level inflators taken from a secondary source (Mather, et al. 2008).

As a poverty measure we use the official food poverty line calculated by the Ministry of Planning and Finance and others (2004) based on another nationally-representative household survey, *Inquérito aos Agregados Familiares* (IAF), which was collected in 2002. Using a cost of basic needs approach, six regional food poverty lines are derived that reflect typical region-specific food bundles. These bundles correspond to a daily recommended calorie intake (differentiated for age and gender) per person of a diet typical for the poor of a particular rural region and are valued with local prices.

The questionnaire for the 2005 wave contains an additional section on shock occurrence and food insecurity. Moreover, information on the use of shock coping strategies is collected from

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[6] For a subsample of 25 percent of all plots, enumerators measured field size with GPS in both survey waves. This makes it possible to calculate a correction factor for self-reported field size, taking into account the level of education of the head of household and district dummies to control for potential biases introduced by enumerators. The procedure used as well as other corrections and imputations carried out on income is detailed in Mather et al. (2008).

a subsample of households that faced food insecurity in 2004. While a wide range of shocks is covered, such as mortality, sickness, uncontrolled fires damaging fields, and livestock diseases, there is reason to expect that most shocks are not randomly distributed across households of different wealth levels. For instance, livestock losses have positive significant effects on asset growth, probably because only relatively wealthy farmers can afford to tend livestock in the first place. For this reason, the analysis only focuses on an extraordinarily severe drought occurring in the 2004–2005 growing season that is expected to affect households randomly.[7] The harvest period for most crops is between March and May; the TIA 2005 survey was collected between mid-September and mid-December 2005. Hence, the time lag between household survey interviews and harvest (revealing the extent of the drought-related income shock) was on average seven months.

Panel surveys typically suffer from sample attrition over time, as people move away, households dissolve in the course of the household life-cycle, or people refuse to be interviewed again (Deaton 1997: 19f.). Overall, the rate of attrition between the TIA 2002 and TIA 2005 surveys of 16.4 percent is relatively low compared to surveys conducted in other sub-Saharan African countries (Mather and Donovan 2008). Attrition may introduce a potential source of bias if attrited households follow systematically different wealth accumulation paths from panel households. Moreover, attrition may be endogenous to shocks if households facing a large negative shock drop out of the panel (Jalan and Ravallion 2004: 110).

We use formalized diagnostic tools to test whether there is attrition bias, following methodological recommendations by Alderman et al. (2001), Foster and Bickman (1996), Verbeek and Nijman (1992), and Wooldridge (2002).[8] First, an added regressor test is

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[7] Drawing on district-level rainfall estimates derived from satellite images, Mather et al. (2008) use a water balance model to estimate the mean number of drought days per growing season. According to these estimates, both 2001–2002 and 2004–2005 had less favorable weather conditions, lying 49.6 and 124.3 percent above the 10-year average of days of drought, respectively. In the following analysis we rely on households' self-reported exposure to drought. The dummy variable takes the value 1 if households indicate having lost at least part of their harvest due to drought. Rainfall data is only publicly available at the provincial level, which is too crude to be of use in the present analysis. Interacting households' self-reported drought exposure with either provincial dummies or agro-ecological zones did not yield significant results.

[8] Different strategies are available for testing whether there is an attrition bias. The key distinction made in the literature is between attrition based on observables and unobservables. If attrition is determined by observable characteristics, weights can be calculated based on these characteristics to correct for a potential selection bias. Some of the tests for attrition based on unobservables require more than two panel waves for applying simultaneous Heckman-type selection models (Verbeek and Nijman 1992; Wooldridge 2002: 581). However, it has been cautioned that these models are not always reliable and assumptions underlying these models are rather strict (Vandecasteele and Debels 2007). Hence, the tests performed here are restricted to detecting and correcting for attrition bias based on observables.

conducted. A dummy variable indicating that a household dropped out of the panel and its interactions with all other regressors were also included in the livelihood regression at the baseline period. While the attrition dummy is individually insignificant, an F-test rejects the null hypothesis that there are no differences in the marginal return to assets across attrited and panel households (F-statistic of 4.08 with 38 degrees of freedom).

Second, a probit regression was conducted on the determinants of the probability that a household is included in the second survey wave. A wide range of assets, household characteristics, and community characteristics are included as independent variables. Findings show that the age of the household head, the origin of the head or his spouse in the community, and the number of children and elderly persons significantly affect the probability that a household is re-interviewed. Very few asset variables are statistically significant, such as the number of crop types grown, the number of goats, and a good quality roof. Overall, the diagnostic tests give some—but not a strong—indication that attrition bias cannot be ignored. Therefore, all subsequent analyses are calculated with inverse probability weights, in addition to survey design weights (Wooldridge 2002), in order to correct for a potential attrition bias.

4 Empirical strategy

To answer the first research question on the existence of a micro-level poverty trap, a version of the Carter and Barrett (2006) model will be estimated. The procedure involves several steps. First, an asset index is derived from a bundle of assets that are likely to shape a household's future well-being. Aggregating assets into one common index is necessary because non-parametric techniques are limited to the estimation of the bivariate relationship between one regressand and one regressor. Following an approach proposed by Adato et al. (2006), the asset index is constructed through a livelihood regression:

$$\lambda_{it} = \sum_{j=1}^{J} \beta_j (A_{it}) A_{ijt} + \varepsilon_{it} \qquad (1)$$

where livelihood λ of household i in time t is a function of a vector of assets A, aggregated over the total number of J assets a household owns. ε is an error term with normal and identical distribution. The livelihood measure on the left-hand side is defined as households' income per adult equivalent divided by the province-specific poverty line. The regression hence assigns weights on assets based on their marginal contribution to a household's livelihood. Equation (1) is estimated using a fixed effects model. The household-specific asset index is then derived by predicting the fitted values from the regression coefficients.

Components of the asset index include land, trees, livestock, tools for farming, human capital, agricultural expertise, and assets that are likely to enhance the productivity of other endowments, such as the quality of housing. A number of continuous assets are included in the regression as log transformations if their distribution of values is positively skewed. The squared terms of several variables are included in order to account for potential diminishing returns on assets and lifecycle effects. Both income and continuous assets that are associated with labor-intensive work are scaled in adult equivalence terms to capture economies of scale in household production and differences in consumption needs across household members of different age and sex (Deaton 1997). Livestock other than goats and chicken (the most prevalent types of livestock) are aggregated in Tropical Livestock Units (TLU).

The livelihood-based asset index, as proposed by Adato et al. (2006), allows us to combine assets that are measured in very different units—such as hectares, heads of animals, and years of education—into one single measure. It provides, therefore, a more realistic picture of rural livelihoods compared to approaches that rely on a single asset, such as livestock. Also, the asset index has a continuous distribution, which avoids econometric challenges due to the lumpiness of assets, as identified by Elbers et al. (2007). Compared to alternative methods of aggregating separate factors into a common index, such as principal component and factor analysis, the livelihood regression has the advantage of drawing on the marginal contribution of each asset to household well-being. Moreover, the livelihood-based asset index is scaled in Poverty Line Units (PLU), which facilitates the interpretation of results. An asset index below 1 indicates households with an income below the poverty line; an asset index above 1 identifies non-poor households.

In a second step, the relationship between current and baseline asset levels is estimated using non-parametric techniques:

$$A_{it} = f\left(A_{it-1}\right) + \varepsilon_i \tag{2}$$

where A represents the asset index of household i, t stands for the current period (2005) and $t\text{-}1$ for the baseline period (2002) and the error term ε is assumed to be normally and identically distributed with zero mean and constant variance. More specifically, a local polynomial regression with Epanechnikov kernel weights is used for estimating equation (2).[9] Compared to linear non-parametric specifications, non-parametric regressions of higher polynomial order reduce the bias in the center of a distribution (Naschold 2005). This is a region where the theory of poverty traps predicts potential unstable equilibria, which makes this method suitable for the research topic. The estimated asset recursion function (2) will be represented graphically to detect a potential poverty trap.

In addition, parametric techniques are employed to control for initial household and community characteristics that may influence a household's accumulation path. In line with studies by Carter et al. (2007), Lybbert et al. (2004), and Naschold (2005), the change in asset levels across the survey years is estimated as the following equation:

$$\Delta A_i = \beta_1 A_{it-1} + \beta_2 A_{it-1}^2 + \beta_3 A_{it-1}^3 + \beta_4 A_{it-1}^4 + \beta_5 H_{it-1} + \beta_6 C_{t-1} + \varepsilon_i \qquad (3)$$

where asset growth ΔA is a function of asset levels A and its fourth degree polynomial of household i at the baseline period $t\text{-}1$, household baseline characteristics H, community baseline characteristics C, and a well-behaved error term ε. Polynomial terms are included to allow for nonlinearities in the center of the distribution, given that parametric estimation techniques tend to impose linearity on the estimated function (Naschold 2005). Yet if the sample size is small (as is the case with most existing studies that test for poverty traps with parametric methods) and if there are very few observations around the unstable threshold, "these observations may not be picked up by the parametric regression, but instead appear as heteroskedastic and autocorrelated error" (Naschold 2005: 6). The advantage of the data at hand is that the sample size is large (with approximately 3,850 panel households with complete information on income and assets), which also raises the number of observations around the unstable threshold. Equation (3) will be estimated with OLS.

The second research question—the impact of shocks and shock coping strategies on household asset accumulation—will be explored by extending the parametric regression. We include a variable indicating that a household experienced a drought occurring in the growing season of 2004–2005 as a covariate income shock:

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[9] The regression is local in the sense that a fitted relationship between current and baseline assets is estimated separately for each baseline asset value (Cameron and Trivedi 2009: 65). Most empirical studies in the micro-level poverty trap literature use similar non-parametric methods, such as LOWESS or other local regression models. Naschold (2005) provides a detailed review of estimation approaches employed in this literature.

$$\Delta A_i = \beta_1 A_{it-1} + \beta_2 A_{it-1}^2 + \beta_3 A_{it-1}^3 + \beta_4 A_{it-1}^4 + \beta_5 H_i + \beta_6 C + \beta_7 \Theta_i (A_{it-1}, K_i L, F) + \varepsilon_i \tag{4}$$

where the impact of drought Θ on household asset growth ΔA is allowed to vary with initial asset level A_{t-1} and credit market access K of household i, as well as labor market conditions L and the availability of unused land for farming F in the community. Drawing on Carter et al. (2007), the latter three variables are assumed to be mediating factors that may mitigate the impact of shocks. Labor market conditions are proxied by mean household income derived from wage work in a given community in 2002, normalized to the wage income of the community with highest wage income. F is captured through a dummy variable taking the value 1 if community leaders state that land is available for agricultural production in a given community. Access to credit markets is proxied by a dummy variable indicating whether a household had received credit during the last 12 months. Note that all mediating factors refer to the baseline period except credit market access, which was solely recorded during the 2005 survey.[10] The common conclusion from the cited literature on household shock coping behavior—that wealthier households tend to maintain consumption levels when facing shocks—is tested by interacting the drought variable with household pre-drought asset levels. One limitation of the data is that inferences can only be derived on the short-term impact of drought. More years of panel data from the post-drought period are required to distinguish households that were temporarily pushed, by the drought, from their accumulation paths from those trapped in poverty.

One analytic challenge emerging in the analysis of income shocks is that their impact on assets is not immediate and exogenous, but rather a result of concurrent household choices. In other words, asset levels measured in 2005 already capture the impact of households' responses to the drought. Endogeneity is potentially an issue and an ideal way to circumvent it would be to rely on predicted post-shock asset levels based on the regression of changes in asset accumulation during the shock period(s) rather than the observed asset level after the shock (for example, Carter, et al. 2007). Yet, such a procedure is only feasible with three waves of panel data collected before, during, and after the occurrence of the shock, which is not given in the data at hand. However, endogeneity may be less severe of a problem in this context given the fact that the data was collected shortly after the drought-related harvest losses (as will be discussed in Section 5.3, below).

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[10] We here make the somewhat arbitrary assumption that access to credit has not substantially changed throughout the survey periods. However, it has to be cautioned that there might be a potential endogeneity bias.

Instead, the approach followed here is to draw on unique information in the TIA data on coping strategies recorded from a subsample of households. Households who indicated suffering from food insecurity during 2004 (which make up 38 percent of the sample) were asked whether they applied any of a stylized list of coping strategies, including reducing meals, consuming seed reserves, and increasing income-generating activities (see Table 1 for summary statistics of coping variables). This allows us to distinguish strategies that reduce a household's asset basis from asset-neutral strategies. These coping strategies will be included as covariates in an extended version of equation (4). Empirical results will be carefully discussed in the light of potential selection bias in the food insecure sample.

5 Results: Explaining Welfare Dynamics in Rural Mozambique

5.1 Asset Trends and Income Mobility

In rural Mozambique, where net revenue from agricultural production accounts for over 60 percent of total household income, land is the most important productive asset. While land markets are barely developed in Mozambique, households still use a variety of channels to access new farming land and land holdings are relatively unequally distributed across households (with a Gini coefficient of 0.45 in 2005) (Brück and Schindler 2009). In the following, land (LANDSIZEAE) is measured as the area under cultivation with annual crops and left fallow in hectares per adult equivalent, where the conversion factors are those proposed by Deaton (1997: 259).[11] Land ownership does not remarkably change over the two periods, with only about 1 percent of households not cultivating any land. However, the cultivated area per adult equivalent increases on average by 15 percentage points between 2002 and 2005.[12]

Average household livestock endowments decrease during the survey years. This development is unexpected against the background of already very low levels of livestock ownership at the end of the war. Moreover, it appears that households do not manage to accumulate more productivity-enhancing assets and skills. While the number of households using animal traction (TOOLTRACT) decreases only marginally, the usage of fertilizers and pesticides (INPUT) decreases quite substantially by about 7 percentage points and the number

[11] Note that this definition of land refers to land use and does not imply ownership in a legal sense.

[12] Summary statistics of all variables discussed in this section are presented in Table 3.

of crop types cultivated (CROPINDEX) reduces by about one unit. Most of the remaining assets increase in levels over the survey years. Within the wide definition of assets applied, this includes knowledge- or skill-based assets such as information from extension agents (EXTINFO), information on agricultural prices (PRICEINFO), engagement in handcraft activities (CRAFT), and education (CLASHEAD and CLASM). In addition, a rising share of households are endowed with non-agricultural assets, such as a bike (BIKE), a radio (RADIO), a table (TABLE), or having a high quality homestead (WALLM and ROOFM).

Moving to dynamics in income space, Figure 2 shows the cumulative density function of income in adult equivalence terms in 2002 and 2005. Note that the definition of income comprises net income (see Section 3 above). Hence, it is plausible that very small incomes are not necessarily due to underreporting of revenues, but may stem from households' exposure to shocks.[13] Moreover, households with income per adult equivalent above the 99 percentile were excluded as they probably represent measurement errors.[14] This reduces the sample of panel households to 4,058 (in all the following analyses).

Both cumulative income distribution curves in Figure 2 have a high density of observations at the lower end of the income distribution. Mean household income has much higher levels and growth rates than median income, suggesting increasing inequality. The cumulative density curves cross, meaning that first order stochastic dominance is violated. Still, the density curves cross at an income level that is below any reasonable poverty line (see the food poverty line as a reference in the graph).[15] It may therefore be argued that the incidence of poverty decreased slightly from 77.9 to 74.8 percent during the period from 2002 to 2005.[16]

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[13] Eight households with negative income were dropped from the sample as they posed computational difficulties.

[14] The income of these households represents more than six times the median income, while their asset endowments are only 1.7 times the median asset level in 2002.

[15] The headcount ratio, poverty gap, and poverty gap squared of the Foster-Green-Torbecke class (Foster et al. 1984) were computed for different poverty lines (food poverty line, food poverty line increased by 20 percent, food poverty line decreased by 20 percent, and total poverty line). Results (not shown) revealed that almost all poverty lines point towards decreasing poverty between 2002 and 2005, irrespective of the poverty measure used. One exception is the food poverty line decreased by 20 percent, which indicates a minimal increase in poverty gap squared from 0.276 in 2002 to 0.278 in 2005.

[16] Note that the incidence of income poverty found in this paper is slightly higher compared to research based on IAF household survey data that calculates poverty rates using household consumption expenditure data. This is due to the tendency of households to underreport income to a larger degree than consumption expenditures, greater annual fluctuations in income than consumption, and the fact that consumption expenditure is valued with retail prices in the IAF survey, while income from agricultural production is valued with (lower) producer prices in the present analysis (Walker et al. 2004: 2).

As shown in Table 2, there was considerable mobility across income quintiles across the years that encompassed movements along the whole range of the income distribution. For instance, 6 percent of sample households belonging to the poorest income quintile in 2002 managed to improve their economic situation and enter the richest quintile in 2005, while 12 percent of households moved in the opposite direction into the poorest quintile in 2005. Given that the data only covers a period of three years, this is an unexpected result.

Furthermore, a poverty profile compares the well-being of (arbitrarily defined) subgroups of households in 2002 and 2005 (Table 3). Households cultivating more than 0.63 hectares of land per adult member have a much lower incidence of poverty in both years. While in 2002, cultivating lots of land went hand in hand with a decrease in the incidence of poverty by 18 percentage points it only does so by 9 percentage points in 2005. Thus, extensive cultivation seems to have lost its importance for income generation during the survey years, contrasting with evidence from the early post-war period (Bozzoli and Brück 2009). This may point towards much lower overall returns on agriculture in 2005. While land as well as livestock are still strong predictors for not being poor, there seems to be a rising importance of knowledge on markets and prices, education, and non-agricultural assets. Particularly, the role of radios and bicycles stands out. Radio and bicycle ownership are coupled with a lower poverty incidence and a lower severity of poverty by 10 to 20 percent in both survey years. A high proportion (90 percent) of households lost crops due to drought in the agricultural season 2001–2002. However, the average damage caused by drought does not appear to be severe, as the poverty headcount of affected households only increases slightly compared to households not affected.

5.2 Testing for the Existence of a Poverty Trap

Table 4 contains a fixed effects household livelihood regression; in other words, household income as a percentage of the poverty line regressed on a bundle of assets, which is used to calculate the asset index. In line with trends in asset composition and their role for well-being as outlined above, land size, education, being engaged in handcraft activities, diversity of crops grown, access to information on crop prices, owning a bicycle, and having a high quality homestead are significantly positively related with livelihood. In order of relative magnitude, being engaged in handcraft activities, high quality housing (modern material of walls and roofs), having access to price information, and having a bike leads to an increase of income in PLU by at least 9 to 18 percentage points. Surprisingly, the results show a relatively low effect of land endowments. A 10 percent increase in the size of land per adult equivalent increases income as a percentage of the poverty line (income in PLU) by 0.4 percentage points. Overall, productive assets in the very wide definition applied here do not explain much of the variation in rural income, with an R-squared of 0.14.[17]

Next, we estimate the non-parametric bivariate relationship between the asset index in the current and baseline period, as shown in Figure 3. A second order polynomial and a kernel bandwidth of 0.2 (balancing the smoothness with a potential bias of the regression function) fit the data best. Both axes are scaled in PLU. The solid line represents the dynamic asset function, with the 95 percent confidence intervals shaded in grey. Overall, the asset indices in both years are relatively densely clustered in a range between -0.44 and 3.33 PLU.

The asset recursion does not show evidence for a poverty trap. Instead, there appears to be a single stable equilibrium towards which all rural households converge. Surprisingly, the equilibrium is at an extremely low income level only slightly above the poverty line (at about 1.11 PLU). This corresponds to a yearly income per adult of about USD 172. The single equilibrium implies that households above the poverty line are better off for stochastic reasons, such as luck, good weather, and favorable local market prices. Their livelihood is not grounded in a sustainable asset base and households are expected to converge downwards until they reach the stable equilibrium. Households below the equilibrium will eventually improve their well-being, approaching the equilibrium from below. The asset recursion curve is very close to the 45 degree line, indicating a rather slow movement towards the equilibrium.

As a robustness test, the asset index was constructed through principal component analysis (Figure 5a), the most commonly used method of aggregating a diverse set of assets into a single index (Filmer and Pritchett 2001; Kolenikov and Angeles 2009). The dynamic asset curve has a similar shape compared to the asset index derived through a livelihood regression and the key result—a single stable equilibrium at a low income level—remains the same. We also tested a different bundle of assets in constructing the livelihood-based asset index. The recursion function presented in Figure 5b is based solely on assets that a household may easily liquidate, such as livestock, a bicycle, and a radio, when facing a shock. Not

[17] Given that R-squared measures derived from fixed effects estimates are difficult to interpret and that a non-negligible part of the total unobserved heterogeneity seems to be due to between-group variation (rho = 0.47), we caution not to draw far-reaching conclusions from this result. In fact, a study by Mather et al. (2008) on the determinants of crop income, drawing on the same TIA waves, also has a similarly low R-squared value around 0.20, despite the very large number of household and community controls used.

surprisingly, the threshold is at a lower asset level, while the shape of the recursion function is very similar to the comprehensive asset index.

Controlling for the potential effects of the choice of the poverty line, the livelihood regression was estimated with different poverty lines—a food poverty line increased by 20 percent (Figure 5c), a food poverty line decreased by 20 percent (Figure 5d), and a total poverty line, including both food and non-food expenses (Figure 5e). Varying the poverty lines may detect potential threshold effects if a large proportion of household income is clustered around the poverty line. Yet, this does not seem to be the case, as the key finding still holds.[18]

Other robustness checks involved estimating the non-parametric bivariate relationship between the current and lagged asset level with random effects, assuming that the unobserved household effect is uncorrelated with asset endowments (Figure 5f);[19] with an asset index based on a log transformation of LIVELIHOOD (Figure 5g);[20] and with the full sample of households, including those with negative and doubtfully high incomes (Figure 5h). Results regarding welfare dynamics are qualitatively similar. In summary, there is no evidence that the key results of the analysis are driven by the choice of assets, poverty line, methods, or restrictions on the sample.

However, when we relax the assumption that households share a common underlying dynamic asset accumulation path, there is evidence for conditional convergence as population subgroups approach group-specific equilibria at different PLU levels. Table 5 displays the equilibria and the 95 percent confidence intervals for various mutually exclusive groups of households based on the non-parametric estimation approach, as specified above. For instance, male-headed and female-headed households are moving towards different thresholds. The latter are expected to settle at an equilibrium that is on average 11 percent lower than that of male-headed households, although confidence intervals of both groups

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[18] Note that, when the total poverty line is used, the asset recursion function crosses the 45 degree line twice, at 0.8 and 1.9 PLU. However, the upper equilibrium is instable, and there is no second stable equilibrium crossing the 45 degree line from above, which would indicate a bifurcating threshold at around the instable equilibrium. In addition, the result is driven by very few observations at the upper end of the asset distribution and the 95 percent confidence interval around the intersection is very large.

[19] Even though a Hausman test rejects random effects in favor of fixed effects, the latter may be misleading if the time span between the panel waves is relatively short and measurement error is present in the independent variables (Wooldridge 2006: 492).

[20] LIVELIHOOD, the dependent variable, has a skewness of 2.20 and a kurtosis of 9.22. Normality assumptions are, hence, violated. In principle, a log transformation of LIVELIHOOD satisfies normality assumptions much better. Still, the asset index based on LIVELIHOOD in levels and all further steps based on this specification are reported in the paper to facilitate a more intuitive interpretation of results.

overlap. The location of equilibria is not closer for male-headed and female-headed households in the northern part of Mozambique, where most societies are matrilineal (Arnfred 2001).

Interestingly, migrant households in which neither head nor spouse were born in the community[21] are moving towards a significantly higher medium-term equilibrium than native households, with estimated equilibria at 1.59 and 0.99 PLU respectively. This indicates that migrant households are able to compensate for their lack of kinship ties to local authorities, which is an important channel through which to access land. Keeping in mind that no other socioeconomic characteristics are controlled for, this finding contradicts the commonly held notion in Mozambique that formerly displaced persons and war refugees, who were not able to return to their native areas, are particularly vulnerable to poverty (for example, Myers et al. 1994).

Education of the head of household has significant positive effects on asset accumulation, with returns on secondary and higher education particularly high. While households with a non-educated head move towards a low equilibrium of 0.98 PLU, those with a head who received primary education and high school education move to an equilibrium above the poverty line of 1.04 and 1.65 PLU respectively (with confidence intervals only slightly overlapping between the first and the second group). Moreover, educational attainment of the head varies greatly across households and is strongly correlated with age. The mean age of the household head without education, with primary education, and with secondary education is 48, 40, and 34 years respectively.

Complementary evidence is derived from parametric regressions. For the sake of comparability, a parametric estimate of equation (2) is depicted graphically in Figure 4. Note that the current asset level is regressed on the asset level at baseline and its fourth polynomial, while no other covariates are included. In other words, the asset recursion diagram in Figure 4 corresponds to the non-parametric regression displayed in Figure 3, except for assumptions on the functional form between past and current assets. The asset recursion from the parametric regression imposes slightly stricter linearity on the relation between past and current assets. It confirms the finding of a single stable equilibrium at a very similar level of 1.12 PLU.

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[21] More precise information that would allow us to reconstruct the displacement of individuals during the war is not available in the survey.

The determinants of asset growth across the two periods—a parametric estimation of equation (3)—are displayed in the first column of Table 6. The purpose of this estimation is to shed light on factors influencing welfare dynamics that are beyond initial asset endowments. Households' initial asset level (ASSETS02) is strongly significant and negative. Consequently, wealthier households tend to grow at a lower rate than poorer households, which supports the finding of a single equilibrium towards which all households converge. The second polynomial term of baseline assets (ASSETS02^2) is individually significant and the null hypothesis that higher order polynomials are jointly zero is strongly rejected (with an F-statistic of 15.24). Therefore, polynomial terms are useful for adjusting the regression fit to nonlinearities in the data. Surprisingly, of all the community infrastructure measures included in the regression, only the presence of an electricity tower in the community (ELECTR) has a significant positive effect on asset growth. There is no evidence for life cycle effects in asset growth, with AGEHEAD and its square term being both individually and jointly statistically insignificant. Male-headed households and larger households have significantly higher asset growth, as have households using improved agricultural techniques (IRRIG) and growing improved varieties of crops (NEWCROPINDEX). This again supports the evidence for the strong impact of education.

To conclude, there is no evidence for a poverty trap that discriminates against households based on their initial asset endowments. This finding contrasts with most other empirical studies on sub-Saharan Africa that do find poverty traps, as has been pointed out in Section 2. Still, better-educated households and households employing more sophisticated agricultural strategies that involve more risk and investment but also higher potential returns are expected to reach higher welfare levels than households with average asset endowments. While this result is not distinct from a typical developing country context, the prospects for households to acquire skills and education appear to vary across households in Mozambique, which may be one severe legacy of the war. In many cases, this has lead to the interruption of education (from already very low levels of education at the time of independence) and skills. Increased public investments in schooling in the post-war period do not seem to have equally benefited the rural population.

5.3 Shocks and Coping Strategies

The lack of differentiation in well-being in rural Mozambique is particularly surprising in view of the relatively high frequency of covariate and idiosyncratic shocks. The estimation of equation (4) assesses the impact of drought in more detail, with OLS estimates displayed in Table 6. At first glance, drought has a counterintuitive effect on asset growth (Column 2): households that report being affected by the 2004–2005 drought (DROUGHT) experience a small but statistically-significant asset growth of 0.03 PLU between the survey years. More nuanced conclusions can be drawn when drought occurrence is interacted with households' initial asset level (Column 3). The relationship between drought and asset growth is significantly negative with increasing wealth levels (ASSETS02†). This is in line with a common finding in the literature that better-off households sacrifice their assets in order to keep consumption levels stable when facing shocks, while poorer households cannot afford to do this as they need to retain a minimum asset base (Dercon and Hoddinott 2005; Ersado, et al. 2003; Hoddinott 2006).

In line with expectations, mediating factors appear to absorb the impact of drought. Access to credit (CREDIT†) for drought-affected households increases their expected asset growth rates significantly by 0.10 PLU, holding other factors constant. Similarly, drought-affected households living in communities characterized by relatively good labor market opportunities (LABORPROP†) have significantly positive asset growth rates. The availability of farm land in the community (LANDAV†) does not play a significant role in mitigating the effects of drought.

The date of interview (IDATE) was included as an additional control variable. The variable is continuously distributed between 1 (households interviewed on September 15, the first day of the TIA 2005 wave) and 96 (households interviewed on December 19, the last day of interview). The coefficient is statistically significant in all regressions, although it has a very small magnitude of -0.003. Hence, the longer the time lag between the occurrence of an income shock and the measurement of household asset levels in survey data, the more the results become intertwined with household coping behavior.

In order to assess in more detail how post-drought asset levels are intertwined with coping strategies applied by households these are included as dummy variables in an extended version of equation (4). However, it is important to note that this can only serve as a very preliminary approach to understand the relationship between coping strategies and asset dynamics, as these are only collected for the pre-survey year of the second panel wave. There may be unobserved factors, which drive both the choice of a particular coping strategy and the growth of assets, such as a households level of risk aversion. It is also not easily possible to identify the correct direction of the relationship, which seems to be an interesting topic for further research.

Given that TIA only records coping strategies of food insecure households, the characteristics of households in the hunger sample are explored in an initial step of analysis. T-tests on differences in mean asset levels reveal that households facing hunger have a slightly (but significantly) lower asset index than food secure households in both periods (t-statistics of 5.56 and 8.64). The difference in asset endowments across these groups of households increased from 8.9 percent in 2002 to 11.1 percent in 2005. A probit regression on the determinants of hunger reveals that experiencing drought has a large and positive coefficient, significant at the 10 percent level (results not shown).

Moreover, a binary Heckman selection model was estimated to detect a possible selection into the food insecure sample (not shown). The dependent variable in this model is a dummy indicating whether a household applied a particular coping strategy (see Table 1 for summary statistics). Each of the five coping dummy variables was regressed on assets, household characteristics, and community characteristics. Several variables on the experience of shocks are only included in the equation for their selection into the hunger sample; in other words, those households that reported the use/non-use of a respective coping strategy. The inverse Mills ratio is insignificant in all five estimations and the null hypothesis of no selection bias cannot be rejected. From these tests it is reasonable to conclude that households facing hunger in the 2004–2005 season do not seem to be chronically deprived, living at the edge of survival in every period. Rather, it appears that these households were pushed temporarily into food insecurity by drought.

The five coping strategies can be grouped into three categories: strategies reducing a household’s asset base (COPEd, COPEe), reducing human capital (COPEa, COPEb), and asset-neutral strategies (COPEc) (see Table 1). Surprisingly, households that sold goods and livestock (COPEe) experience significant positive asset growth. As livestock is already included in the asset index, this may indicate a shift from unproductive assets not included in the asset index, such as jewelry, to productive assets that are protected and even augmented through investments.

Reducing the number of meals (COPEb) is accompanied by significantly lower asset growth. In contrast to the cited literature on coping, this finding indicates a mix of strategies: it seems that Mozambican households do not opt for either asset smoothing or consumption smoothing, but in fact do both. While reducing calorie intake may help households to safeguard their physical asset base for their future livelihood, it comes at a large cost in terms of human capital, particularly for children. Hence, this strategy more indirectly jeopardizes household assets in the long term (Dercon and Hoddinott 2005). If food reduction is taken to the extreme, Dasgupta (1997) cautions that this may lead households into a nutritional poverty trap, where individuals become too weak to generate sufficient income as their labor productivity becomes insufficiently low and, in turn, cannot meet their most basic nutritional needs. Such a scenario appears unlikely for the majority of households facing hunger, as their asset base is only slightly lower than other households. Qualitative fieldwork conducted in northern Mozambique by the second author revealed that at least some groups of households—typically those headed by the elderly or women—are constrained in their income-generating activities by undernourishment and physical weakness. Still, this appears to be a regional phenomenon, as TIA data shows that the head of food insecure households is on average only two years older than in food secure households.

Lastly, food insecure households that increase the number of income-generating activities (COPEc) even experience significantly positive asset growth, keeping other factors constant. However, it is likely that this strategy is not a feasible option for every household, but may be conditioned through networks and prior experience. For instance, even working in the farm wage sector—that generally has few requirements, other than physical strength—may not be equally possible for persons of different gender, religion, or networks.

6 Conclusion

This paper has analyzed household welfare dynamics within a medium-term time horizon in post-war rural Mozambique. Using household panel data with detailed information on income and assets, the asset-based approach to poverty was applied to this context to test whether a poverty trap is to be seen in rural Mozambique.

Results reveal that while household incomes fluctuate considerably between 2002 and 2005, there is little differentiation in productive asset endowments across households, or over time. Using an asset-based approach indeed seems to provide a much more realistic picture of true poverty dynamics, which shows no evidence of a poverty trap that discriminates against some households based on their initial welfare endowments. Rather, all rural households are expected to converge to a common low level equilibrium in the medium term, indicating an overall development trap. However, there is evidence of group-specific convergence, with migrant households and households having access to credit being expected to reach higher equilibria than others. Particularly, education and improved farming skills shift households to higher welfare levels.

Drought has a significant impact on asset accumulation in the short term, which helps explaining the finding of a single equilibrium. Preliminary evidence shows that households at different points in the wealth distribution apply different shock coping strategies. Relatively "asset wealthy" households appear to sell assets when facing drought in order to maintain their consumption levels, thus approaching the equilibrium from above. In contrast, the strategies of poorer households are more complex than is often assumed in the literature, reducing assets and consumption simultaneously.

There are plausible explanations for the finding of relative stagnation in rural Mozambique, which differs from the scenario found in many of the prior studies on micro-level poverty traps in sub-Saharan Africa. Of course, measurement error may be one cause of the lack of differentiation of rural households. As pointed out earlier, income data may be less reliable than expected. Also, the TIA data captures only a few dimensions of social capital, while information on kinship ties within the community, membership in religious organizations, and political and traditional posts held are expected to be related to income-generating opportunities and asset growth. These components are missing in the current analysis of asset dynamics and are considered an interesting topic for future research. In addition, the time span in between the panel waves may be too short to pick up any differentiation processes.

However, we believe that there are substantive reasons, which illuminate the limited evidence for a bifurcation of welfare trajectories. On the one hand, several of the studies that have found evidence of poverty traps examined confined geographical sites with very distinct conditions, such as herding communities in which very few assets determine households' livelihoods. On the other, the long-term impact of the civil war is assumed to make Mozambique different from other sub-Saharan Africa countries. It may have amplified the impact of unfavorable economic conditions in rural Mozambique, including low population density, low degree of market integration, high transport costs, high frequency of natural disasters, and very few off-farm employment opportunities.

Furthermore, qualitative fieldwork conducted in northern Mozambique revealed that some households were more successful than others in establishing new livelihoods around urban settlements during the war. This has also been found in other regions of Mozambique (for example, Chingono 2001). One may speculate about a selection of better-off households to urban areas that began in the early post-war period, which is beyond the coverage of the household panel data analyzed here. Possibly, most returnees to rural areas did not succeed during the war, having less economic incentives to stay on in urban settlements. War-related patterns of return migration may have equalized the distribution of endowments among the returnees. While there is no evidence of a poverty trap within rural areas, one may think of the rural farm-based economy as such being trapped in poverty compared to the urban economy. In contrast to other African contexts, there seem to be few prospects of significantly-improved livelihoods based on farming in rural Mozambique. The extremely low overall equilibrium just around the official poverty line may even point towards the division of welfare patterns, as demonstrated in early theories of the urban bias (Lipton 1977), or core-periphery models (Krugman 1991). Targeted interventions of social safety nets to lift households above a critical threshold would, hence, not necessarily trigger the expected dynamic gains. Rather, this would point towards the need for structural changes in the rural areas, including the improved access to, and integration of, markets. Household panel data that cover both rural and urban areas are still needed to explore this hypothesis in more detail.

7 Appendix

Table 1: Summary Statistics of Variables

Variable	Description	Mean (2002)	Mean (2005)	Standard error of mean (2002)	Standard error of mean (2005)	Min	Max	Number of observations
Asset index								
ASSETS02*	Constructed asset index in 2002	0.64		0.01		-0.23	3.08	3,978
ASSETS05*	Constructed asset index in 2005		0.78		0.01	-0.58	3.14	3,978
Productive assets								
LANDSIZEAE*	Size of land cultivated by household with annual crops and fallow land per adult equivalent, in hectares	0.44	0.51	0.01	0.01	0	31	4,058
FIELDNUM	Number of fields household owns	2.46	2.24	0.02	0.02	0	12	4,058
GOATNUM*	Number of goats household owns	1.59	1.55	0.19	0.15	0	150	4,058
CHICKENNUM*	Number of chicken household owns	7.26	4.36	0.21	0.19	0	500	4,058
LIVESTOCK*	Number of livestock (other than goats, chicken, and donkeys) household owns, in tropical livestock units	0.54	0.59	0.11	0.13	0	98	4,058
CASHEWTREE*	Number of productive cashew trees household owns	9.29	7.11	1.23	0.55	0	980	4,058
COCOTREE*	Number of coco trees household owns	4.98	6.79	0.83	0.69	0	1460	4,058
TOOLTRACT	Household uses animal traction (oxen, donkey, plough, or oxcart) (d)	0.11	0.09	0.01	0.01	0	1	4,058
TOOLBIG	Household uses large agricultural tools (mill, thresher or oil press) (d)	0.54	0.61	0.01	0.01	0	1	4,058
BIKE	Household owns a bike (d)	0.23	0.30	0.01	0.01	0	1	4,058
Human capital								
ECONACTNUM	Number of economically active household members	2.31	2.40	0.03	0.03	0	26	4,058
CLASHEAD	Number of classes completed by head of household	2.23	2.61	0.04	0.04	0	13	4,058
CLASM	Number of classes completed by household members per member other than head	0.76	1.65	0.01	0.03	0	24	4,058
HEALTHPROP	Proportion of healthy members over household size	0.98	0.95	0.00	0.00	0	1	4,058
CRAFT	Household engages in handcraft or agro-processing activities (d)	0.15	0.16	0.01	0.01	0	1	4,058
Agricultural expertise								
CROPINDEX	Number of crop types grown by household	8.27	7.05	0.06	0.05	0	18	4,058
ASSOC	At least one household member engages in an association (d)	0.03	0.06	0.00	0.00	0	1	4,058

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Variable	Description	Mean (2002)	Mean (2005)	Standard error of mean (2002)	Standard error of mean (2005)	Min	Max	Number of observations
EXTINFO	Household receives information on agricultural extension services (d)	0.13	0.15	0.01	0.01	0	1	4,058
PRICEINFO	Household receives price information (d)	0.34	0.40	0.01	0.01	0	1	4,058
VAC	Household had its livestock vaccinated (d)	0.04	0.04	0.01	0.01	0	1	4,058
INPUT	Household uses productivity-enhancing inputs (chemical fertilizer, pesticides, dung) (d)	0.13	0.09	0.01	0.01	0	1	4,058
Other assets								
RADIO	Household owns radio (d)	0.49	0.53	0.01	0.01	0	1	4,058
TABLE	Household owns table (d)	0.29	0.34	0.01	0.01	0	1	4,058
WALLM	Wall of homestead is of high-quality material (d)	0.05	0.06	0.00	0.00	0	1	4,058
ROOFM	Roof of homestead is of high-quality material (d)	0.12	0.16	0.01	0.01	0	1	4,058
LATRIN	Household owns latrine (d)	0.37	0.41	0.01	0.01	0	1	4,058
LANTERN	Household owns lantern (d)	0.55	0.46	0.01	0.01	0	1	4,058
Household characteristics at baseline (2002)								
AGEHEAD	Age of head of household	42.01		0.23		15	99	4,058
HHSIZE	Household size	4.96		0.05		1	47	4,058
FHEAD	Household is female-headed (d)	0.24		0.01		0	1	4,058
BORN	Head of household or spouse were born in this community (d)	0.76		0.01		0	1	4,058
IRRIG	Index of improved agricultural practices used	1.64		0.01		0	3	4,058
CREDIT	Household received credit in the past (d)		0.03		0.00	0	1	4,058
NEWCROPINDEX	Index of improved crop types cultivated by household		0.14		0.01	0	7	4,058
IDATE	Date of interview		51.94		0.29	1	96	4,058
Community characteristics at baseline (2002)								
FIRM	There is at least one company in the community (d)	0.02		0.00		0	1	4,043
MARKET	Community has a regular market (d)	0.32		0.01		0	1	4,043
ELECTR1	There is an electricity tower in the community (d)		0.19		0.01	0	1	3,963
PAVEDROAD	Main feeder road to community is paved (d)	0.20		0.01		0	1	4,043
CROPINDEXC	Index of crop types grown in the community	15.92		0.08		2	27	4,030
LANDAV	Unused land is available for farming in this community (d)	0.74		0.01		0	1	4,043
LABORPROP	Average wage earnings over all households in a district (normalized to the highest value)	0.11		0.00		0	1	4,043

table is continued on next page

Variable	Description	Mean (2002)	Mean (2005)	Standard error of mean (2002)	Standard error of mean (2005)	Min	Max	Number of observations
Agro-ecological zones								
AGRO1	Dry ecological zone (southern coast and interior) (d)	0.18		0.01		0	1	4,058
AGRO2	Saturated ecological zone (Zambezia valley, north central coast) (d)	0.32		0.01		0	1	4,058
AGRO3	Wet saturated ecological zone (central coast, mid-elevations central and north central, high-altitude central north) (d)	0.50		0.01		0	1	4,058
Shocks and coping strategies								
DROUGHT	Household was affected by drought in 2004/2005 (d)		0.89		0.00	0	1	4,058
HUNGER	Household suffered from hunger during last 12 months (d)		0.38		0.01	0	1	4,058
COPEa	Household reduced quality of meals (d)		0.87		0.01	0	1	1,677
COPEb	Household reduced number of meals (d)		0.82		0.01	0	1	1,677
COPEc	Household increased income-generating activities (d)		0.36		0.01	0	1	1,677
COPEd	Household consumed reserved seeds (d)		0.53		0.01	0	1	1,677
COPEe	Household sold goods and livestock (d)		0.12		0.01	0	1	1,677

Sample: TIA 2002/2005 panel households. Population weights and inverse probability weights are used. If variables are captured in both years, minimum and maximum refer to 2005. Agricultural expertise, shocks, and coping strategies refer to the agricultural period 2004–2005. Households with negative income or income per adult equivalent above the 99th income percentile are excluded (as in all following tables and figures). (d) indicates dummy variables; † natural logarithm used in regression. In order to avoid losing observations with zero values, a value slightly smaller than the minimum of a variable was added to the distribution before taking the natural logarithm (Cameron and Trivedi 2009: 532). The questionnaire only records the coping strategies of households who suffered from hunger.

Table 2: Mobility Across Quintiles of Income

		Income per adult equivalent (2005)					
		Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5	Total
Income per adult equivalent (2002)	Quintile 1	0.33	0.26	0.19	0.13	0.06	1
	Quintile 2	0.24	0.25	0.24	0.16	0.08	1
	Quintile 3	0.18	0.25	0.24	0.21	0.09	1
	Quintile 4	0.13	0.21	0.24	0.26	0.12	1
	Quintile 5	0.12	0.13	0.18	0.25	0.30	1
	Total	0.21	0.22	0.22	0.20	0.13	

Sample: TIA 2002/2005 panel households. Population weights and inverse probability weights are used. Figures indicate percentages.

Table 3: Poverty Profile

		Population share (in %)		Mean household income per adult equiv. (in MZN)*		Poverty headcount (P_0) (in %)		Poverty gap (P_1) (in %)	
		2002	2005	2002	2005	2002	2005	2002	2005
All households (N=4,021)		1	1	2,256	2,722	0.80	0.76	0.49	0.48
Household cultivates large area of land per adult	no	0.81	0.66	1,911	2,229	0.83	0.79	0.53	0.52
	yes	0.19	0.34	3,739	3,611	0.65	0.70	0.35	0.38
Household owns livestock	no	0.23	0.31	2,012	2,288	0.81	0.80	0.54	0.52
	yes	0.77	0.69	2,324	2,866	0.79	0.74	0.48	0.46
Household owns bike	no	0.76	0.68	2,063	2,646	0.83	0.79	0.53	0.51
	yes	0.24	0.32	2,883	2,788	0.71	0.70	0.37	0.41
At least one member was sick for one month or longer	no	0.94	0.86	2,231	2,715	0.79	0.75	0.49	0.47
	yes	0.06	0.14	2,652	2,527	0.86	0.79	0.55	0.51
Household uses fertilizers or pesticides	no	0.85	0.89	2,098	2,567	0.81	0.77	0.51	0.49
	yes	0.15	0.11	3,187	3,775	0.74	0.68	0.51	0.35
Household owns radio	no	0.49	0.47	1,690	1,776	0.86	0.86	0.56	0.56
	yes	0.51	0.53	2,807	3,486	0.74	0.67	0.42	0.40
Household experienced drought in 2004	no		0.10		2,053		0.74		0.46
	yes		0.89		1,935		0.76		0.48

Sample: TIA 2002/2005 panel households. Population weights and inverse probability weights are used. Regional-specific food poverty lines used. *At constant 2005 values.

Table 4: Livelihood Regression to Derive Asset Index

	Dependent variable: income per adult equiv. / poverty line	
	Coefficient	t-statistic
D2005	0.10	(2.70)***
LANDSIZEAElog	0.04	(1.83)*
LANDSIZEAE2log	0.02	(2.74)***
FIELDNUM	0.03	(1.17)
FIELDNUM2	-0.00	(-0.05)
CASHEWTREEPRODlog	0.00	(0.16)
CASHEWTREEPROD2log	0.01	(0.98)
COCOTREElog	0.03	(0.94)
COCOTREE2log	-0.00	(-0.11)
GOATNUMlog	0.03	(0.93)
GOATNUM2log	0.02	(1.64)
CHICKENNUMlog	0.02	(1.22)
CHICKENNUM2log	-0.01	(-0.74)
LIVESTOCKOtlulog	0.02	(1.21)
LIVESTOCKOtlu2log	0.01	(0.36)
ECONACTNUM	-0.06	(-3.27)***
CLASHEAD	0.00	(0.07)
CLASHEAD2	0.01	(2.68)***
CLASMlog	0.05	(2.13)**
CLASM2log	0.00	(0.61)
HEALTHPROP	-0.10	(-0.50)
CRAFT	0.17	(2.98)***
TOOLBIG	0.01	(0.34)
TOOLTRACT	0.08	(0.96)
INPUT	0.07	(1.10)
CROPINDEX	0.03	(3.65)***
CROPINDEX2	-0.00	(-0.77)
ASSOC	0.06	(0.81)
EXTINFO	-0.01	(-0.21)
PRICEINFO	0.14	(3.36)***
VAC	-0.05	(-0.49)
BIKE	0.09	(1.84)*
RADIO	0.07	(1.57)
TABLE	0.07	(1.40)
WALLM	0.18	(1.65)*
ROOFM	0.14	(1.76)*
LATRIN	0.07	(1.42)
LANTERN	0.04	(0.94)
Constant	0.35	(1.40)
Sigma_u	0.69	
Sigma_e	0.73	
Rho	0.47	
Observations	3,978	
R-squared	0.14	

Sample: TIA 2002/2005 panel households. Fixed effects regression. Standard errors are corrected for clustering. * p<0.1, ** p<0.05, *** p<0.01. Population weights and inverse probability weights are used.

Table 5: Non-parametric Regressions Differentiated by Groups of Households

	Location of equilibrium		
	Mean	Lower 95% confidence interval bound	Upper 95% confidence interval bound
Whole sample, non-parametric regression	1.11	1.02	1.3
Whole sample, parametric regression	1.12	1.05	1.23
Male head of household	1.1	1	1.22
Female head of household	0.98	0.88	1.18
Head and spouse born elsewhere	1.59	1.09	1.76
Head or spouse born in community	0.99	0.92	1.11
Head has no education	0.92	0.84	1
Head has primary education	1.04	0.97	1.13
Head has secondary education	1.65	1.3	1.78
No access to credit	1.04	0.97	1.21
Access to credit	1.28	1.18	1.44
Drought-affected	1.07	0.99	1.22
Not drought-affected	1.07	0.72	not determined
Hunger	0.91	0.85	0.98
No hunger	1.26	1.12	1.62

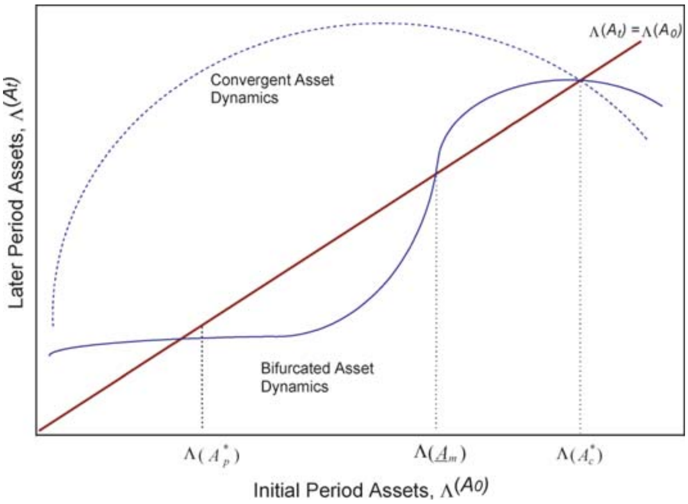
Sample: TIA 2002-2005 panel households. Non-parametric local polynomial regression with Epanechnikov kernel weights. Population weights and inverse probability weights are used. A threshold is not determined if the upper bound of the 95 percent confidence interval does not cross the 45-degree line in the observed range of the asset index.

Table 6: Parametric Regression on the Determinants of Asset Growth

	Dependent variable: asset growth between 2002-2005							
	(1)		(2)		(3)		(4)	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
ASSETS02	-0.46	(-15.99)***	-0.46	(-16.18)***	-0.31	(-4.43)***	-0.51	(-9.86)***
ASSETS02^2	0.25	(4.64)***	0.25	(4.66)***	0.27	(5.04)***	0.35	(4.31)***
ASSETS02^3	0.01	(0.13)	0.01	(0.09)	-0.02	(-0.26)	0.19	(1.26)
ASSETS02^4	-0.06	(-0.78)	-0.06	(-0.77)	-0.05	(-0.63)	-0.26	(-2.33)**
AGEHEAD	-0.00	(-0.43)	-0.00	(-0.42)	-0.00	(-0.33)	0.00	(1.36)
AGEHEAD2	0.00	(0.33)	0.00	(0.32)	0.00	(0.30)	-0.00	(-0.80)
FHEAD	-0.06	(-4.82)***	-0.06	(-4.80)***	-0.06	(-5.09)***	-0.06	(-3.75)***
HHSIZE	0.00	(1.70)*	0.00	(1.73)*	0.00	(1.66)*	0.00	(0.41)
BORN	-0.01	(-0.99)	-0.02	(-1.05)	-0.02	(-1.05)	-0.04	(-1.50)
IRRIG	0.06	(9.04)***	0.06	(8.89)***	0.05	(8.77)***	0.07	(6.58)***
NEWCROPINDEX	0.05	(5.44)***	0.05	(5.51)***	0.04	(5.34)***	0.04	(3.79)***
FIRM	0.03	(0.89)	0.02	(0.86)	0.02	(0.72)	-0.01	(-0.21)
MARKET	0.01	(1.28)	0.02	(1.33)	0.02	(1.45)	0.01	(0.37)
ELECTR1	0.07	(4.38)***	0.07	(4.43)***	0.07	(4.16)***	0.06	(2.30)**
PAVEDROADa	0.02	(1.15)	0.02	(1.21)	0.02	(1.27)	0.03	(1.13)
CROPINDEXC	0.00	(0.26)	0.00	(0.21)	0.00	(0.25)	-0.00	(-0.60)
AGRO1	0.28	(19.36)***	0.28	(19.38)***	0.11	(1.79)*	0.28	(16.11)***
AGRO2	-0.00	(-0.07)	-0.01	(-0.12)	-0.02	(-0.39)	0.16	(1.88)*
IDATE	-0.00	(-1.92)*	-0.00	(-2.04)**	-0.00	(-2.07)**		
DROUGHT			0.03	(1.81)*	0.02	(0.89)		
ASSETS02†					-0.17	(-2.61)***		
CREDIT†					0.10	(3.70)***		
LABORPROP†					0.13	(2.57)**		
LANDAV†					-0.02	(-1.13)		
COPE14a							-0.02	(-0.93)
COPE14b							-0.04	(-1.93)*
COPE14c							0.04	(2.73)***
COPE14d							0.01	(0.32)
COPE14e							0.06	(2.47)**
Constant	0.34	(2.94)***	0.32	(2.76)***	0.23	(2.17)**	0.06	(0.94)
Observations	3,858		3,858		3,858		1,604	
R-squared	0.28		0.28		0.28		0.35	

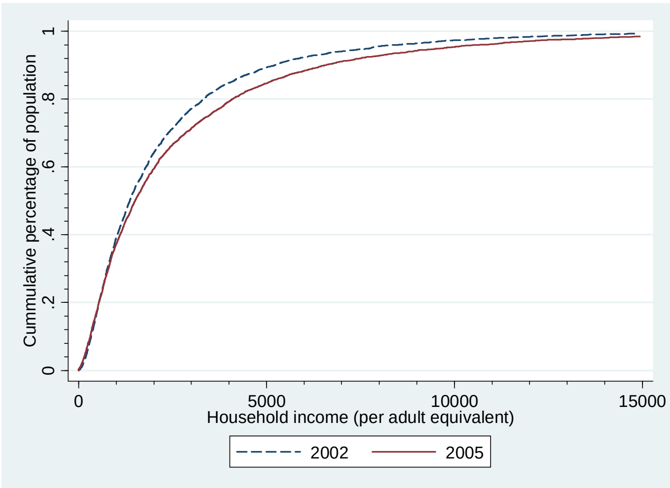
Sample: TIA 2002/2005 panel households. OLS regression. Population weights and inverse probability weights are used. † indicates that a variable is interacted.

Fig. 1: Hypothetical Asset Dynamics



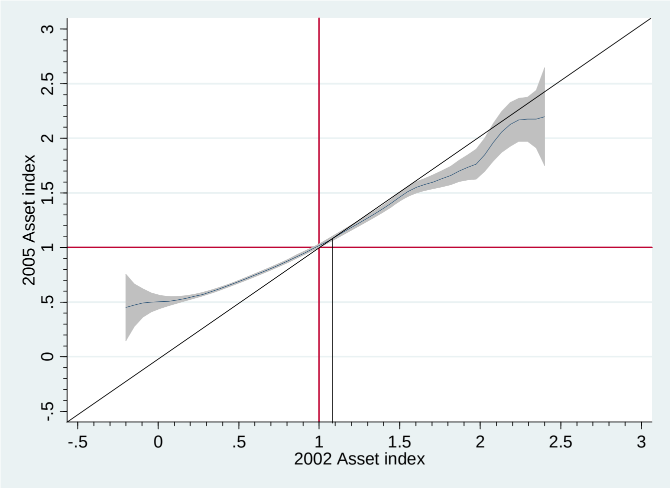
Source: Adato et al. (2006: 232)

Fig. 2: Cumulative Distribution Function of Income in 2002 and 2005



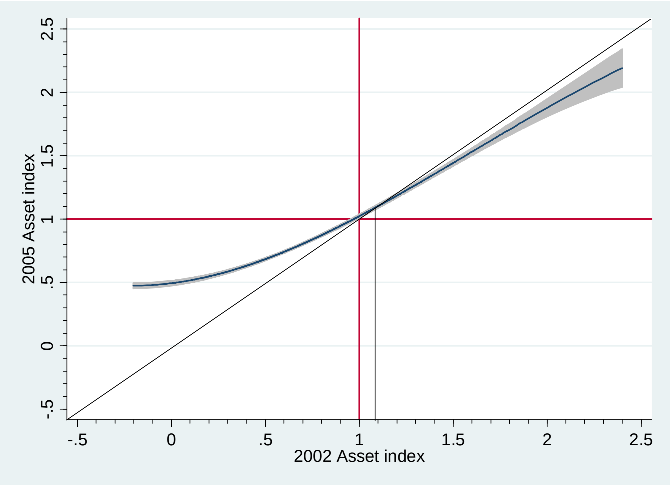
Sample: TIA 2002/2005 panel households. Population weights and inverse probability weights are used.

Fig. 3: Asset Recursion Diagram



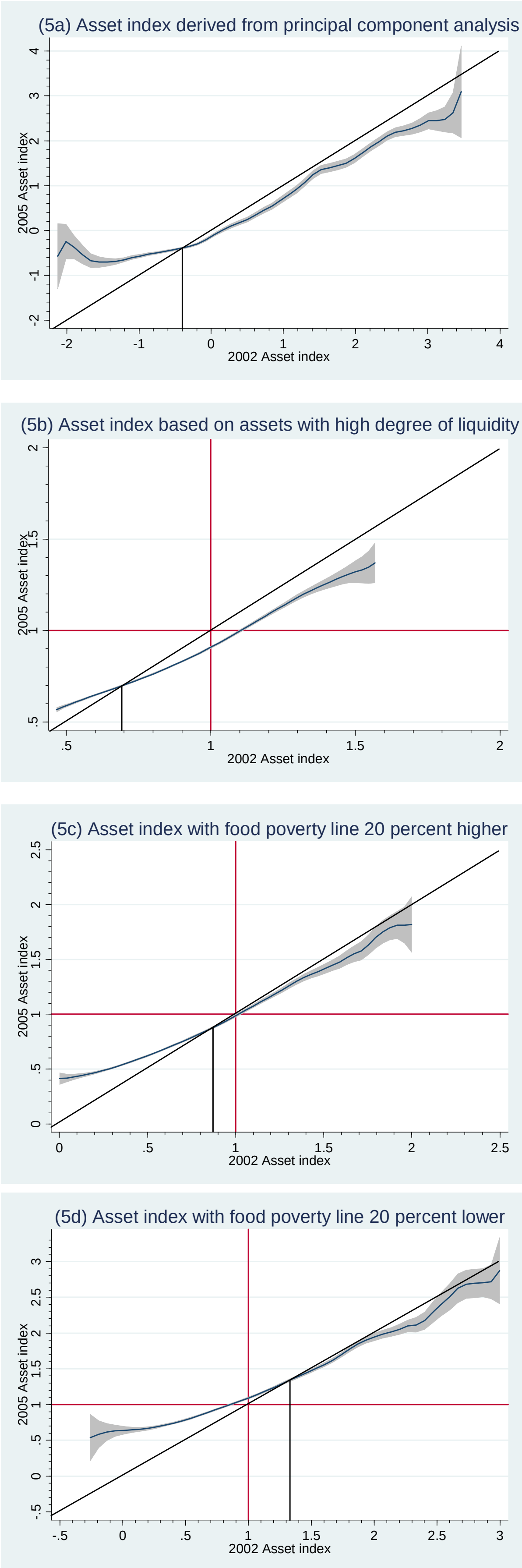
Sample: TIA 2002/2005 panel households. Non-parametric local polynomial regression with Epanechnikov kernel weights. The second order degree and a kernel bandwidth of 0.2 are used. A value of 1 on either axis indicates the food poverty line in a given year.

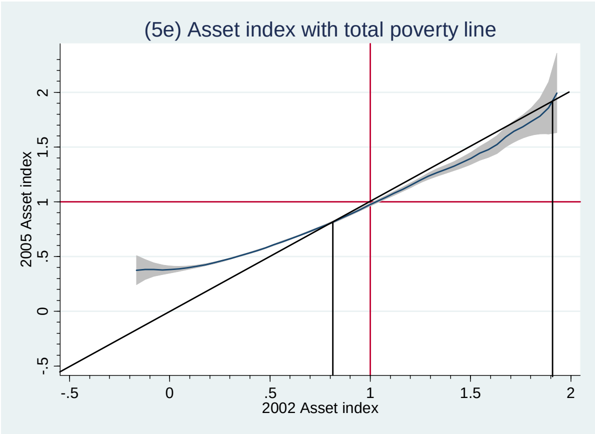
Fig. 4: Asset Recursion Diagram

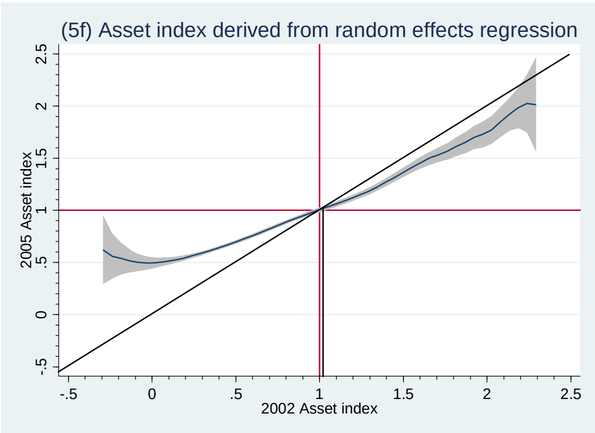


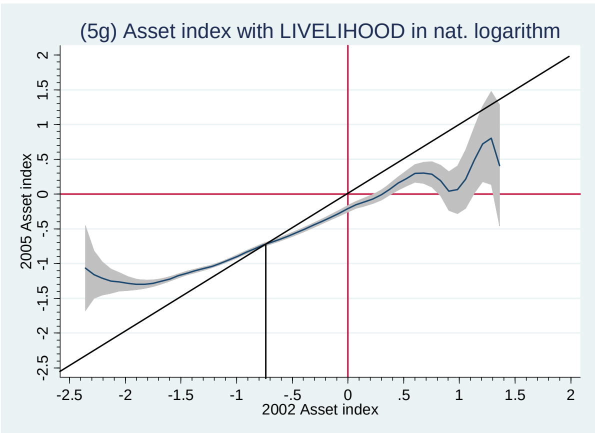
Sample: TIA 2002/2005 panel households. Parametric OLS regression with fourth order polynomial of 2002 asset index. The parametric regression does not include covariates other than baseline assets and its fourth polynomial. A value of 1 on either axis indicates the food poverty line in a given year.

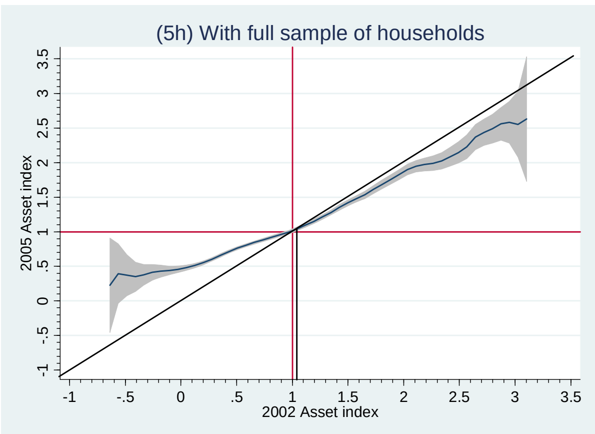
Fig. 5: Robustness Tests of Non-parametric Regressions











Sample: TIA 2002/2005 panel households. If applicable, the horizontal and vertical solid lines indicate food poverty lines.

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