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IFPRI Discussion Paper 01215

October 2012

Nonlinear Dynamics of Livestock Assets

Evidence from Ethiopia

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PARTNERS AND CONTRIBUTORS

IFPRI gratefully acknowledges the generous unrestricted funding from Australia, Canada, China, Denmark, Finland, France, Germany, India, Ireland, Italy, Japan, the Netherlands, Norway, the Philippines, South Africa, Sweden, Switzerland, the United Kingdom, the United States, and the World Bank.

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ABSTRACT

Recent research on the intertemporal dynamics of poverty using microeconomic data often hints at the existence of poverty traps, where some find themselves trapped at a low-level stable equilibrium while others enjoy a higher stable equilibrium. Without a sizable positive shock to well-being, those trapped at the low equilibrium will not automatically outgrow destitution, but merely fluctuate around that low-level equilibrium. Given the dramatic policy consequences implied by such a theory, knowledge about the location of the different equilibria would be extremely helpful. In this paper, we explore the possibilities of threshold-type models to identify those crucial parameters. We illustrate the method by searching for traps in the dynamics of livestock asset holdings in rural Ethiopia. We find evidence of distribution-dependent dynamics and multiple equilibria for tropical livestock units.

Keywords: poverty traps; livestock assets; multiple equilibria

1. INTRODUCTION

Encouraged by the increasing availability of longitudinal micro data from developing countries, researchers working on poverty are focusing their attention more and more on the dynamics of poverty. It has been found that there is considerable mobility in and out of poverty. For instance, in Ethiopia, Dercon and Krishnan (2000) estimate that about a third to half of the households in poverty appears to move out of it in the next period. Part of this mobility can be attributed to shocks and subsequent recovery. This highlights the importance of risk management mechanisms: when an adverse shock affects households, at least some of them can recover after some time. The story also holds in the other direction. Households that enjoy windfall gains will eventually bounce back to their steady-state income. In addition, some households outgrow poverty without having experienced a shock. Such households are the structural growers that, for instance, are able to gradually expand their asset base and/or increase their productivity. However, a disturbingly large share of the world's poorest, especially in Africa, suffer chronic poverty (Grootaert, Kanbur, and Oh 1997; Baulch and Hoddinott 2000). Their lack of mobility is often attributed to *poverty traps.*

A poverty trap is a dynamic process characterized by multiple equilibria. Through time, conditional on where the household or individual was in the past, some of the population will converge to a high-level stable equilibrium while others will be trapped at a low-level equilibrium. Such a process will also exhibit a point where convergence to the low equilibrium changes to convergence to the high equilibrium. Passing that *unstable equilibrium* will have dramatic consequences in both ways. If a household that was trapped in poverty receives a positive shock sufficient to lift it above the threshold, it is likely to converge to the high-level equilibrium. If a household that converges to the high-level equilibrium receives a negative shock sufficient to bring it below the threshold, it will, without further income shocks, converge to the low-level equilibrium. This threshold is sometimes referred to as the Micawber threshold (Carter and Barrett 2006).

Various reasons are cited for the existence of poverty traps in general, and traps in asset holdings more specifically. Probably the best known cause of long-term destitution springs from theoretical models of nutrition-based efficiency wages in developing countries (Leibenstein 1957). Here, a worker's expected productivity (and hence wage) depends on his or her consumption. This may hold equally well for livestock assets, as their productivity will also depend a great deal on their nutritional status. Similar arguments can be made for a household member's health, and again for the health status of livestock (Strauss and Thomas 1998). In general, poverty traps in the dynamics of a process can arise if the process is characterized by a feedback mechanism, together with a factor or a combination of factors that creates discontinuities. Such factors can take various forms, like credit market imperfections, indivisibilities, institutional constraints, and so on.

Whatever the reasons, if poverty traps are a reality, they have dramatic policy consequences and knowledge about the dynamics of poverty (or asset holdings) would be extremely helpful. In particular, knowledge on the location of this threshold would be very welcome. We will review some of the attempts made in previous studies to identify this critical parameter. Then, we will outline our strategy to empirically estimate the dynamics of income. Our method will also return estimates of other interesting parameters, like the level of the stable equilibria and the speed at which households converge to those stable equilibria.

The empirical part of the paper searches for the existence of livestock asset poverty traps in rural Ethiopia. Using data on livestock ownership taken from six rounds of the Ethiopian Rural Household Survey, we first test for nonlinearities in the dynamics of livestock ownership. Conditional on the testing results, we estimate autoregressive models or self-exciting threshold autoregressive (SETAR) models in a panel data context.

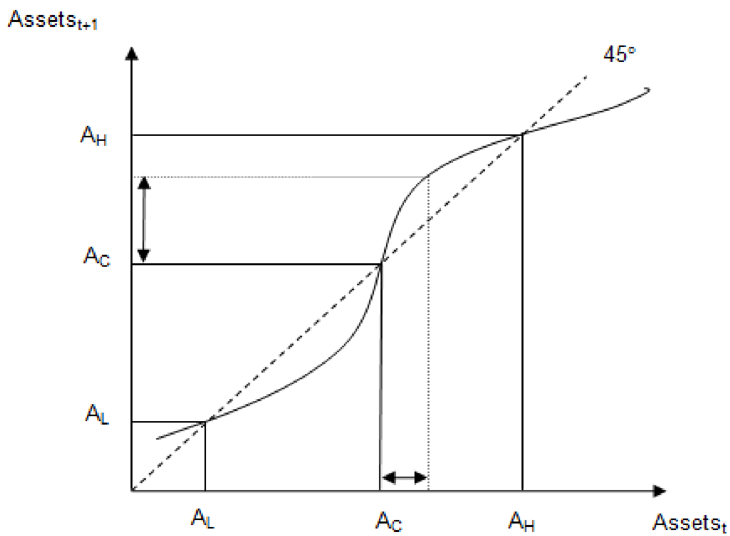
This paper adds to a fast-growing literature that attempts to measure poverty traps directly. More in particular, it belongs to the class of studies that looks at poverty traps using parametric methods (for example, Jalan and Ravallion 2004) as opposed to nonparametric methods (for example, Adato, Carter, and May 2006). We also agree that an asset-based approach (for example, Carter and Barrett 2006) is likely to be more appropriate than looking at poverty traps using outcome variables (for example, Lokshin and Ravallion 2004). Since it is not straightforward to aggregate productive assets in one measure (Carter et al. 2007), we restrict ourselves to livestock (for example, Lybbert et al. 2004). The methodology we use is essentially the same as the one used in Carter et al. (2007), but we allow for individual heterogeneity, as in Antman and McKenzie (2007).

The paper is organized as follows. Section 2 defines the term *poverty trap* and lists some of the factors that could give rise to the existence of this phenomenon. Section 3 presents a selected review of related studies. Section 4 explains the empirical strategy to test for and estimate the different equilibria. Sections 5 and 6 present an application to livestock asset dynamics in rural Ethiopia. The last section concludes.

2. ASSET POVERTY TRAPS

Let us explain the (asset) poverty trap by a simple example. Suppose we have a household that lives in an environment characterized by land abundance. Furthermore, we assume indivisibilities in assets, together with imperfect or missing credit markets. In such a setting, a poor household may not be able to buy an ox that it needs to plow a plot to lift productivity above subsistence level. If the household receives windfall gains and can make the investment, that will bring it to a high income path, and the likelihood of becoming poor again reduces dramatically. A situation like this can be summarized as in the graph in Figure 2.1, which can be thought of as the graphical equivalent of a transition matrix.

Figure 2.1—Multiple equilibria in asset dynamics



Source: Authors' design.

The figure illustrates how asset holdings evolve over time. This figure, or variations thereof, has been used in many papers on poverty traps to explain the concept (for example, Figure 7 in Azariadis and Stachurski 2005 and Figure 1 in Antman and McKenzie 2007). The figure shows three equilibria. A_C is an unstable equilibrium in the sense that if an individual or household has A_C in period t, it is predicted to have A_C in the next period as well. However, if the relationship is stochastic (for instance, by augmenting it with a mean zero shock ε), then any nonzero shock will drive the individual or household away from A_C. For instance, if the shock is positive, then asset holdings will be $A_C + \varepsilon$ in the next period, which in turn will result in assets that are higher than the shock. This will then go on until the household arrives at A_H, the high-level stable equilibrium. The reverse happens when the household starts from the unstable equilibrium and experiences a negative shock. In that case, it will end up with the low equilibrium A_L. Hence, the high and low equilibria function as local attractors, where the basins of attraction are delineated by the unstable fixed point A_C (Azariadis and Stachurski 2005).

These days, there is a considerable literature on poverty traps, both in macroeconomic growth theory and in more microeconomic development studies. Whereas some studies look for evidence of the existence of traps in the data, others look for the reasons poverty traps may exist. Most such studies present models that result in distribution dependency of an outcome variable, like income or productivity. However, most of the arguments used also apply when we look at the evolution of livestock assets over time.

The most widely documented reason for poverty traps in general microeconomic development is the biomedical phenomenon of undernourishment (Dasgupta 1997). In the simplest version of the model, a household is assumed to derive income solely from labor earnings, and as in the efficiency wage hypothesis, we assume productivity and the wages depend on consumption. It is then further assumed that labor productivity and hence earnings are zero at a low but positive level of consumption. Only if consumption rises above a threshold does the worker start to be productive.

We could use similar arguments for livestock assets. Suppose a household to a large extent depends on its livestock assets for income generation. If the productivity of the asset is a function of household income in the previous period, that creates persistence in the dynamics of productivity. The persistence is a precondition for traps to take root. Traps can emerge because assets are bulky. To give a more concrete example, suppose a household has one ox, but it is old and not productive enough to plow the whole field. The yield of the area the ox can plow is just sufficient to keep the ox alive. Missing credit markets and the bulkiness of oxen trap the household at a low-level equilibrium. Another example could be a household that generates income from selling milk. After an adverse shock, the cow might give less milk, which leads to lower household income. The fraction of income reinvested in the cow is also smaller, such that the amount of milk the cow delivers never recovers from the shock.

Dasgupta (1997) associated poverty traps with high birth rates and deterioration of the local environmental resources base. Jalan and Ravallion (2004) also note that social exclusion may lead to distribution-dependent wealth dynamics. Dercon (2004b) presents three core market failures that together with initial asset inequalities may lead to poverty traps.

But also on the macro and meso levels, some researchers have argued that poverty traps are likely to be important. For instance, Matsuyama (2004) presents a model where credit market imperfection leads to unequal outcomes in the context of financial globalization. It has even been argued that traps at different levels are not unrelated. Indeed traps on the micro level may reinforce traps on other levels and vice versa, a phenomenon that has been termed fractal poverty traps (Barrett and Swallow 2006).

If multiple equilibria and poverty traps exist, they have dramatic policy implications. In that case, according to Jalan and Ravallion (2004), effective social protection from transient poverty would be an investment with lasting benefits. Furthermore, the existence of poverty traps suggests beneficial effects from pro-poor redistributive policies (see also Dercon 2004a). It also implies that small interventions may not be effective, but that instead a big push is needed to lift households above the threshold. It has been argued that this idea is implicit in the Millennium Development Goals (see Barrett and Swallow 2006).

3. RELATED STUDIES

Jalan and Ravallion (2004) look for nonlinearities in income and consumption dynamics in China. To do so, they estimate a cubic function of lagged income (or consumption). Since they are working with a six-year panel, they estimate the function using the Arellano and Bond (1991) generalized method of moments (GMM) framework. Although they find evidence of nonlinearities in the evolution of income and consumption over time, they find no evidence of an effective poverty trap. However, their results do indicate that the speed of recovery from an income shock is slower for the poor.

Lokshin and Ravallion (2004) also estimate a cubic function of lagged income. They account for endogenous attrition and estimate a system of simultaneous equations using semiparametric full information maximum likelihood. They find evidence of nonlinearities in the dynamics of income, but not of poverty traps: in general, households bounce back from transient shocks, though the process is not fast.

Another article that estimates third-order polynomials is that of Antman and McKenzie (2007). Using a pseudo-panel from urban Mexico, they investigate labor earnings and income and expenditure dynamics. They explicitly allow for heterogeneity to account for the fact that particular types of individuals may face traps while the average person does not. They also show how dynamic pseudo-panel methods can mitigate the problems of short panels, attrition, and measurement error. In their application, they find evidence of nonlinearities in household income dynamics, but no evidence of a poverty trap for any group.

Dercon and Outes (2009) look at income dynamics in rural India using 30 years of data from six ICRISAT villages. They opt for a cubic polynomial in a GMM framework, just as Jalan and Ravallion (2004). However, instead of relying on internal instruments, they use rainfall data. They also allow for household-level heterogeneity and find that those with higher assets, especially in the form of initial levels of education in the family in the 1970s, higher land holdings, and/or high physical capital faced a much lower level of income at which a downward spiral could have followed.

On a macroeconomic level, Krüger (2009) estimates the usual convergence regressions, but augmented with quadratic and cubic terms. Furthermore, Krüger proposes to use quantile regression techniques instead of regression to the mean, as, citing Durlauf and Quah (1999), " 'explaining distribution dynamics' needs to go beyond representative economy-analysis."[1] Regressing the log of GDP per capita growth on the log of GDP per capita in this way, he finds that for the lowest quintile there is indeed a fixed stable point at relatively low levels of per capita income and an unstable point at about US$5,000 per capita in 2000, hinting at the existence of a poverty trap. This is different for the other quintiles, where the cubic function is above the 45-degree line over the domain. He comes to the same findings when scaling GDP by the number of workers.

Carter and Barrett (2006) look at poverty traps from an asset-based perspective. They argue that statistical tests that rely on household income or expenditure cannot differentiate between a situations where a household experiences a shock that does not degrade its resource base versus one that does. As they define a poverty trap as "a threshold in asset space around which accumulation dynamics bifurcate and the existence of some range over which increasing returns might prevail," they propose to restrict attention to the dynamics of assets when searching for poverty traps.

Lybbert et al. (2004) study wealth dynamics among a group of pastoralists in southern Ethiopia. Part of their study involves investigating livestock-holding dynamics, since in their context, such assets are very important determinants of income. Using recursion diagrams and smoothing techniques, they find that biophysical shocks move households between multiple dynamic equilibria. They find that households with a herd size of less than 15 head fall into a sedentarization zone, whereas households with more than 15 head converge to an upper equilibrium of about 75. Above that level, accumulation becomes too costly to be sustainable.

[1] In a similar setting, Fiaschi and Lavezzi (2007) argue that "the pooling of cross-country data can mislead the researcher in the identification of the actual growth patterns, as it identifies a 'representative' growth path." (p. 274). Their solution is to use a state-space definition and construct transition matrices.

Barrett et al. (2006) study welfare dynamics in rural Kenya and Madagascar. They use qualitative and quantitative evidence to see what causes persistent poverty. They find evidence of S-shaped asset dynamics using both nonparametric regressions and a fourth-order polynomial regression. In a similar paper, Adato, Carter, and May (2006) explore poverty traps and social exclusion in South Africa using qualitative and quantitative data. They construct a livelihood-weighted asset index, which is expressed in poverty line units (PLUs).[2] Using nonparametric techniques, they find a poverty trap when the asset index is about 1 PLU, whereas the unstable equilibrium is just over 2 PLUs.

Carter et al. (2007) investigate livestock dynamics in the context of natural shocks. They investigate whether asset recovery is different once a household falls below a critical threshold using threshold estimation and sample-splitting methods. They find evidence of a threshold effect in asset recovery after Hurricane Mitch in Honduras and after the 1998–2000 drought in northeastern Ethiopia. The evidence for an actual poverty trap below the threshold is less convincing, as in both cases asset growth is positive over most of the range of initial assets, and the asset equilibrium of the lower regime is only slightly below the threshold value.

McKenzie and Woodruff (2006) test whether self-employment production technologies contain indivisibilities that place credit-constrained individuals in poverty traps for a sample of Mexican microenterprises. They do this by investigating the shape of the production function using nonparametric regressions. They find no support for the hypothesis that poor people cannot enter the microenterprise sector in general, but caution poverty traps may exist in transportation and professional services. In addition, there are signs of nonconvexities in the US$1,000-to- US$2,000-investment-level range, suggesting that a hurdle has to be taken in the transition out of the informal into the formal sector.

The present study is closely related to those of Jalan and Ravallion (2004) and Lokshin and Ravallion (2004) in that we use autoregressive models to estimate the parameters of interest. But unlike those studies, we do not look at outcome variables like income or consumption, but concentrate on the dynamics of livestock asset holdings. As such, the present study is also related to the studies that take an asset-based approach. Furthermore, as in Antman and McKenzie (2007) and Dercon and Outes (2009), we allow explicitly for (household) heterogeneity in asset dynamics.

[2] It is the livelihood that the assets predict, expressed relative to the poverty line.

4. THE ECONOMETRIC MODEL

The basic idea behind the econometric model is that we can identify the previously mentioned attractors and the threshold using time-series estimation methods. More in particular, we can use methods similar to threshold autoregression to identify the stable and unstable equilibria. An added advantage is that we can also get an estimate of the speed at which households or individuals converge to their equilibrium.

Let $A_{i,t}$ denote some asset-holding indicator of household *i* at time *t*, and therefore $\Delta A_{i,t} = A_{i,t} - A_{i,t-1}$ denotes the change in assets of household *i* over one period of time. A model with two attractors and one threshold[3] can be written as

$$\Delta A_{i,t} = \beta_L.(A_{i,t-1} - A_L).I_{(A_{i,t-1}<A_C)} + \beta_H.(A_{i,t-1} - A_H).I_{(A_{i,t-1}\geq A_C)} + (\eta_i + \varepsilon_{i,t}), \tag{1}$$

where $I_{(A_{i,t-1}<A_C)}$ and $I_{(A_{i,t-1}\geq A_C)}$ are indicator functions that take the value of 1 if the condition indicated in the brackets is satisfied and zero otherwise, η_i is an unobserved individual-specific time-invariant effect that allows for heterogeneity in the mean growth of assets across households, and $\varepsilon_{i,t}$ is a residual, which is assumed to be independent across individuals. Noting that $I_{(A_{i,t-1}\geq A_C)} = 1 - I_{(A_{i,t-1}<A_C)}$, equation (1) can be written as

$$\Delta A_{i,t} = \beta_L.(A_{i,t-1} - A_L).I_{(A_{i,t-1}<A_C)} + \beta_H.(A_{i,t-1} - A_H).(1 - I_{(A_{i,t-1}>A_C)}) + (\eta_i + \varepsilon_{i,t}). \tag{2}$$

In this equation, A_L can then be interpreted as a low-level stable equilibrium to which asset holdings converge if asset holdings were below A_C in the previous period. The parameter β_L is the convergence speed to the low-level stable equilibrium, indicating at what rate a discrepancy from the stable equilibrium in the previous period is corrected in the current period. The same reasoning holds if asset holdings in the previous period surpassed A_C. In this domain, there is convergence to a high-level stable equilibrium A_H at a rate of β_H.

The model in equation (2) is essentially a dynamic panel data model, which can be seen if we rewrite it as

$$\begin{aligned} A_{i,t} &= \beta_L.I_{(A_{i,t-1}<A_C)}.A_{i,t-1} - \beta_L.I_{(A_{i,t-1}<A_C)} + \beta_H.A_{i,7-1} - \beta_H.A_H - \beta_H.I_{(A_{i,t-1}<A_C)}.A_{i,t-1} \\ &+ \beta_H.I_{(A_{i,t-1}<A_C)}.A_{i,t-1} + A_{i,t-1} + (\eta_i + \varepsilon_{i,t}) \end{aligned} \tag{3}$$

or

$$\begin{aligned} A_{i,t} &= (\beta_L - \beta_H).I_{(A_{i,t-1}<A_C)}.A_{i,t-1} + (\beta_H + 1).A_{i,t-1} \\ &+ (\beta_H.A_H - \beta_L.A_L).I_{(A_{i,t-1}<A_C)} - \beta_H.A_H + (\eta_i + \varepsilon_{i,t}). \end{aligned} \tag{4}$$

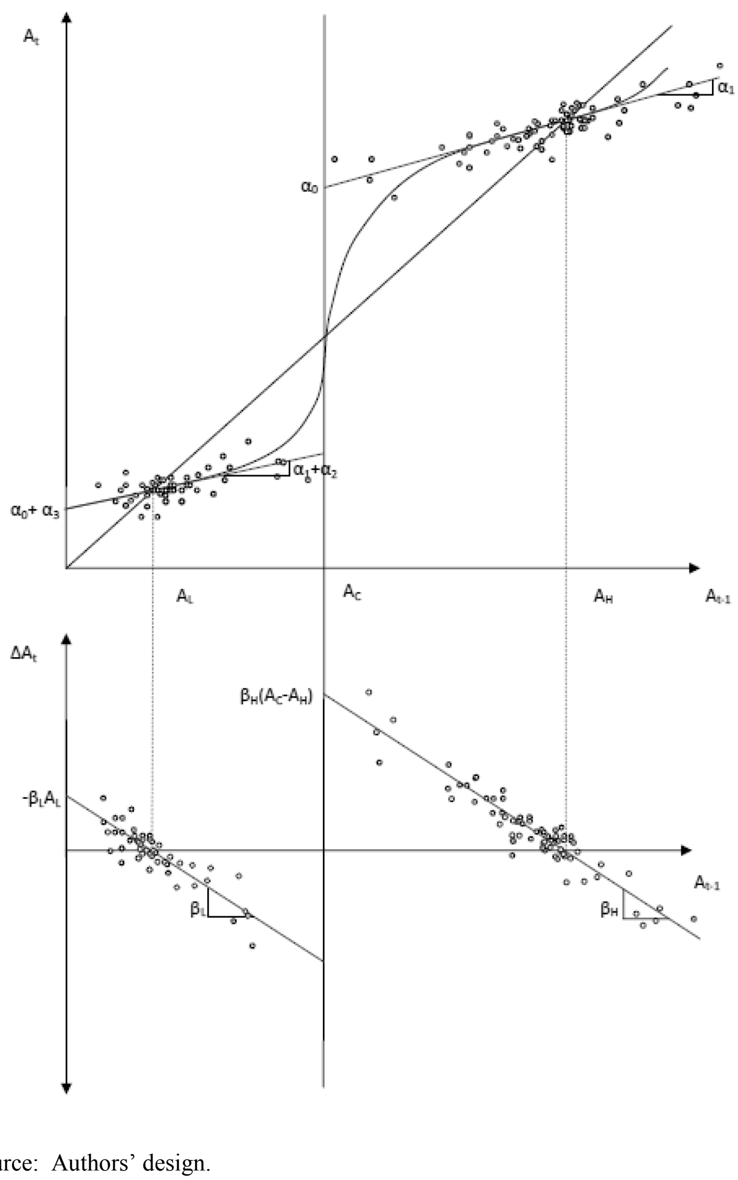
[3] We should stress that such a model describes a specific form of asset dynamics and that in reality the dynamics may be more complex or less complex, with more or less equilibria. We discuss how we determine the number of equilibria later. For now, we assume a model with two stable and one unstable equilibria, as that corresponds to the prototype asset poverty traps case as depicted in Figure 2.1.

If we redefine $\alpha_0 = -\beta_H.A_H$, $\alpha_1 = (\beta_H + 1)$, $\alpha_2 = (\beta_L - \beta_H)$, and $\alpha_3 = (\beta_H.A_H - \beta_L.A_L)$, equation (4) becomes

$$A_{i,t} = \alpha_0 + \alpha_1.A_{i,t-1} + \alpha_2.I_{(A_{i,t-1}<A_C)}.A_{i,t-1} + \alpha_3.I_{(A_{i,t-1}<A_C)} + (\eta_i + \varepsilon_{i,t}). \tag{5}$$

Figure 4.1 depicts equations (5) and (1) for a representative household. The top panel depicts equation (5), showing the intercepts and slopes in the two regimes. The bottom panel shows the corresponding difference equation (1) of the recurrence relation (5).

Figure 4.1—Recursive diagram and difference equation



Source: Authors' design.

Figure 4.1 also illustrates one reason we think piecewise linear regressions may be more appropriate for the problem at hand than nonparametric smoothing techniques or polynomial regressions used in earlier work. As mentioned earlier, studies on poverty traps often depict income (or asset) dynamics as following smooth S-shaped functions. However, we do not see why the derivative of the function should increase as one approaches the threshold from the left. Similarly, we do not see a theoretical reason why the rate of convergence to the high-level stable equilibrium should become greater as one approaches the threshold from the right, as is implied by such a function. The definition of a poverty trap does not imply that the derivative of this function varies over the domain of each regime (but it may differ between the regimes).

If the stable equilibria are interpreted as attractors within the different regimes separated by the threshold(s), the simplest way to model conditional convergence is to assume a variable is a linear function of its deviation from the stable equilibrium in the previous period. If that is the case, a piecewise linear regression like the one we propose may be more accurate than polynomial or kernel regressions that normally feature in applied work.[4] The preceding reasoning suggests that in the case of linear adjustment to the stable equilibria, polynomial and kernel regression methods will underestimate the true dynamics of the process.[5] This will be especially so for kernel regressions with a high bandwidth.

But estimation of linear dynamic panel data models such as the one described in equation (5) is challenging. It is well known that ordinary least squares (OLS) estimates of (5) are inconsistent, since the explanatory variable $A_{i,t-1}$ is positively correlated with the error term $(\eta_i + \varepsilon_{i,t})$ due to the presence of the individual effect (Bond 2002). Using a within-groups transformation to eliminate the individual-specific time-invariant effects is also not satisfactory, as it introduces, at least in panels with a fixed number of observations over time, non-negligible correlation between the transformed lagged dependent variable and the transformed error term (Nickell 1981). An alternative is to use a first-difference transformation, as that eliminates the individual effects without introducing all realizations of the disturbances into the transformed error term:

$$\begin{aligned} A_{i,t} - A_{i,t-1} &= \alpha_1.(A_{i,t-1} - A_{i,t-2}) + \alpha_2.\left(I_{(A_{i,t-1}<A_C)}.A_{i,t-1} - I_{(A_{i,t-2}<A_C)}.A_{i,t-2}\right) \\ &+ \alpha_3.\left(I_{(A_{i,t-1}<A_C)} - I_{(A_{i,t-2}<A_C)}\right) + (\varepsilon_{i,t} - \varepsilon_{i,t-1}) . \end{aligned} \tag{6}$$

But here, as well, OLS is inconsistent, due to the correlation between $\varepsilon_{i,t-1}$ and $A_{i,t-1}$. However, consistent estimates can be obtained using instrumental variables that are both correlated with the endogenous variables and orthogonal to the first-differenced error term. $A_{i,t-2}$ is one such candidate, but $A_{i,t-2} - A_{i,t-3}$ would be a valid instrument as well (Anderson and Hsiao 1981), suggesting two different instrumental variables (IV) estimators.

Arellano and Bond (1991) recast the preceding in a GMM framework. That has several advantages. Noting that each of the aforementioned IV estimators imposes one moment condition in estimation,[6] the two estimators can be unified in a GMM framework. This eliminates the disadvantage of

[4] Indeed, if a poverty trap is seen as a threshold one has to overcome to fall into a regime with a different steady state, a model with a discontinuity like the TAR model seems apt. Seeing poverty traps as the manifestation of a dynamic discontinuity is not uncommon.

[5] Even if the data-generating process is not linear in the deviation from the previous period, there is no a priori reason to assume the particular S-shaped function (apart from the fact that they are better suited to model with nonparametric methods). Put differently, there is no reason adjustment should be faster the further one is from the stable equilibrium.

[6] This can be seen by noting that plim $\frac{1}{N(T-1)}\sum_{i=1}^{N}\sum_{t=2}^{T}(\varepsilon_{i,t} - \varepsilon_{i,t-1})A_{i,t-2} = E\{(\varepsilon_{i,t} - \varepsilon_{i,t-1})A_{i,t-2}\} = 0$ and plim

the second IV estimator that the sample size is reduced further by one period. Furthermore, imposing additional moment conditions increases the efficiency of estimators. In a GMM framework, one can exploit additional moment conditions when T increases. For instance, if t = 2, we can only exploit $E\{(\varepsilon_{i,2}-\varepsilon_{i,1})A_{i,0}\}=0$. When t = 3, we can use $E\{(\varepsilon_{i,2}-\varepsilon_{i,1})A_{i,0}\}=0$, as well as $E\{(\varepsilon_{i,3}-\varepsilon_{i,2})A_{i,1}\}=0$. Arellano and Bover (1995) note that if other explanatory variables are present and one is willing to assume that the first differences of this variable are uncorrelated with the individual-specific effects, suitably lagged differences of this explanatory variable can be used as instrumental variables for the levels equation. Building on this, Blundell and Bond (1998) suggest that lagged differences may also be valid instruments for the levels equations in autoregressive models. They combine this into an estimator that uses suitably lagged levels as instruments in the difference equation and suitably lagged differences as instruments in the levels equation. This estimator is sometimes referred to as the system GMM estimator.

Given that we estimate equation (5), the preceding translates to our case as follows: For the equation in first difference, we instrument the first three terms $\alpha_1 A_{i,t-1}$, $\alpha_2 .I_{(A_{i,t-1}<A_C)}.A_{i,t-1}$, and $\alpha_3 .I_{(A_{i,t-1}<A_C)}$ with their lagged levels two, three, four, and five periods back (GMM type). We also use first-differences exogenous variables as standard instruments. For the levels equation, we use lagged first differences of the three terms (GMM type) and levels of the exogenous variables as standard instruments.

Once we obtain consistent parameter estimates for (6), the variables of interest from equation (1) (the adjustment speeds β_H and β_L and the stable equilibria A_L and A_H) can be calculated. Since these variables are (nonlinear) functions of the coefficients of (5), we use the delta method to approximate their standard errors (Oehlert 1992).[7] The value of A_C can be found through standard sample-splitting and threshold estimation techniques as in Hansen (2000). More particularly, the method consists of performing a grid search over the domain of candidate thresholds. That domain consists of all[8] possible values of $A_{i,t-1}$. For each of the candidate thresholds, the indicator functions are computed (hence the name *sample splitting*) and model (1) is estimated. The threshold that results in the model with the best fit, according to some criterion, is then selected. In time-series models, this criterion is taken to be either the sum of squared residuals (SSR) or the log likelihood. For our panel data model, as the GMM estimator for a parameter vector θ minimizes the weighted quadratic distance $\left[\frac{1}{N}\sum_{i=1}^{N} g_i(\theta)\right]' W_N^{-1}\left[\frac{1}{N}\sum_{i=1}^{N} g_i(\theta)\right]$, we take this minimized value to be our criterion. In other words, this is our GMM equivalent of the SSR.

In real-world applications, the dynamics of the process one is studying may be less complex than what is depicted in Figure 2.1 and its counterpart given in equation (1). We would like to do some formal testing to see whether there is indeed threshold behavior present. In other words, we would like to test whether the model in (1) is statistically significant relative to a linear version such as

$$\Delta A_{i,t} = \beta.(A_{i,t-1}-A_S)+(\eta_i+\varepsilon_{i,t}), \tag{7}$$

$$\frac{1}{N(T-2)}\sum_{i=1}^{N}\sum_{t=3}^{T}(\varepsilon_{i,t}-\varepsilon_{i,t-1})(A_{i,t-2}-A_{i,t-3}) = E\{(\varepsilon_{i,t}-\varepsilon_{i,t-1})(A_{i,t-2}-A_{i,t-3})\}=0$$

[7] Alternatively, simulation techniques could be used to get the standard errors (see for instance Gelman and Hill 2007).

[8] Since we need a minimum number of observations in each regime, not all $A_{i,t-1}$'s are candidate thresholds. See also the explanation of the SETAR model in the general introduction.

where there is adjustment to a single stable equilibrium A_S at a speed of β. Similar to equation (4), this can be rewritten as

$$A_{i,t} = (\beta + 1).A_{i,t-1} - \beta.A_S + (\eta_i + \varepsilon_{i,t}), \tag{8}$$

or, redefining $\alpha_0 = -\beta.A_S$ and $\alpha_1 = (\beta + 1)$, as

$$A_{i,t} = \alpha_0 + \alpha_1 A_{i,t-1} + (\eta_i + \varepsilon_{i,t}). \tag{9}$$

Hansen (1999) investigates testing for linearity in the context of self-exciting threshold autoregressive (SETAR) models. He notes that SETAR models are nested and that a conventional Wald test based on the residual sum of squares can be used. The natural candidate for a test statistic would be the following F-test:

$$F = n\left(\frac{SSR_{AR} - SSR_{TAR}}{SSR_{TAR}}\right), \tag{10}$$

where SSR_{AR} is the residual sum of the squared errors of model (7) and SSR_{TAR} is the residual sum of the squared errors of model (1).

The problem here is that the threshold is not identified under the null, and hence the distribution of (10) does not follow the usual F-distribution (Davies 1987). However, we can use the testing methodology suggested by Hansen (1996, 1997). To approximate the distribution for this test statistic, we follow a bootstrap procedure. We do this a sufficient number of times to enable us to draw the empirical distribution. The p-value can then be obtained by counting the percentage of bootstrapped F's that exceed the test statistic. A large value of F leads us to reject the null.

However, again because of the panel nature of our data and the GMM procedure we apply, we cannot use a test that is based on the residual sum of squared errors. Instead, we use the likelihood ratio–type statistic suggested by Bond, Bowsher, and Windmeijer (2001). This is computed simply as the difference between the standard GMM tests of overidentifying restrictions in the restricted and unrestricted models multiplied by the number of observations. They call this statistic the D_{RU}:

$$D_{RU} = N\left(J(\tilde{\theta}) - J(\hat{\theta})\right), \tag{11}$$

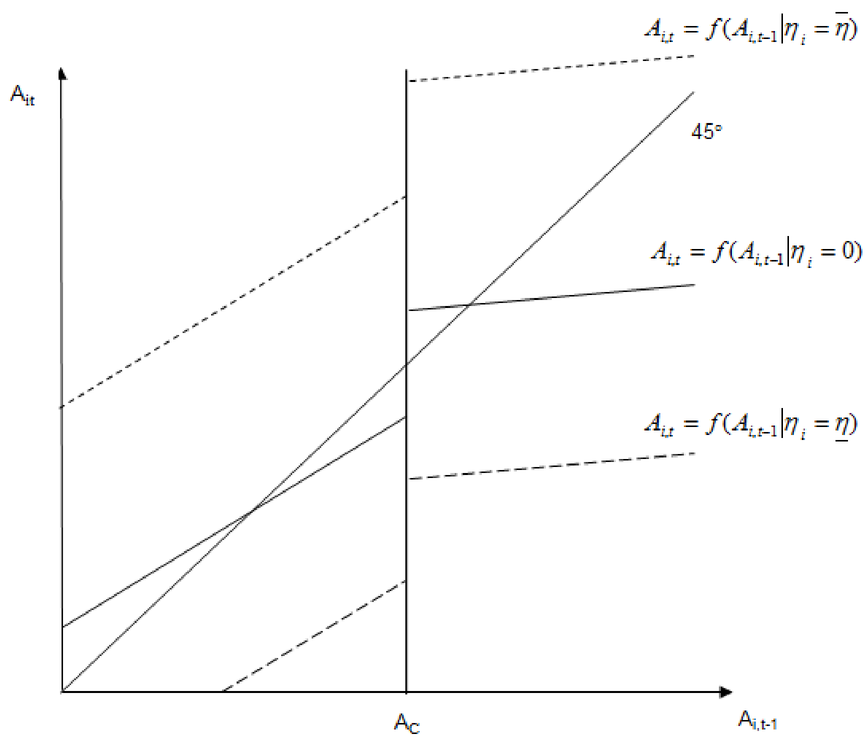
where $\hat{\theta}$ is the GMM estimator of the unrestricted model (1) and $\tilde{\theta}$ is the GMM estimator of the restricted model (7), based on the same set of moment conditions. Under the null hypothesis that the restrictions are valid, the statistic has an asymptotic χ^2-distribution with degrees of freedom equal to the number of restrictions. However, as argued earlier, due to the presence of an unidentified nuisance parameter under the null, the distribution will be nonstandard. We will use a bootstrap procedure similar to Hansen (1996, 1997) to calculate the empirical distribution.

In equation (5) we control only for household-specific individual time-invariant effects. It is unlikely that those effects and the autoregressive effect are the only determinants of asset dynamics. For instance, we expect that larger households will need larger asset holdings ceteris paribus. To the extent that household size varies over time, this is not captured in our model. We thus add a vector of other exogenous controls $X_{i,t}$ to our model. The final model thus becomes

$$A_{i,t} = \alpha_0 + \alpha_1.A_{i,t-1} + \alpha_2.I_{(A_{i,t-1}<A_C)}.A_{i,t-1} + \alpha_3.I_{(A_{i,t-1}<A_C)} + \alpha_4.X_{i,t} + (\eta_i + \varepsilon_{i,t}) \quad (12)$$

As in Antman and McKenzie (2007) and Dercon and Outes (2009), our model allows for individual heterogeneity. The inclusion of time-invariant individual-specific effects allows for a situation where particular groups of people experience an asset poverty trap while other groups do not. This is illustrated in Figure 4.2, where we plot asset dynamics for three hypothetical groups of households.

Figure 4.2—Individual/household heterogeneity in asset dynamics



Source: Authors' design.

The full line in Figure 4.2 shows a situation where there is a single unstable equilibrium at A_C for the average household. Such a household will converge either to the higher or the lower stable equilibrium. However, due to some (possibly unobservable) household-specific time-invariant effect, another household may be able to expand its asset base much faster than the average one. The upper dashed line depicts such a situation. As this line does not intersect the 45-degree line over the entire domain, this household will, in theory, keep expanding its asset base. But the other extreme may also occur. The lower dashed line shows a household that is affected by a household characteristic that results in a consistently lower subsequent asset stock than that of the average household. The function that describes the asset dynamics for this particular household does not intersect the 45-degree line either, but this one is less lucky. As its function is everywhere below the 45-degree line, the household will quickly lose all its assets.

Location is an example of such a household-specific effect. Suppose the average household lives in an area where livestock reproduces at a normal rate. The household represented by the top dashed line is luckier in terms of location. We will assume that household lives in an area characterized by an abundance of pasture, causing a higher rate of reproduction. The household represented by the bottom dashed line may live in a dry area or an overgrazed area. This may cause below-average reproduction rates.

The graph in Figure 4.2 shows that our model assumes that the “production function” is the same for everyone, but that unobserved effects can shift the function up or down. Put differently, all households face the same threshold,[9] but with (possibly) different consequences. This may seem to be an unrealistic feature of the model. However, as we typically think of discontinuities in terms of indivisibilities in input factors, one could argue that individual heterogeneity should not affect these technical constraints. For instance, it is not because one lives in a higher-potential area that one can plow with, say, one and a half oxen. Rather, it is because one lives in a higher-potential area that plowing with two oxen yields enough to keep plowing with two oxen in the future.

The method we have described has some additional advantages over nonparametric methods commonly used to describe poverty and asset dynamics. First of all, it relieves the researcher from having to decide the bandwidth and kernel. Second, our method also returns the adjustment speed to the equilibria. When the observations are made at fixed time intervals, such parameters can tell us how long it takes to get to the equilibrium after a shock has occurred.

[9] At least in the univariate case depicted in Figure 4.2. Note that in the final regression, we also condition on other exogenous variables.

5. CONTEXT, DATA, AND DESCRIPTIVE STATISTICS

As in many of the poorest countries in the world, livestock is by far the most important marketable asset and typically accounts for more than 90 percent of the value of assets in Ethiopia (Dercon 2004b). That is no surprise if one realizes that Ethiopia has the largest livestock population in Sub-Saharan Africa. In addition, hides and skins make up Ethiopia's second-biggest export product. Livestock is obviously important for the large pastoralist population of southern Ethiopia. But for people depending on sedentary farming systems livestock is also important, not only for production but also as a form of savings.

Cereal production using the oxen-drawn plow is typically the most important food and income source in these mixed farming systems. The use of draught oxen for traction has a long history in Ethiopia and the traditional plow, locally called a *maresha,*" has been used for the past several centuries and is still in use without any significant changes (Urga and Abayneh 2007). By using plows, farmers can both increase the amount of land cultivated and improve yields of certain crops that require more intensive soil preparation (Stanford and Ashley 2008). The relatively high reliance on animal traction (out of the estimated 30 million cattle, about 10 million are oxen according to Urga and Abayneh 2007) may be a source of asset poverty traps, as there are indivisibilities to overcome.

In this part, we investigate the dynamics of livestock holdings by applying the previously described methods to livestock data from the Ethiopian Rural Household Survey (ERHS). We decided to look for asset-holding thresholds for an aggregate measure of livestock, since we do not expect effects from indivisibilities for oxen alone. This aggregation at the household level is done by calculating tropical livestock units, or TLUs. See the Appendix for the weights given to the TLUs. We used six rounds of the panel: 1994a, 1994b, 1995, 1997, 1999, and 2004. The sample is drawn in such a way that it is self-weighting and broadly consistent with the three main sedentary farming systems—plow-based cereals farming systems of the Northern and Central Highlands, mixed plow/hoe cereals farming systems, and farming systems based around enset. The sample does not include pastoral households or urban areas. For more information on the data, see Dercon (2004b).

The problem with this panel is that the interview interval is not the same. This is needed for interpretation of the adjustment speed. If the data are yearly, the results can be interpreted as yearly adjustment rates. We judged this to be a problem mainly in the last three rounds. Dercon et al. (2009) look at the consequences of this. They argue that differences in the timing between interviews can be interpreted as missing data. We can apply their arguments to a SETAR model. Take

$$A_{i,t} - A_{i,t-1} = \rho_1 \left(A_{i,t-1} - F_1\right).I_{\left(A_{i,t-1} \le \theta\right)} + \rho_2 \left(A_{i,t-1} - F_2\right).I_{\left(A_{i,t-1} > \theta\right)} + \eta_i + \varepsilon_{i,t} \tag{13}$$

and

$$A_{i,t-1} - A_{i,t-2} = \rho_1 \left(A_{i,t-2} - F_1\right).I_{\left(A_{i,t-2} \le \theta\right)} + \rho_2 \left(A_{i,t-2} - F_2\right).I_{\left(A_{i,t-2} > \theta\right)} + \eta_i + \varepsilon_{i,t-1}, \tag{14}$$

and now suppose that we observe only *t – 2* and *t*. Adding the preceding equations and then dividing by 2 gives

$$\begin{aligned} \left[A_{i,t} - A_{i,t-2}\right]/2 &= \rho_1 \left[\left(A_{i,t-1} - F_1\right).I_{\left(A_{i,t-1} \le \theta\right)} + \left(A_{i,t-2} - F_1\right).I_{\left(A_{i,t-2} \le \theta\right)}\right]/2 \\ &+ \rho_1 \left[\left(A_{i,t-1} - F_1\right).I_{\left(A_{i,t-1} > \theta\right)} + \left(A_{i,t-2} - F_1\right).I_{\left(A_{i,t-2} > \theta\right)}\right]/2 + \eta_i . \end{aligned} \tag{15}$$

As can be seen, the left-hand side of this equation simply has a mean change over the period of time. To be able to estimate the parameters, we have to make an additional assumption. The route taken by Dercon et al. (2009) is to argue that changes over time are very small and therefore to set $A_{t-1} = A_{t-2}$.

In other words, we assume that for the time-dependent variables, the period averages are equal to the initial level. If we make that assumption, we see that

$$\lfloor A_{i,t} - A_{i,t-2} \rfloor / 2 = \rho_1 \left(A_{t-2} - F_1\right).I_{\left(A_{t-2} \le \theta\right)} + \rho_2 \left(A_{t-2} - F_2\right).I_{\left(A_{t-2} > \theta\right)}. \tag{16}$$

This can easily be generalized to cases where p periods are missing.

$$\begin{aligned}\lfloor A_{i,t} - A_{i,t-p} \rfloor / p = {} & \rho_1 \left\lfloor \left(A_{i,t-1} - F_1\right).I_{\left(A_{i,t-1} \le \theta\right)} + \left(A_{i,t-2} - F_1\right).I_{\left(A_{i,t-2} \le \theta\right)} + \ldots + \left(A_{i,t-p} - F_1\right).I_{\left(A_{i,t-p} \le \theta\right)} \right\rfloor / p \\ & + \rho_1 \left\lfloor \left(A_{i,t-1} - F_1\right).I_{\left(A_{i,t-1} > \theta\right)} + \left(A_{i,t-2} - F_1\right).I_{\left(A_{i,t-2} > \theta\right)} + \ldots + \left(A_{i,t-p} - F_1\right).I_{\left(A_{i,t-p} >. \theta\right)} \right\rfloor / p.\end{aligned} \tag{17}$$

And again making the assumption that $A_{i,t-1} = A_{i,t-2} = \ldots = A_{i,t-p}$, we get

$$\lfloor A_{i,t} - A_{i,t-p} \rfloor / p = \rho_1 \left(A_{i,t-p} - F_1\right).I_{\left(A_{i,t-p} \le \theta\right)} + \rho_2 \left(A_{i,t-p} - F_2\right).I_{\left(A_{i,t-p} > \theta\right)}. \tag{18}$$

The assumption that $A_{i,t-1} = A_{i,t-2} = \ldots = A_{i,t-p}$ seems unrealistic, especially since this defines a considerable part of our explanatory variable. It would mean that all observed changes are attributable to the last period. We propose to take a different assumption: linear interpolation for the missing rounds. Going back to the two-period case of (13), we then assume that $A_{i,t-1} = A_{i,t-2} + \left(A_{i,t} - A_{i,t-2}\right)/2$. It can then easily be checked that

$$A_{i,t} - A_{i,t-2} = \rho_1 \left(\frac{A_{i,t} - A_{i,t-2}}{2} - F_1 \right).I_{\left(\frac{A_{i,t} - A_{i,t-2}}{2} \le \theta\right)} + \rho_2 \left(\frac{A_{i,t} - A_{i,t-2}}{2} - F_2 \right).I_{\left(\frac{A_{i,t} - A_{i,t-2}}{2} > \theta\right)} \tag{19}$$

Again, as earlier, we can generalize this to cases where p periods are missing as

$$\begin{aligned}A_{i,t} - A_{i,t-p} = {} & \rho_1 \left(\left(pA_{i,t-p} + \frac{p(p+1)}{2} \left(\frac{A_{i,t} - A_{i,t-p}}{p} \right) \right) - F_1 \right) I_{\left(pA_{i,t-p} + \frac{p(p+1)}{2} \left(\frac{A_{i,t} - A_{i,t-p}}{p} \right) \le \theta \right)} \\ & + \rho_2 \left(\left(pA_{i,t-p} + \frac{p(p+1)}{2} \left(\frac{A_{i,t} - A_{i,t-p}}{p} \right) \right) - F_2 \right) I_{\left(pA_{i,t-p} + \frac{p(p+1)}{2} \left(\frac{A_{i,t} - A_{i,t-p}}{p} \right) > \theta \right)}.\end{aligned} \tag{20}$$

The same reasoning can be followed for other time-varying control variables contained in the X matrix of equation (12). The individual-specific effects are, for the obvious reason that they do not change over time, unaffected by missing rounds.

We decided to include household size in the X matrix. We expect to find a positive correlation with TLUs for two reasons. First, when livestock is seen as a production factor (for instance, for milk), larger households will need more livestock. Second, larger households may mean more labor is available that can be used as a supplemental input factor for livestock assets. Since this is also variable over time, we interpolated household size as explained earlier. Further controls are included for the sex of the household head. We also control for common shocks by inserting dummies for the rounds.[10]

[10] We also experimented with more controls, such as the education level of the household head and access to credit, but a combination of insignificant coefficients and a loss in degrees of freedom when adding more controls led to the present model.

Table 5.1 presents some descriptive statistics of our main variable. It gives an idea of evolution over time of TLUs, both at the household level and per capita. Very few households report zero livestock. We note a slight expansion of the average livestock asset base, at both the household level and the individual level. We also observe a small dip in 1997. Note that median livestock assets also show an upward trend but seem to level off in the last round. Median asset stocks also reduce slightly if expressed per capita. Inequality in livestock asset holdings expressed in TLUs, although initially very high, seems to improve over time.

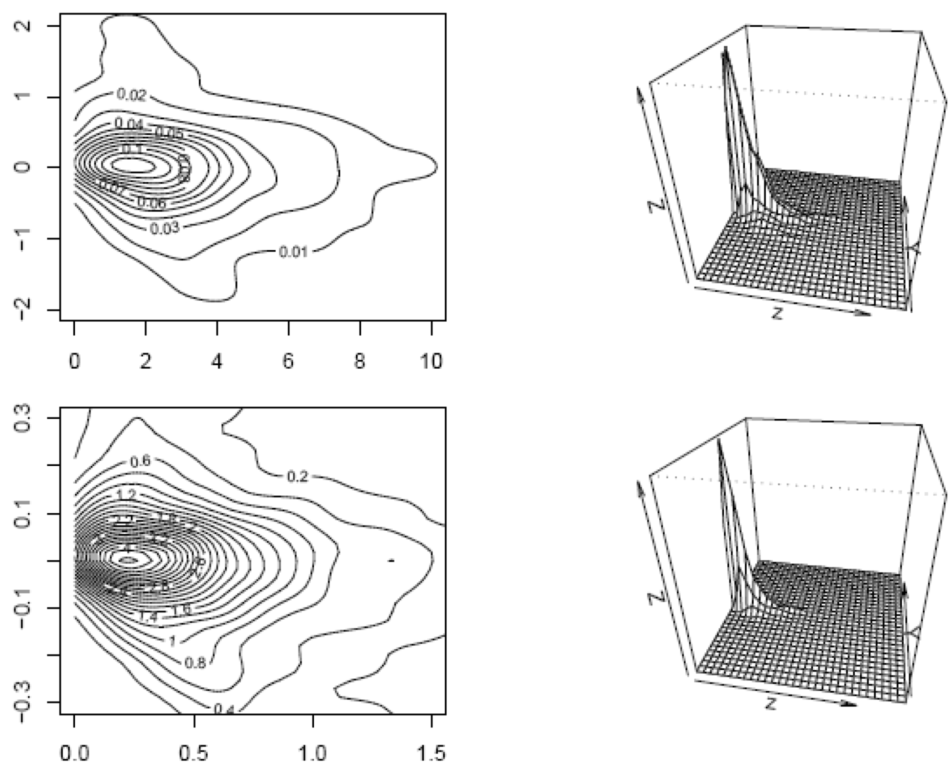
Table 5.1—Evolution of TLUs over different rounds

		1993	1994	1995	1997	1999	2004
Livestock assets	Mean	3.25	4.04	4.56	4.20	4.61	4.63
	Median	2.15	2.70	3.20	3.45	3.70	3.57
	Gini	0.50	0.48	0.46	0.38	0.39	0.39
Livestock assets per capita	Mean	0.57	0.68	0.77	0.67	0.76	0.75
	Median	0.35	0.45	0.54	0.52	0.58	0.58
	Gini	0.50	0.49	0.48	0.43	0.39	0.39

Source: Authors' calculations based on the Ethiopian Rural Household Survey data.

We can also simply pool all our observations and plot them in a phase diagram. We can plot the change in asset holdings against asset holdings in the previous period. In other words, we can plot a figure like the bottom one in Figure 4.1. Producing a simple scatter plot suffered from severe overplotting, so we decided to apply a two-dimensional kernel density estimator and visualize the results using contour plots and perspective plots. Figure 5.1 shows the results.

Figure 5.1—Contour and perspective plots of the phase diagram



Source: Authors' calculations based on the Ethiopian Rural Household Survey data.

The top graphs in Figure 5.1 show that density is highest where households have about 2 TLUs in the previous period. Only one peak is evident in the distribution, unlike what we would expect when we have two stable equilibria. The shape of the contours suggests a weak negative relationship between previous asset holdings and the change in asset holdings. The perspective plot shows the same information but makes it easier to look at the peaks. Although a definite peak exists at around 2 TLUs, the picture is less clear in the upper end of the distribution, with many different local bumps.

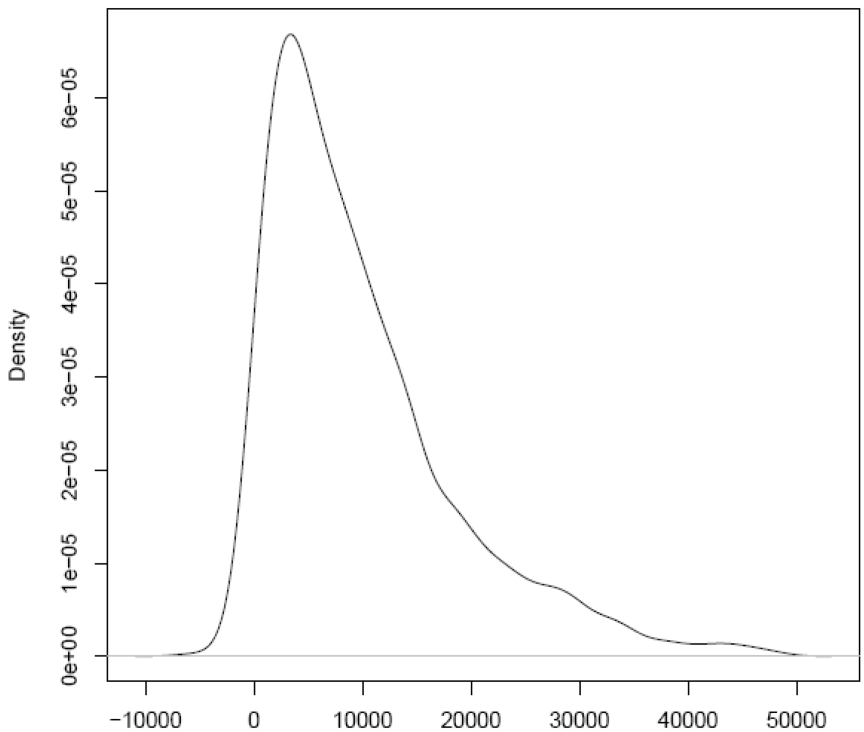
The top graphs pool all datapoints. They do not take household heterogeneity into account. We also do not control for time periods. Furthermore, in our final model we will also include some variables that control for time-variant household characteristics. Probably the most important of those is household size, since the stock of livestock assets is measured at the household level and there is considerable variation in household size, both within and between households. While the overall mean household size is about 6 or 7 individuals, the standard deviation between households is about 3 (and about 0.7 within households). Hence, to control for such differences, we calculated TLUs per capita and redid the phase diagrams.

The results appear in the bottom part of Figure 5.1. The peak is now more pronounced at about 0.25 TLUs/capita. However, a local maximum now emerges at about 1.3 TLUs/capita. The shape of the contours now also suggests a stronger negative relationship in the lower part of the distribution. However, as before, one has to keep in mind that apart from controlling for household size, all observations are lumped together in these figures.

6. ANALYSIS AND RESULTS

In this section, we estimate the model in equation (12), that is, a model with two stable equilibria and one unstable equilibrium. However, as stated before, we should first check whether there are indeed two stable equilibria instead of one single equilibrium. We therefore start our analysis by performing a linearity test on the number of TLUs held by the households (conditional on household size, female-headedness, and common shocks). In other words, we test whether a model like (12) is significantly different from a model like (7). We find a value of 12775519 for our D_{RU} statistic from equation (11). Figure 6.1 shows the kernel density estimate from our bootstrap analysis. As can be seen, our unrestricted model is significantly different from the simple model without a threshold. The associated p-value is 0.000.

Figure 6.1—Empirical likelihood



Source: Authors' calculations based on the Ethiopian Rural Household Survey data.

Let us now turn to the estimation results, summarized in Table 6.1. Although as noted in the previous paragraph, we reject the model represented by equation (7) in favor of model (6), we report both models for comparison.

Table 6.1—Estimation results

		Coefficient	Standard error	Z	P > |z|
Model (7)	Adjustment speed	–0.213	0.025	–8.52	0.000
	Stable equilibrium	4.479	0.109	41.09	0.000
	Household size	0.016	0.013	1.18	0.237
	Female head	–0.274	0.102	–2.68	0.007
Model (1)	Adjustment speed (L)	–0.386	0.124	–3.11	0.002
	Stable equilibrium (L)	2.257	0.344	6.561	0.000
	Threshold	6.787			
	Adjustment speed (H)	–1.245	0.113	–11.02	0.000
	Stable equilibrium (H)	11.141	1.086	10.26	0.000
	Household size	0.033	0.018	1.83	0.068
	Female head	–0.196	0.128	–1.54	0.124

Source: Authors' calculations based on the Ethiopian Rural Household Survey data.

Note: Both models include year dummies (not reported). Reported results are one-step generalized method of moments estimates.

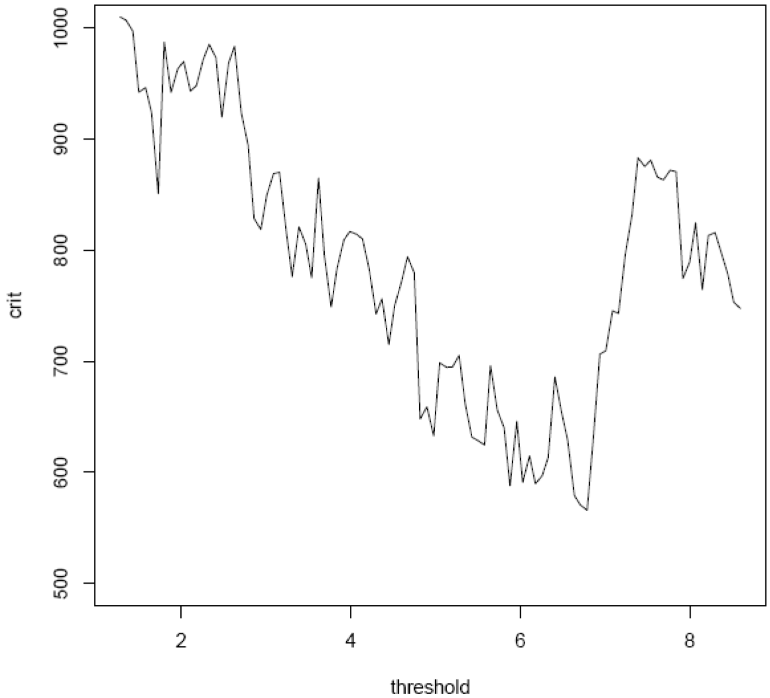
For the (misspecified) model without a threshold, we find that households converge to a stable equilibrium of about 4.49 TLUs. Deviations from this stable equilibrium are corrected by about 21 percent per year. This means that it takes on average almost three years for a shock away from this equilibrium to return to half its initial value.[11] We also note that the coefficient on household size has the expected sign (that is, larger households hold more assets), but it is not significant at conventional levels. Female-headed households have on average 0.27 TLU less than male-headed households.

We see a rather different picture when we estimate a model with one threshold. The grid search returns an unstable equilibrium of about 6.79 TLUs. Households that are below this threshold converge to a low-level stable equilibrium of about 2.26 TLUs. Note that, as expected, the adjustment speed is slightly higher (in absolute values) than it is in a model that does not take into account the discontinuity caused by the threshold. Households that move away from this stable equilibrium (but stay below the 6.79 TLU threshold) will correct almost 40 percent of the distance from the stable equilibrium within one year. The associated half-life is about one and a half years. Households above the threshold converge to a high-level stable equilibrium of about 11.14 TLUs. The adjustment speed to this stable equilibrium is in absolute value higher than one, implying some amount of *overshooting*. It means that in this region, a loss is compensated for by more than the loss. However, in the next period, the amount of overshooting is corrected again, but with some overshooting in the other direction. Eventually, this will converge to the stable equilibrium. Since we model the adjustment process as being symmetric, the adjustment speed in the higher regime will correspond to –0.755. The implied half-life is thus about six months. The coefficients of the control variables have the same sign as in the model without a threshold, but now household size is significant and female-headedness is not.

One of the major disadvantages of estimating TAR models is that the grid search procedure does not return an estimator for the precision of the estimated parameter. However, following Hansen (1997), one can get a sense of the precision of the unstable equilibrium by plotting the criterion (in our case the weighted quadratic distance of the GMM estimator referred to earlier) against the domain of candidate threshold values. This is depicted in Figure 6.2.

[11] This is called the half-life. A half-life is the time needed for a given shock to return to half its initial value: it is the solution for T in $m_{t+T} = \frac{m_t}{2}$. It is calculated as $T = \frac{\ln(0.5)}{\ln(1+\rho)}$.

Figure 6.2—Criterion sequence



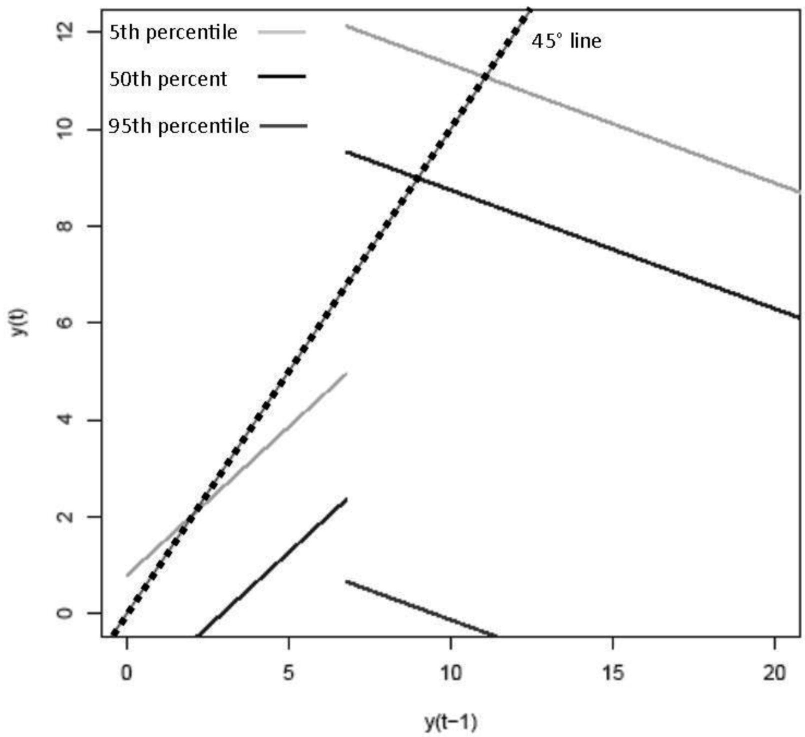
Source: Authors' calculations based on the Ethiopian Rural Household Survey data.

Figure 6.2 shows that the global minimum is found at 6.787. The figure also shows that there may be some uncertainty to the left of this value, as the value of the criterion at a threshold of about 6 is close to the value of the criterion for the threshold of 6.787. Note also that the minimum is not too close to the boundaries of the domain. There, the estimation of the threshold may not be accurate due to the small sample size in one of the two regimes.

But what do these numbers mean for the households? Recall that these are just conditional averages. Some groups of households (for example, the ones living in areas more suited for livestock holding) may have higher growth rates than others. As Figure 4.2 illustrated, the individual-specific effects shift the entire function up or down. The result is that some households face poverty traps in the sense that they have to overcome a certain threshold to arrive at a new stable equilibrium, whereas others are simply chronically poor. Households with good characteristics may be above the line over the entire domain, meaning that their asset stock will keep increasing indefinitely.

That is why it is necessary to analyze the individual-specific time-invariant effects. It may be that such effects dominate, so that no household actually faces a poverty trap in the sense we have just described. The individual effects can be estimated easily by calculating household means of all explanatory variables and then subtracting those means multiplied by the estimated coefficients from the household means of the response variable. We can then look at some percentiles and see what their predicted livestock holdings look like over the domain of asset holdings in the previous period. In Figure 6.3, we plot this for the fifth, 50th, and 95th percentiles.

Figure 6.3—Predicted livestock holdings



Source: Authors' calculations based on the Ethiopian Rural Household Survey data.

The black line plots the predicted value for the 50th percentile of the individual-specific effects. Keeping all other condition values on their means, we see that this household converges to a high-level stable equilibrium of about 9 TLUs if livestock asset holdings were above the threshold in the past. If the household falls in the low regime, the function does not cross the 45-degree line, meaning the household will eventually lose all their livestock. The light grey line depicts the 95th percentile. This household converges to a stable equilibrium of about 2 TLUs if it starts below 6.787. If, however, this household has more than 6.787, it will converge to about 11 TLUs. Finally, the red line represents the fifth percentile. For households with such characteristics, the function is everywhere below the 45-degree line, meaning that this household will eventually converge to zero TLUs.

Apparently, only a few households (less than 10 percent of our sample) are subject to a poverty trap as usually understood in the literature and depicted in Figure 2.1. The dynamics of livestock assets in our dataset seem to suggest that most households will either converge to zero TLUs if they start in the low regime or to a high-level stable equilibrium if they start with more than 6.787 TLUs. About 35 percent of our sample has an estimated individual-specific effect below the threshold. Those are the households that are everywhere below the 45-degree line and for which livestock depletion is the only certainty.

7. CONCLUSION

This paper combines advances in dynamic panel data methods with recently developed sample-splitting methods and threshold models to analyze the dynamics of livestock asset holdings. More specifically, it looks for poverty traps and identifies the different equilibria that underlie such dynamics. We present a simple model inspired by (threshold) autoregressions. Due to its nested nature, we can test for linearity. If the linear model has been rejected in favor of a threshold model, we can estimate the threshold that divides the chronic asset poor from those that converge to the high-level equilibrium. We can also calculate the low- and high-level stable equilibria from the parameters of the TAR model. Another interesting parameter is the adjustment speed in each regime of the model. This tells us how fast adjustment to the equilibria occurs.

We apply the method to data from the Ethiopian Rural Household Survey. Since livestock is an important asset that to a large extent determines well-being, we decided to examine the dynamics of such assets. We analyzed the dynamics of an aggregate of livestock assets called tropical livestock units, or TLUs, using six rounds of the survey.

Our findings are as follows. We convincingly reject the hypothesis of linear livestock dynamics. In other words, Ethiopian households do not seem to converge to a single stable equilibrium. When we account for nonlinearities in the dynamics of livestock, we find an unstable equilibrium of about 6.787 TLUs. Households that fall below that threshold converge to a low-level stable equilibrium of about 2.257 TLUs. Households that have TLUs above that threshold in the previous period are likely to converge to a high-level stable equilibrium of about 11.141 TLUs. Convergence to the high-level equilibrium is more than twice as fast as convergence to the low-level equilibrium.

Our model allows for household-specific heterogeneity. To get a sense of the relative importance of household characteristics, we estimate such effects and look at how they shift the piecewise linear regression up or down. We find that only a few households face poverty traps with two stable nonzero equilibria. However, most households do face a discontinuity at 6.787 TLUs. If they fall below that level, they will converge to zero. If, on the other hand, households can overcome that threshold, they will converge to a high-level stable equilibrium. Finally, a further 35 percent of our sample is trapped in poverty without any option to escape.

APPENDIX: SUPPLEMENTARY TABLE

Table A.1—Tropical livestock unit weights

Animal	Weight
Bull	0.75
Ox	1
Young bull	0.4
Cow	0.7
Heifer	0.4
Calf	0.3
Sheep	0.1
Goat	0.1
Horse	0.5
Camel	0.5
Donkey	0.25
Mule	1
Crossbred cow	0.7
Crossbred bull	0.75
Crossbred ox	1
Crossbred young bull	0.4
Crossbred heifer	0.4
Crossbred calf	0.3
Exotic and Friesian cow	0.7
Chicken	0
Exotic heifer	0.4
Exotic young bull	0.4

Source: FAO 1999.

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