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Heterogeneous Wealth Dynamics
On the Roles of Risk and Ability

Paulo Santos and Christopher B. Barrett

7.1 Introduction

Contemporary policy debates are rife with discussion of "poverty traps" (see, e.g., Sachs 2005; United Nations Millennium Project 2005). Several theoretical models combine some nonconvex technology with some market failure to explain why "the poor stay poor and the rich stay rich."[1] But

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1. See Azariadis and Stachurski (2005) or Bowles, Durlauf, and Hoff (2006) for earlier reviews of the theoretical and empirical literature on poverty traps.

do poverty traps exist in the data? One prominent strand of the empirical literature that addresses this question focused on searching for a threshold associated with nonlinear growth that would lead to multiple equilibria, with one such equilibrium below a poverty line. Recent reviews of this literature suggest that the support for the existence of such a threshold is quite mixed (see Barrett and Carter 2013; Kraay and McKenzie 2014; Barrett, Garg, and McBride 2016).

In this chapter, we use data from a poor population, Boran pastoralists in southern Ethiopia, where the presence of such a threshold has been previously identified. Among this population, the evolution of livestock (in many cases, the only nonhuman asset held by these households) is characterized by boom-and-bust cycles determined by drought and biological reproduction. Using seventeen-year herd-history data collected by Desta (1999), Lybbert et al. (2004) find herd dynamics that follow an S-shaped curve with two stable dynamic equilibria (at roughly one and thirty-five to forty cattle), separated by an unstable dynamic equilibrium, a threshold at fifteen to twenty cattle.[2] The authors' conjecture is that this threshold results from a minimum critical herd size necessary to undertake migratory herding to deal with spatiotemporal variability in forage and water availability. Further work by Toth (2015) corroborates that herd mobility is sharply increasing in herd size in the neighborhood of the herd-size threshold that Lybbert et al. (2004) identify, while Santos and Barrett (2011) find that informal credit arrangements behave as one would expect in the presence of this threshold, largely excluding the persistently poor from informal insurance. These findings from East African pastoralists are recognized as being among the strongest empirical evidence Kraay and McKenzie (2014) find in support of the threshold-based poverty traps hypothesis.

We build on this work to explore one additional question: If poverty traps exist, do they exist for everyone? We frame this discussion using a general representation of wealth dynamics:

$$y_{ist} = \begin{cases} g^c_{sA}(y_{it-1} \mid \theta_i) + \varepsilon_{ist} \text{ if } y_{it-1} \geq \gamma^c \\ g^c_{sB}(y_{it-1} \mid \theta_i) + \varepsilon_{ist} \text{ if } y_{it-1} < \gamma^c \end{cases} \quad (1)$$

where y_{ist} is a measure of wealth of individual i, who belongs to cohort c, in state s in period t, and growth dynamics may differ above and below any (possibly cohort-specific) threshold, $\gamma^c > 0$. If a threshold exists, expected dynamics may bifurcate, as reflected in different parameters describing the growth function above (A) and below (B) the threshold. We use this formulation to recognize that multiple mechanisms, in particular, both the individual's characteristics, θ_i, and its initial conditions, y_{it-1}, could be at play simultaneously. This is a more compact representation of the dynamics developed by Ikegami et al. (chapter 6, this volume).

2. Barrett et al. (2006) find similar herd patterns in herd-dynamics data from similar communities in northern Kenya.

This recognition matters because the policy implications differ markedly depending on which mechanism is at play. If poverty is an equilibrium because of immutable individual characteristics, ongoing social transfers may be the only available remedy for an unacceptably low standard of living. But if poverty results from initial asset holdings insufficient to clear a critical asset threshold, then policies such as asset transfers, or financial intermediation to encourage investment or to insure asset holdings, can lead to increases in wealth that move beneficiaries toward a higher-level equilibrium, thereby reducing the need for ongoing transfers (Carter 1998). If both processes are at play within a population, then effective targeting of appropriate interventions depends on identifying the relevant subpopulation to which a given poor household belongs.

Despite the very different policy implications, identifying the mechanisms that underpin persistent poverty is quite difficult methodologically. Barrett and Carter (2013) and Barrett, Garg, and McBride (2016) identify a range of confounding factors that challenge the econometric identification of poverty trap mechanisms, several of which our unusual data let us overcome, as we argue in more detail in the next section. We study a relatively simple system in which a single variable (livestock holdings) serves as an excellent proxy for overall wealth, we have household-level panel data that permit us to establish initial conditions and to estimate herd management ability, and we have data on households' expected herd growth conditional on particular states of nature, which we collected so as to explore the role of shocks and ability in shaping wealth dynamics. These attributes permit a deeper exploration of the genesis of multiple dynamic wealth equilibria than has been feasible previously.

Empirically, we focus on two mechanisms. First, in section 7.3, we confirm the possibility, first suggested in this context by Lybbert et al. (2004), that negative shocks may generate persistent poverty if they drive individuals below the threshold. We analyze data on pastoralists' expectations of herd size one year ahead, given different values of initial herd size. We disaggregate these dynamics as a function of rainfall states and find a nonlinear relation between initial and future wealth only under adverse states of nature. Under favorable rainfall regimes, respondents' subjective perceptions suggest a smooth asset growth process. We use these data to simulate long-run equilibria that we show correspond closely with those identified by Lybbert et al. (2004) in the historical data. We also note considerably larger variation among households in expected herd dynamics under adverse states of nature, which raises the possibility of household or individual characteristics that might generate such cross-sectional variation.

Second, we explore the possibility that characteristics such as skills or ability may explain the observed heterogeneity in expected growth. Perhaps the talented can more easily escape poverty regardless of initial wealth, or better manage their wealth in the face of negative shocks. Of particular relevance to this chapter, Schultz (1975) emphasizes the central importance of individual ability to reallocate scarce resources in response to shocks, what he terms "the ability to deal with disequilibria." He applies the concept to a different setting, with particular reference to technology shocks and the structural transformation of rural economies. But his core concept applies here, as it does to other aspects of that transformation.[3] In section 7.4 we use stochastic frontier estimation to obtain household-specific estimates of technical efficiency, which we use as proxy for herding ability. We use these estimates to address the hypothesis that herder ability conditions wealth dynamics. This appears true in the data. Low-ability herders (which we define as those in the bottom quartile of the efficiency distribution) are expected to slide into poverty regardless of initial wealth; we observe multiple dynamic herd-size equilibria only for the cohort of herders of higher ability. Finally, in section 7.5 we stress the policy implications of these findings with respect to complex wealth dynamics and the centrality of shocks and individual ability to understanding the existence of multiple equilibria in this system and raise some questions for future research. Section 7.6 concludes.

7.2 Data

We use data from a household survey fielded among a random sample of 120 Boran pastoralist households, in the same four communities of southern Ethiopia as those studied by Lybbert et al. (2004), although among different households. These data were collected by the Pastoral Risk Management (PARIMA) project every three months, March 2000–June 2002, and then annually each September–October starting in 2003. The focus of the project, and consequently, of the data collected, was on understanding the importance of shocks as a source of poverty persistence in this context, and the data include rich detail on household composition, migration histories, changes in herds, shocks, informal transfers of assets, and so forth. Barrett et al. (2004) describe the location, survey methods, and available variables. In section 7.4 we use these data, briefly summarized in table 7.1, to estimate herd frontiers, from which we can estimate household-specific ability.

The respondents are, as a rule, male, experienced in herd management and, to a large extent, have not migrated from where they were born. Conditional on owning livestock, cattle represents approximately 85 percent of their total tropical livestock units, and only seven households own more livestock in species other than cattle. An important fraction (close to one in five households) owns no cattle. These households are sedentarized and depend

3. See, for example, Feder, Just, and Zilberman (1985) for a review of the importance of human capital in the process of technology adoption.

Table 7.1 **PARIMA data: definition and descriptive statistics**

Variable	Definition	Mean	Std. err.
Cattle	As % of TLU	0.85	0.22
Herd size at t	Herd size at t	9.18	12.87
Herd size at $t-1$	Herd size at $t-1$	8.12	11.35
No cattle at $t-1$	= 1 if owns no cattle at $t-1$, 0 otherwise	0.19	0.39
Herd below threshold at $t-1$	= 1 if 0 < herd size at $t-1$ < 15, 0 otherwise	0.68	0.47
Herd above threshold at $t-1$	= 1 if herd size at $t-1$ > 15	0.14	0.35
Labor	Family size at t	5.50	3.36
Land	Land cropped in June 2000	1.12	2.25
Sex	= 1 if male	0.64	0.48
Experience	Years since start of herd management	20.26	14.07
Migrant	= 1 if migrated to where currently lives	0.21	0.41

heavily on relief food distribution in towns. They own few, if any, other nonhuman assets, so even for these stockless households livestock holdings serve as a reasonable proxy for wealth (McPeak, Little, and Doss 2011). An even more important fraction (slightly above two in three households) owns herds that are smaller than fifteen cattle, the accumulation threshold identified in Lybbert et al. (2004), which does not account for possible heterogeneity. During the period for which we have data, the average herd did grow, from an average herd size of 8.1 cattle in 2000 to 9.2 cattle in 2003 (the equivalent of a growth rate of 4.3 percent per year). However, this average masks important heterogeneity in terms of growth experiences: focusing only on households who owned cattle, growth episodes were almost as likely as decreases or stagnation in herd size.

In 2004 we collected data on households' subjective expectations of herd dynamics, designed to complement the data routinely collected by PARIMA. The use of elicited expectations to study decision-making has now been applied extensively for testing economic hypotheses in both developed and developing countries (for reviews, see Manski 2004; Hurd 2009; Delavande 2014; Delavande, Giné, and McKenzie 2011). That said, it is worth explaining in some detail how we elicited these data.

We started by randomly selecting four hypothetical initial herd sizes for each respondent, one from each of the intervals defined by the equilibria identified by Lybbert et al. (2004).[4] Respondents were then asked to characterize their expectations of rainfall during the coming year, choosing between

4. The intervals are [1,5), [5, 15), [15, 40) and [40, 60] tropical livestock units (TLU) where 1 TLU = 1 cattle = 0.7 camels = 10 goats or sheep. The TLU measure allows aggregation across species on the basis of animals' average adult metabolic weight. Among the Boran we study, the overwhelming majority of TLU are held in the form of cattle.

good, normal, or bad.[5] Because the data were collected well into the rainy season, these answers should not be interpreted as uninformed priors that could merely reflect differences in optimism.[6] Respondents were also asked to assume a herd of standard composition for the region (in terms of age and sex of the animals). In one site, and in a second separate interview, we additionally asked respondents to consider what would happen to their herd (with an identical randomly allocated initial herd size) in the case of more extreme weather conditions, namely, severe drought and a very good year.[7]

After thus framing the problem, we asked each respondent to define the maximum and the minimum herd size they would expect to have one year later if they themselves started the year with the randomly assigned initial herd size. These bounds provide a natural anchor for the next step, in which we asked respondents to distribute on a board twenty stones among herd sizes between the minimum and the maximum previously elicited, thereby describing their subjective herd-size distribution one year ahead conditional on the randomly assigned initial herd size and the statement about rainfall. Finally, each respondent was asked if s/he had ever managed a herd approximately equal in size to the initial value provided as the random seed. The elicitation of the probability distribution function is an appropriate technique under these circumstances (Morgan and Henrion 1990) and allows us to compute conditional distributions and their moments. In addition, and because hypothetical initial wealth was randomly assigned to the respondent, it eliminates the prospective endogeneity of initial herd size in determining the estimated herd dynamics.

In total, we have 460 observations collected among 115 respondents for rainfall conditions labeled as good/normal or bad. Of these, nineteen do not

5. In this and several other African rangelands ecosystems, pasture biomass covaries strongly with rainfall. In recent years, the density of grazing livestock and wildlife has been insufficient to affect biomass sufficiently to alter herd dynamics, with stocking rates well below carrying capacity outside of a relatively small cluster of overgrazed areas around settlements (McPeak, Little, and Doss 2011). While climate change or a significant increase in human population and stocking rates could change the relationship between herd sizes and range vegetation dynamics, at the current time both appear driven largely by variation in weather. So the rainfall states we study should suffice to capture the stochastic dynamics of interest. This sort of trinomial rainfall characterization is familiar to respondents, as it corresponds to published rainfall forecasts such as those disseminated by the regional Drought Monitoring Centre and government and nongovernmental organization extension officers. See the analysis in Luseno et al. (2003) and Lybbert et al. (2007), who previously studied pastoralists' rainfall expectations.

6. The geographical concentration of pastoralists' expectations regarding rainfall further reinforces this interpretation: in two sites, over 90 percent of the respondents expected bad rainfall, while in the other two sites expectations were equally divided between bad rainfall and good rainfall.

7. In particular, we asked respondents to consider herd evolution "as if" in 1999, the last major drought, or "as if" in a very good year, which we asked them to define based on their own experience.

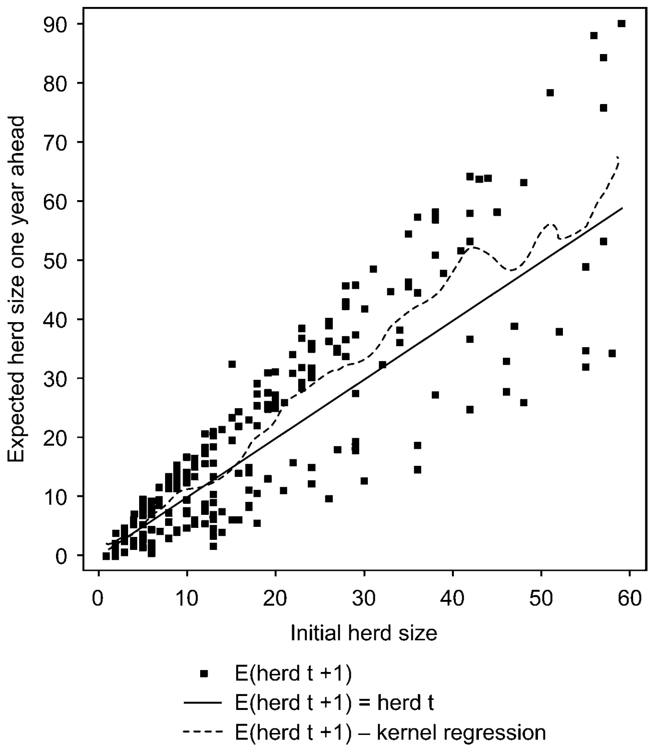

Fig. 7.1 Unconditional subjective expected herd dynamics

include a herd-size prediction, usually because respondents were unable to distribute the stones across the board, a problem that occurred mainly for bigger initial herd sizes when the difference between the maximum and the minimum was sometimes quite large. Of the remaining 441 observations, the respondents had prior personal experience managing a herd of comparable size in 288 cases (65.3 percent). In addition, we have sixty-one similar observations for very good and very bad years.

We finish this brief description of the data we use by presenting in figure 7.1 the scatter plot and kernel regression relating expected herd size one year ahead and initial herd size, conditional on ever having had a herd with a similar size, but *unconditional on weather conditions*.[8] Several points emerge from comparing pastoralists' subjective expectations of one-year-ahead herd dynamics (figure 7.1) with the dynamics revealed by Desta/Lybbert

8. We estimate Nadaraya-Watson nonparametric regressions with the Epanechnikov kernel and bandwidth of 4.545. The value of bandwidth was selected using Silverman (1986) rule of thumb, as determined by the "bounds for Stata" package (Beresteanu and Manski 2000).

et al.'s herd-history data (in particular, the dashed line in figure 4 of Lybbert et al. 2004, which reflects one-year-ahead dynamics).

First, both these data and the prior studies exhibit multiple dynamic equilibria consistent with the notion of a poverty trap. Second, however, the equilibria identified by pastoralists appear to differ markedly from those apparent in herd-history data, both with respect to their location and stability. Notably, herd accumulation occurs for a wider range of initial herd sizes, while herd losses seem a relatively marginal occurrence, contradicting detailed studies of this system (Coppock 1994) and the dynamics suggested by herd-history data.

These casual comparisons invite more disaggregated analysis. Our data on herders' subjective expectations of herd dynamics (figure 7.1) represent only one-year-ahead expectations under necessarily limited variability in rainfall regimes. By contrast, the pattern exhibited in the actual herd-history data used by Desta/Lybbert et al. are the result of a mixture of environmental conditions over a period of seventeen years.[9] These differences are made clear in table 7.2, which summarizes the data on expected herd size one year ahead, conditional on the state of nature and on having had a herd with a similar size, and its representation in figures 7.2 and 7.3, where we present the scatter plot and kernel regression relating expected herd size one year ahead and initial herd size for bad and normal/good years.[10]

These plots, and the summary statistics in table 7.2, suggest two insights. First, the relation between expected and initial herd size is nonlinear only in the case of bad rainfall conditions. Under good or normal climatic conditions (and perhaps unsurprisingly), almost all herders expect herd growth no matter the initial herd size. This disaggregation implies that adverse weather shocks drive the nonlinear dynamics revealed by the analysis of herd-history data.

Second, the dispersion around the expected herd-growth values is much bigger under conditions of bad rainfall than in a normal/good year, as reflected by the max.-min. spreads. Herders exhibit far more heterogeneous beliefs about their ability to deal with adverse states of nature than with favorable ones. If, following Schultz (1975), one interprets this variation as at least partly reflecting pastoralist herding ability then "the ability to deal with disequilibria" seems to play a significant role in wealth dynamics. Put differently, risk and ability may intersect to generate the complex herd dynamics observed in this system.

9. For example, Kamara, Swallow, and Kirk (2004) identify three major droughts (1984/85, 1991/92, and 1995/96) and two periods of excessive rains (1980/81 and 1997/98) in this region over the period covered by the Desta/Lybbert et al. data. To these natural disasters, one may add the generalized ethnic clashes between the Boran and the Gabra in 1992, following the fall of the Derg regime. Barrett and Santos (2014) explore how changing rainfall distributions might affect observed herd dynamics.

10. To conserve space, we omit figures reflecting the data and nonparametric regressions under extreme weather conditions, which show that during severe drought everyone expects to lose cattle.

Table 7.2 **Expected herd size, one year ahead: the effect of rainfall and initial wealth**

	Very bad			Bad			Good			Very good		
$E(\text{herd})_{t+1}$	Min.	Mean	Max.	Min.	Mean	Max.	Min.	Mean	Max.	Min.	Mean	Max.
$\text{Herd}_t \in [1, 5)$	0	0.6	1.6	0	1.6	5.6	0.8	4.5	6.9	1.8	3.7	6.6
$\text{Herd}_t \in [5, 15)$	0.8	3.5	12	0.3	7.8	15.6	4.5	12.8	21.2	3.3	12.5	21.6
$\text{Herd}_t \in [15, 40)$	1.4	6.0	13.9	5.5	23.3	50.9	14.1	36.3	57.9	18.3	31.9	50.6
$\text{Herd}_t \in [40, 60)$	4.4	13.3	27.7	24.6	42.6	79.1	63.0	74.4	89.9	56.3	64.9	78.4

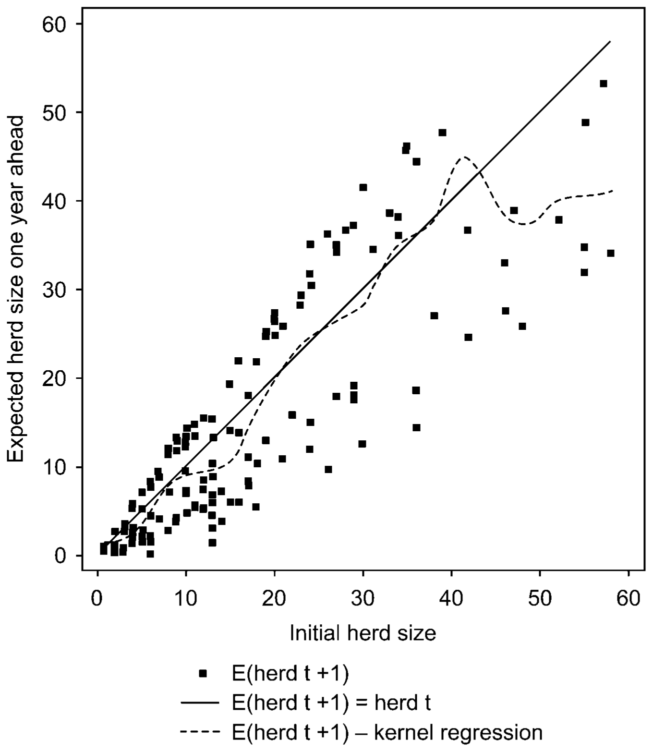

Fig. 7.2 Expected herd dynamics under bad rainfall conditions

7.3 Expected Herd Dynamics in a Stochastic Environment

In order to generate herders' subjective expectations of herd dynamics under a mixture of states of nature, we need to integrate data on herd-growth expectations conditional on rainfall (the elicited expectations data previously described) with historical rainfall data (in practice, monthly rainfall data for the four sites over the period 1991–2001).[11] With this information we can then simulate herd evolution over longer periods than just one year ahead. Since we must predict out-of-sample in simulating herd evolution for large values of initial herd size, we estimate the parametric relation between initial and expected herd sizes (hereafter, $herd_0$ and $herd_1$,

11. Average rainfall was 490 mm/year, with a standard deviation of 152 mm/year. Given the skewness and the kurtosis of this distribution, we cannot reject the null hypothesis that rainfall follows a normal distribution. The minimum annual rainfall over the period was registered in 1999 (259 mm) and the maximum in 1997 (765 mm). The probability of such events is 0.064 and 0.035. Given these results, we assumed, for simulation purposes, a symmetric distribution, with a probability of extreme events (drought; or very good year) equal to 0.10. In a separate analysis (Barrett and Santos 2014) we show that the results are relatively sensitive to changes in the rainfall distribution, reflecting the dependency of this system on rainfall and its vulnerability to climate change.

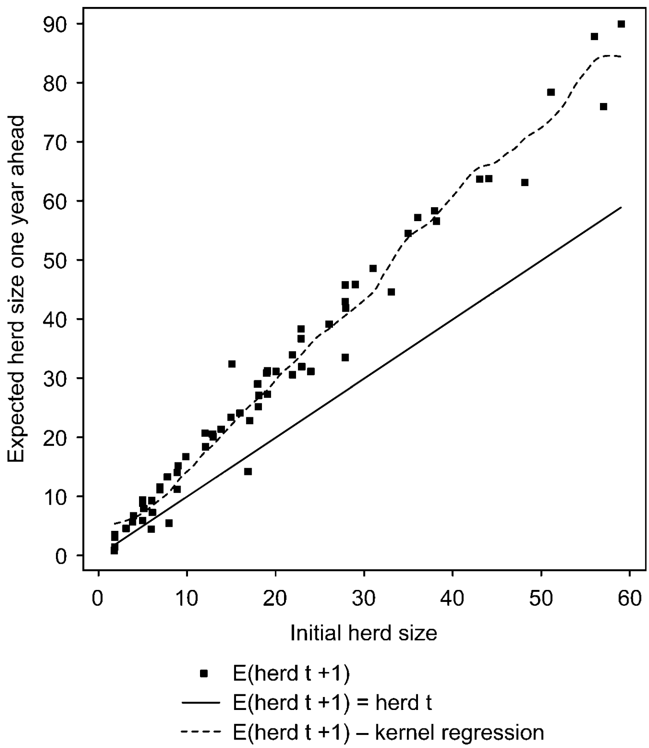

Fig. 7.3 Expected herd dynamics under good or normal rainfall conditions

respectively) conditional on each of the four rainfall scenarios (drought [very bad], bad, normal/good, and very good). We estimate this relation with a respondent fixed effect specification, α_i, taking advantage of having repeated observations, r, across different herd-size intervals for each individual i. We thus estimate

$$\text{herd}_{1ir} = f(\text{herd}_{0ir}) + \alpha_i + \varepsilon_{ir} \tag{2}$$

where $f(\text{herd}_{0ir})$ is a polynomial function of initial herd size.[12] Table 7.3 presents the estimates, which reflect the same results displayed visually in figures 7.2 and 7.3, and suggested in table 7.2: unambiguous linear expected growth under normal/good/very good rainfall conditions, a nonlinear relation between herd_1 and herd_0 under conditions of poor rainfall and drought,

12. Besides the assumptions on the functional form of $f(\cdot)$, we also assumed that $\varepsilon_{ir} \sim N(0, \sigma^2)$. Other specifications that replace the fixed effect with other regressors that could affect subjective expectations, such as gender, age, experience, and migrant status, were considered, but none of those variables proved statistically significant, so we omit these results. We omit higher-order polynomial terms in the very good and good/normal year specifications because they added nothing given the good fit already achieved with a simple linear specification with fixed effects.

Table 7.3 **Estimates of expected herd dynamics conditional on rainfall**

Variable	Very good	Good	Bad	Very bad
$Herd_0$	1.293	1.477	0.528	0.246
	(0.000)	(0.019)	(0.224)	(0.246)
$Herd_0^2$			0.026	0.009
			(0.010)	(0.010)
$Herd_0^3$			−0.00039	−.00017
			(0.0001)	(0.0001)
Constant	0.897	0.179	0.513	−0.575
	(0.448)	(0.416)	(1.185)	(1.083)
N	61	96	192	61
R^2	0.986	0.994	0.792	0.589

Note: Values within parentheses are robust standard errors.

and with considerable dispersion so that the precision of those estimates (as measured by the R^2) is far less than under favorable rainfall regimes.

We then use these estimates to simulate the expected evolution of herd sizes.[13] Figure 7.4 presents the basic structure of the simulation procedure we used, while figure 7.5 presents the mean of ten-year-ahead herd size for 500 replicates of this simulation with initial herd sizes between one and sixty.

The results are remarkably similar to the dynamics revealed by the herd-history data (the solid line in figure 4 of Lybbert et al. 2004), both in the general shape of the curve and in the location of the different equilibria. This strongly suggests that the mismatch between the one-year-ahead transitions predicted by the two data sets that we discussed above arose because of differences in the underlying distribution of the states of nature. Once we account for historical rainfall patterns and simulate the longer-term herd dynamics, it appears that Boran pastoralists' subjective expectations reflect a remarkably accurate understanding of the nature of how their herds have evolved over the past generation. In particular, they expect that, on average, someone with a herd below approximately fifteen cattle will eventually lose almost all of his wealth, collapsing into a destitute equilibrium with just one cow.

Can we be sure that multiple equilibria exist? Given the small sample size, the answer is no; the lower confidence band crosses the equilibrium line only once, from above, at the lower-level equilibrium (one animal). But as we show below, this merely reflects our current assumption that all herders

13. We calibrate these estimates to impose basic biological rules for livestock. More precisely, we do not allow for negative herds and impose that biological growth under good rainfall conditions is delayed by two years, that is, enough for cows to reproduce in accordance with basic gestational patterns. We also constrain the predicted values for initial herd sizes above fifty-two (poor rainfall) and forty-five (drought) to be linear, with a slope of 0.033 and 0.009, respectively, preventing unbelievable predictions due to the parameter estimates at the boundaries of our sample.

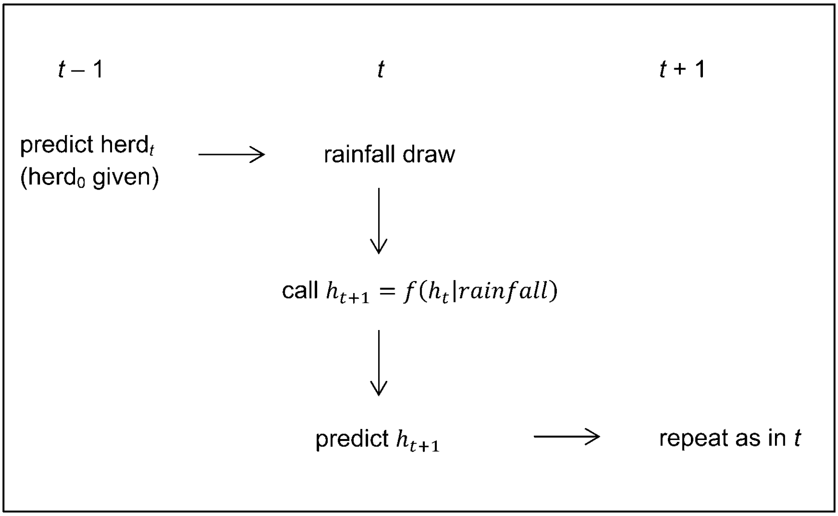

Fig. 7.4 Simulation procedure

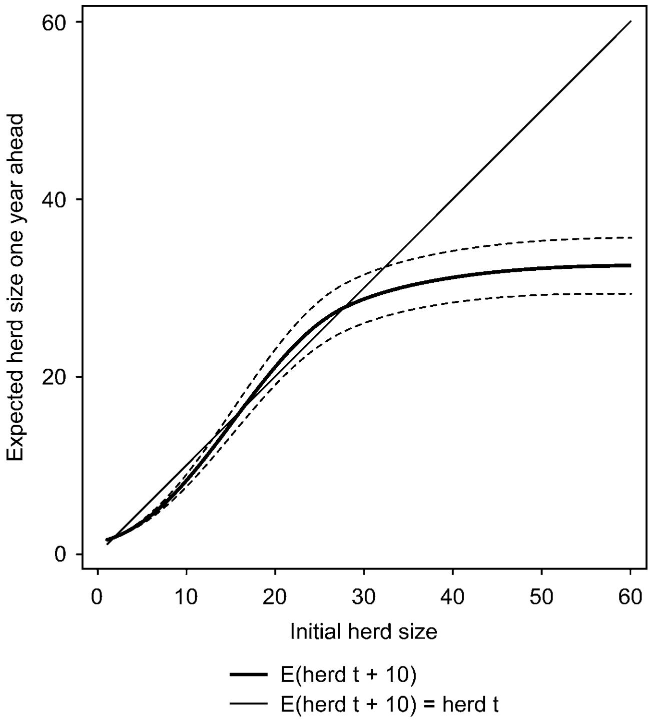

Fig. 7.5 Simulated expected herd dynamics

Table 7.4 **Estimated herd size ten-year transition matrix**

Herd_{t+10}	0–4	5–14	15–39	>40
Herd_t				
0–4	0.879	0.113	0.009	0.000
5–14	0.575	0.262	0.133	0.030
15–39	0.204	0.280	0.255	0.261
>40	0.136	0.230	0.291	0.342

follow the same growth path. When we abandon the strong assumption that all herders follow the same dynamics and disaggregate by herder ability, the precision of our estimates improves significantly.

Concentrating on our average estimates, do these nonlinearities lead to a poverty trap? The answer depends, in part, on what one means by a "poverty trap." In table 7.4 we quantify the probability of moving between equilibria over a ten-year period given the stochastic nature of these shocks. There is a positive probability that a herder starting with a herd between one and four cattle will, ten years later, have grown his herd. Indeed, there is even a very small probability (less than 1 percent) that he finishes above the accumulation threshold. Hence, the strictest interpretation of a poverty trap—that initial conditions totally determine future wealth and the system is nonergodic, thus the probability of growing to a higher equilibrium is zero—finds no support in our data. However, the probability of moving out of poverty is quite low (less than 12 percent), suggesting that, in this context, the idea of a poverty trap is most usefully conceptualized as a high probability that agents will remain at lower levels of welfare, a weaker but perhaps more realistic interpretation of the concept in stochastic environments (Azariadis and Stachurski 2005).

Summarizing the results so far, we find that Boran pastoralists accurately perceive long-term herd dynamics characterized by multiple wealth equilibria consistent with the notion of a poverty trap: shocks almost totally prevent wealth accumulation that would allow herders at a low initial wealth level from escaping poverty. However, these dynamics seem entirely the result of heterogeneity in growth rates under different rainfall conditions. Growth is universally expected in good years, while S-shaped dynamics seem to result from wealth-differentiated capacity to deal with bad rainfall conditions.[14]

Our data also show that, even in bad years, not all herders expect their herds to shrink. The considerable dispersion of beliefs about herd dynamics

14. This could explain why, for example, Mogues (2011), studying livestock accumulation in other regions of Ethiopia in the period 2000/03, with no major shocks in between, does not find evidence of such nonlinearities, and why Barrett et al. (2006) find evidence of an S-shaped curve for asset dynamics in the northern Kenya PARIMA sample, which included a major drought ending in 2001.

under adverse states of nature suggests that herder-specific characteristics, which we summarize as ability, may likewise play a central role in conditioning wealth dynamics. The next section investigates this possibility.

7.4 Ability and Expected Herd Dynamics

Herding in semiarid environments is a difficult livelihood. One must know how to treat livestock diseases and injuries, protect cattle against predators, manage their nutrition, navigate to distant grazing and watering sites, assist in difficult calving episodes, and so forth. Not everyone learns and practices these diverse skills equally well. One would expect herders with greater animal husbandry skills to be able to manage larger herds and to be less subject to adverse shocks to herd size than less skilled herders. Put differently, the herd dynamics explored in the historical data and in the previous section may ignore important differences in herder ability.

We explore the impact of differences in herding ability on herd dynamics by using the data coming from three rounds of the PARIMA panel of pastoralist households, described in section 7.2, to estimate herder ability using stochastic parametric frontier estimation methods for panel data (Kumbhakar and Lovell 2000). More precisely, we estimate the herd frontier that explains individual i's herd size at the beginning of period t, h_{it}, conditional on a vector of household attributes, X_{it-1}, and herd size and labor endowments (the two most important inputs for which we have information) at the beginning of the prior period, using a composed error term that includes a normally distributed random component reflecting standard sampling and measurement error, ψ, and a one-sided term reflecting observation-specific but time-invariant inefficiency, $\phi_i \geq 0$, which we assume follows a truncated normal distribution, $N^+(\mu, \sigma^2)$:

$$h_{it} = f(h_{it-1}, l_{it-1}) + \beta X_{it-1} - \phi_i + \psi_{it}. \tag{3}$$

We allow for $f(h_{it-1}, l_{it-1})$ to reflect the possibility of two different growth paths, depending on whether the initial herd is above or below the fifteen-cattle threshold identified by Lybbert et al. (2004).[15]

Since these households were surveyed repeatedly from 2000 to 2003, we can take advantage of multiple observations for each herder to compute consistent herder-specific mean efficiency measures, that is, each pastoralist's proximity to the herd frontier. The inefficiency parameter ϕ_i captures any time-

15. In equation (1) we make clear that there is no necessary equivalence between the threshold identified for the average household—which would correspond to the value estimated by Lybbert et al. (2004)—and a possible cohort-specific threshold. However, given the analysis cited in section 7.1 that seems to suggest changes in household behavior for herd sizes around the average threshold, this value seemed a natural starting point for the analysis. One alternative that we did not pursue would be to agnostically address this problem using a search and testing approach similar to the one suggested in Hansen (2000).

invariant—and period-average time-varying—unobservables associated with systematic deviation from the herd frontier. This parameter can clearly capture factors beyond the herder's unobserved ability, such as the quality of local grazing lands, but ϕ_i is almost surely strongly correlated with ability. Moreover, it is an open question whether it matters for targeting and programming if the features that cause systematic underperformance are intrinsic, immutable individual skills or community-level or slow-changing individual characteristics. The key is that there exist distinct groups of households who routinely outperform or underperform their neighbors, however we understand the structural genesis of those relative performance differences.

The interpretation of these estimates as proxies for ability can still be contested on at least two grounds. First, the lagged values of herd size are clearly related to lagged (and current) ability, hence our estimates of inefficiency are likely inconsistent. This would matter if we were interested in cardinal measures of inefficiency. But we focus only on the ordinal measures, grouping households into low- and high-ability cohorts. So long as the correlation between lagged wealth and ability does not affect the ordering of each observation within the inefficiency distribution, the possible bias in point estimates will be of no consequence for present purposes.

Second, we estimate inefficiency by imposing a specific functional form, a specific distribution for the inefficiency parameter, and a specific accumulation threshold that, from the existing literature (in particular, Lybbert et al. 2004), seems valid for the *average* herder in this setting. These assumptions can introduce misspecification error that may be easily conflated with inefficiency (Sherlund, Barrett, and Adesina 2002). As with the prior concern about inconsistent parameter estimates, our reliance purely on the ordering of the estimates sharply limits the relevance of such concerns. Nonetheless, an alternative approach is to use more flexible, nonparametric efficiency estimation methods, in particular data envelopment analysis, that can easily allow for variable returns to scale without imposing specific assumptions about functional or distributional forms (see Coelli et al. 2005). Our analysis is robust to this alternative way of estimating inefficiency, so we maintain that the ordinal inefficiency estimates we estimate provide a reasonable proxy for relative herder ability/skill and thus serve present purposes well.[16]

Table 7.5 presents estimates of the herd frontier based on 2000–2001, 2001–2002, and 2002–2003 annual observations for the 113 households for which we have complete data on each of the covariates.[17] The results indicate statistically significant (p-value = 0.053) differences in the asset dynamics above and below the threshold, with expected herd growth (collapse)

16. The DEA estimates were obtained using the -dea- command in Stata (Ji and Lee 2010). The results are available from the lead author by request.

17. Because one of the households is the successor of an initial household, we only have data for the last two years. Hence, we're using an unbalanced panel with 338 observations.

Table 7.5 **Stochastic parametric herd frontier estimates**

Variable	Coefficient	Std. err.	*P*-value
Herd size at $t-1$ * above threshold	1.022	0.093	0.000
Herd size at $t-1$ squared * above threshold	0.000	0.001	0.689
Herd size at $t-1$ * below threshold	0.890	0.307	0.004
Herd size at $t-1$ squared * below threshold	−0.009	0.022	0.681
No cattle at $t-1$	−1.126	1.245	0.366
Labor * above threshold	−0.089	0.174	0.611
Labor * below threshold	0.099	0.125	0.427
Land	0.022	0.152	0.885
Sex	1.333	0.702	0.057
Experience	0.137	0.071	0.052
Experience squared	−0.002	0.001	0.174
Migrant	−0.605	0.998	0.544
2000–2001	−0.740	0.531	0.164
2001–2002	1.553	0.525	0.003
Dida Hara	1.870	1.110	0.092
Qorate	0.026	1.229	0.983
Wachille	0.827	1.131	0.465
Constant	13.012	195.554	0.947
μ	14.671	195.551	0.940
N		338	
R^2		0.230	

above (below) the threshold. The estimated frontier is piecewise quadratic, as higher-order polynomial terms of lagged herd size have no statistically significant effect.[18] Household labor and land endowments have no effect at the margin on expected herd size, signaling that these are not limiting in this environment for most households. Male-headed households enjoy significantly larger herd sizes, which may partly capture household composition effects (with male-headed households having more men available to herd, especially on treks away from base camp lasting days or weeks, holding labor availability constant). There exist statistically significant, albeit diminishing, marginal returns to herding experience. And there are marginally significant fixed effects associated with location and year (in particular, for 2001–2002, the year of recovery after the severe 1999–2000 drought), the latter result

18. Table 7.1 defines these variables and presents the descriptive statistics. We also estimated this regression using cubic and quartic terms, but none of the higher-order polynomials were statistically significantly different from zero and one could not reject the null hypothesis that the higher-order terms jointly have no effect on next period's herd size, once one allows for the threshold effect. The variable "no cattle at $t-1$" is included to control for the fact that herd growth is different when one has no cattle—growth can then only occur through purchases or gifts, both of which are very infrequent (Lybbert et al. 2004)—than when one has a positive herd size. Although the point estimate on this variable is not statistically significantly different from zero, when we do not control for this effect the estimated coefficients on lagged herd size and its various interactions become far more imprecise.

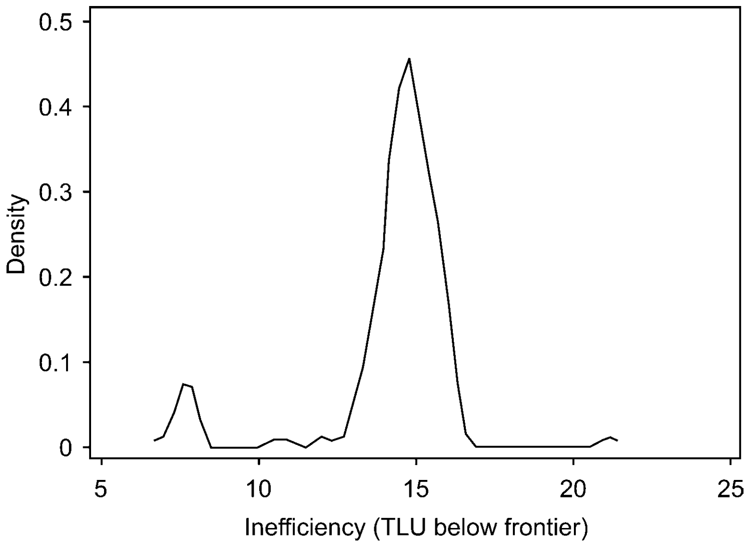

Fig. 7.6 Empirical density function of herd-size inefficiency estimates

reinforcing our earlier finding about state-dependent growth. The estimated distribution of the inefficiency estimates (with cattle as the units of measure) is presented in figure 7.6,[19] allowing a visual analysis of the within-sample variation.

Using the predicted value of each herder's estimated inefficiency, we then divide our sample into two subsamples: lower-ability (those in the 4th quartile of the inefficiency estimates with $\phi_i > 15.38$) and a complementary category of higher-ability herders. The observations are concentrated around just a few points ranges of inefficiency estimates, suggesting that there may be little value to further subdivision of the sample.[20] For each of these two classes we reestimate equation (2), obtaining estimates of the parametric models that relate expected and initial herd size for each subsample, after which we performed the same simulation as above.[21] Figure 7.7 shows the nonparametric conditional expectation function (and 95 percent confidence intervals) of ten-year-ahead herd size obtained for 500 replicates with initial

19. Estimated using the Epanechnikov kernel, with a bandwidth of 0.24697.

20. We also experimented with splitting the higher-ability herders into two categories, those of highest ability (the 1st quartile of the inefficiency distribution) and a residual medium-ability class (the 2nd and 3rd quartiles). The qualitative results are similar, so we present the simpler approach here. Results of the most disaggregated analysis are available from the lead author by request.

21. These eight parametric models (four states of nature × two ability classes) are qualitatively similar to the ones presented in table 7.2. To conserve space we omit them here, but they are available from the lead author by request.

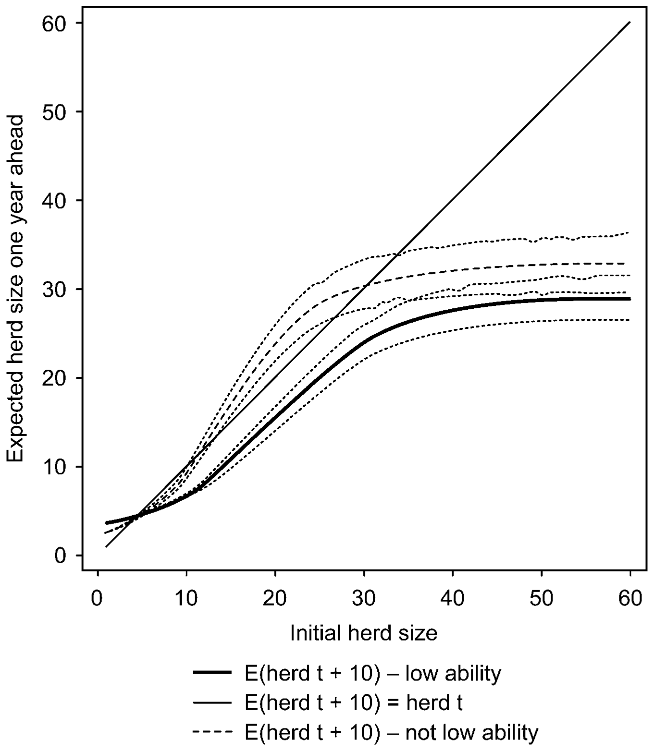

Fig. 7.7 Simulated expected herd dynamics—the effect of ability

herd sizes between one and sixty cattle for each ability class. The results are easily summarized.

Although those in the lowest ability quartile exhibit S-shaped expected herd dynamics, these lie everywhere beneath the dynamic equilibrium line (the solid 45° line in figure 7.7). Thus, low-ability herders are expected to converge toward the low-level dynamic asset equilibrium of one to two head of cattle over time. Recall that all herders expect to grow their herds during good and normal rainfall years. So this expected long-run herd-size collapse arises entirely from low-ability herders' difficulty in managing and recovering from adverse weather shocks.

Higher-ability herders likewise exhibit S-shaped expected herd dynamics. However, they face multiple dynamic equilibria, with an accumulation threshold at eleven to seventeen cattle, similar to the threshold estimated by Lybbert et al. (2004) from the herd-history data. Notice also that, when we allow for different growth paths conditional on ability, we get much more precise estimates of the herd dynamics. In particular, both confidence bands for the higher-ability herders cross the dynamic equilibrium line in three points, two of which represent stable dynamic equilibria, at one to two and twenty-nine to thirty-five cattle, respectively. The implication, reflected in figure 7.7, is that S-shaped herd dynamics characteristic of a multiple equilibrium poverty trap are not followed by all herders. Low-ability herders face a unique dynamic equilibrium at lower levels of welfare, giving rise to a different sort of poverty trap than that faced by herders with higher ability, who expect to accumulate wealth so long as they maintain an herd size above the twelve to seventeen cattle threshold. These results clearly raise important practical questions with respect to any asset redistribution or transfer policy, as ability is not easily and quickly identified in conventional survey methods, at least not by outsiders such as the governmental and nongovernmental agencies that typically provide transfers and public safety net programs.

7.5 The Policy Challenge: Targeting with Imperfectly Known Dynamics

The possibility that multiple mechanisms underpin wealth dynamics poses a challenge for policymakers. To illustrate how an understanding of wealth dynamics might affect the design and performance of an intervention, we explore the effectiveness of herd restocking in this system, as this is perhaps the most common form of postdrought assistance provided to pastoralists by donors and governments in the region.

We simulate the effect of three different scenarios under the maintained assumption that growth does depend on ability (as represented in figure 7.7) and using a constant budget. In Scenario 1, all herds below five cattle (a customary, Boran-defined poverty line) are given animals to boost their herd to five head, irrespective of the recipient herder's ability. This reflects the dominant current paradigm of progressive transfers to the poorest. In our simulations, in aggregate that rule leads to a transfer of thirty-six cattle to seventeen beneficiaries in our 2003 sample of ninety-seven households. Those thirty-six cattle become the fixed "budget" that we maintain in the next two scenarios. In Scenario 2, we simulate the effects of a transfer targeted so as to maximize the number of "viable" herders, that is, those that have a herd that is larger than the estimated minimum accumulation threshold of eleven cattle. Although we assume that growth depends on ability, we also assume that there exists no effective mechanism to elicit herder ability; so, transfers are conditioned solely on observable herd sizes. Then, in Scenario 3, we assume one can accurately identify herder by ability group and, as with Scenario 2, again target transfers so as to maximize asset growth. Scenario 3 involves transfers to sixteen higher-ability herders, with limited overlap in identity with the seventeen recipients under Scenario 1. The main difference between these scenarios is evident in figure 7.8, where we draw the expected herd-size gains associated with the transfer of one cattle, conditional on herder ability.

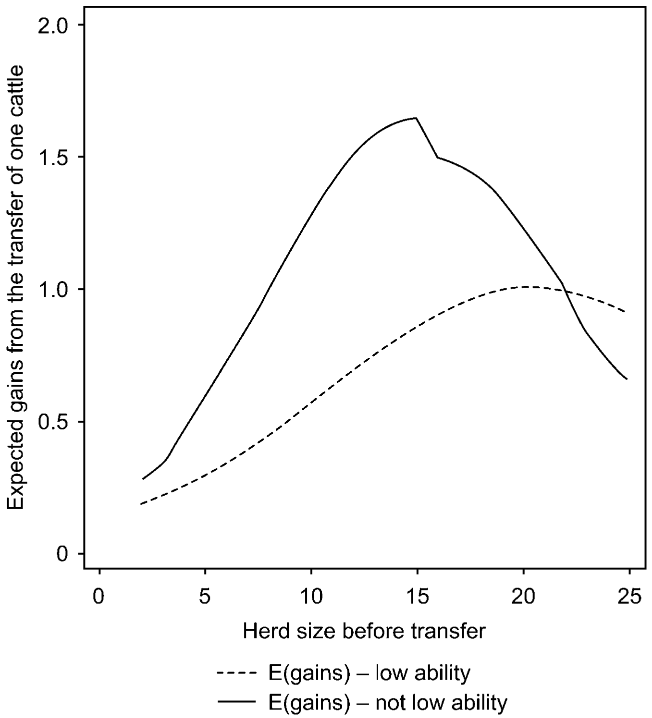

Fig. 7.8 Expected gains from the transfer of one cattle

Given expected herd dynamics over the decade following the hypothesized transfer, the transfer is expected to generate herd growth, net of the one cattle transfer (i.e., expected gains > 1), only for higher-ability recipients with ex ante herd size between nine and twenty-two head. Herders of low ability or, if of higher ability, with the smallest (or largest) herds are expected to lose some of their posttransfer herd over the ensuing decade, signaling negative medium- to long-term growth returns on livestock transfers to the poorest (or wealthiest) herders of higher ability. The expected herd gain is maximized for a transfer to a higher-ability herder with an ex ante herd size of fifteen cattle, a significantly larger herd than is typical of restocking program participants, since such interventions are typically targeted following some poverty-reduction criteria, like Scenario 1.

Table 7.6 presents the results of a comparison among these three different scenarios for targeting herd-restocking transfers that reflect both this discussion and, implicitly, the distribution of low- and high-ability types as a function of pretransfer wealth, as represented in figure 7.9.

As one would expect based on the dynamics of this system, restocking targeted to lower-wealth households (specifically, those fewer than five cattle)

Table 7.6 Expected effects of restocking under different targeting assumptions

Scenario	Number	Average transfer	Average herd size (2003)	Expected herd size (2013) w/ transfer	Expected herd size (2013) w/out transfer	Expected gains from transfer
1. Beneficiaries	17	2.12	2.88	4.46	3.63	0.86
2. Beneficiaries	23	2	10	12.20	9.34	2.86
3. Beneficiaries	18	1.94	10.05	13.40	10.09	3.3

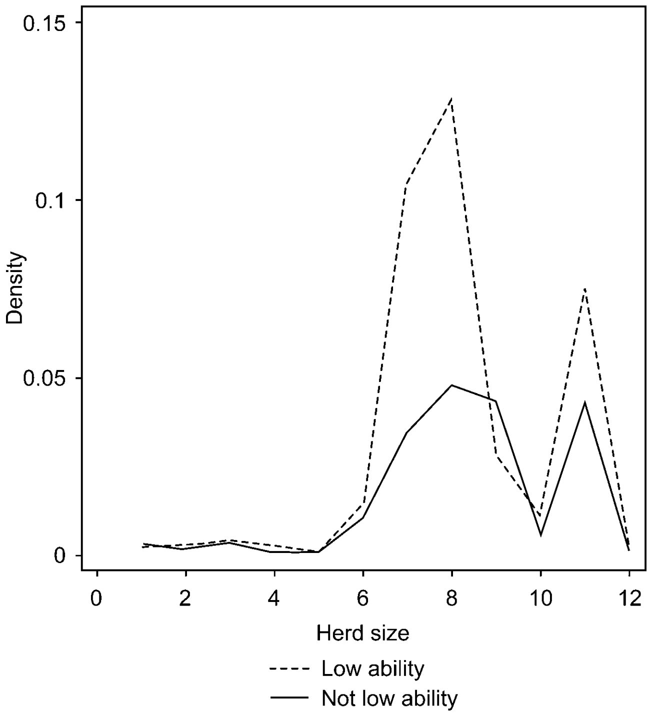

Fig. 7.9 Distribution of high- and low-ability types as a function of initial wealth

fails to promote growth among the poor. After ten years, beneficiaries enjoy an expected gain of 0.86 cattle, but from an average transfer of 2.12 cattle. This implies a −4.4 percent compound annual return on investment in transfer resources, reflecting expected herd losses below the critical herd-size threshold. The growth-promoting impacts of herd restocking become more satisfactory in the other two scenarios that target those who can reach the herd accumulation threshold through transfers rather than the ex ante poorest households. Under Scenario 2, the average net returns to this policy after ten years are 43 percent (3.6 percent annually). These returns significantly increase to 70 percent (5.4 percent annually), under Scenario 3, showing that the payoff to the design of a reliable mechanism for identifying herding ability is potentially considerable, given that ability seems to matter a great deal to wealth dynamics in this system. But targeting the accumulation threshold is the main factor that drives achieving a positive long-run rate of return on transfer resources.

This payoff naturally depends on the distribution of ability types. As shown in figure 7.9 there is, in this system at least, a correlation between ex ante wealth and ability that reflects the joint operation of the dynamics described in this chapter—with low-ability types expected to fall into and remain in poverty regardless of initial wealth—and the insufficiency of informal insurance, particularly among the poor (Santos and Barrett 2011). Roughly half of the herders with less than five cattle are classified as low ability (which, recall, we defined as being in the lower quartile of the distribution of our estimates of technical efficiency). The frequency of low-ability herders then diminishes with wealth: 22 percent of the beneficiaries of transfers under Scenario 2 (with herds between nine and eleven cattle) are classified as low ability, and only little more than 10 percent of the herders with wealth above the accumulation threshold are classified as such. The challenge intrinsic to restocking projects targeted at those with small herds is that it implicitly favors those with the least ability to manage the livestock they receive. This finding lends support to recent policy initiatives in the East African drylands that focus more on cash transfers than livestock transfers to support the poorest community members.

7.6 Conclusions

Using unique data on subjective herd-growth expectations conditional on expected rainfall, we find that southern Ethiopian pastoralists appear to understand the nonstationary herd dynamics that long-term herd-history data suggest characterize their system, corroborating Lybbert et al. (2004) and related results using different data and methods. Moreover, pastoralists' responses reveal that multiple dynamic equilibria arise purely due to adverse shocks associated with low rainfall years and only among pastoralists of higher herding ability. Lower-ability herders appear to converge toward a unique, low-level equilibrium herd size. When adverse weather events strike, they lose livestock and, in expectation, cannot recover quickly enough before the next drought hits. Thus, the data suggest that even among a seemingly homogeneous population in an ethnically uniform region offering effectively only one livelihood option—livestock herding—there exist complex wealth dynamics characterized by distinct convergence clubs defined by individual ability, with multiple dynamic equilibria existing for only a subset of those clubs and a unique, low-level equilibrium for the other club.

These findings carry two main policy implications. First, the need for interventions to lift people out of—or to prevent their collapse into—poverty traps, seems to depend on the nature of the adverse shocks, in particular, whether their severity and frequency is such that growth under favorable states of nature is often and sharply reversed, making accumulation below a critical threshold unlikely (albeit not impossible). Risk mitigation or transfer methods to limit the frequency or magnitude of shocks may be as or more valuable than transfers to facilitate growth among the poorest, a point made as well in Ikegami et al. (chapter 6, this volume). Second, the appropriate design and targeting of social protection in this stochastic environment depend very much on individual characteristics, perhaps including difficult-to-observe characteristics such as ability. Identifying ability may be operationally difficult, but failure to take such characteristics into account may lead to ill-conceived efforts and wasted scarce resources.

Finally, these findings also carry implications in terms of future research. First, the need to understand how important is heterogeneity in poverty dynamics. Recent work analyzing poverty-graduation programs seems to suggest that unobserved heterogeneity matters (see, e.g., Bandiera et al. 2017; Gobin, Santos, and Toth 2017). Second, what can be done to understand what lies under the frequently used, but rarely defined, concept of "ability." In this chapter, we equated ability with the (estimates of) technical efficiency, as the capacity to produce more with the same resources seems an intuitively acceptable approximation of ability. A natural next step is to "reduce the residual" by measuring the skills that, so far and to a large extent, have been left unmeasured. Dean, Schilbach, and Schofield's (chapter 2, this volume) discussion of the potential importance of noncognitive skills such self-control, attention, and memory as psychological determinants of productivity seems a natural starting point, although much needs to be understood regarding the practical difficulties of such measurement (Laajaj and Macours 2017).

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