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Heterogeneous wealth dynamics: On the roles of risk and ability

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Heterogeneous wealth dynamics: On the roles of risk and ability

Abstract:
This paper builds on recent evidence of nonlinear wealth dynamics among Boran pastoralists in southern Ethiopia, consistent with the hypothesis of poverty traps. We study the causal mechanisms behind apparent poverty traps, exploring in particular the roles of adverse weather shocks and herder-specific ability to cope with such shocks in conditioning wealth dynamics. Using original data collected among the same population, we establish pastoralists' expectations of herd dynamics and show both that Boran pastoralists perceive the nonlinear long-term dynamics that characterize livestock wealth in the region and that this pattern results from adverse weather shocks. This result underscores the criticality of asset protection against exogenous shocks to facilitate wealth accumulation and economic growth. We then disaggregate the sample, estimating a stochastic herd growth frontier to generate herder-specific estimates of unobservable ability so as to be able to condition wealth dynamics on ability. We then find that those with low ability converge to a unique dynamic equilibrium at a small herd size, while those with high or medium estimated ability exhibit multiple stable dynamic wealth equilibria. This result points to the importance of taking indicators of ability into consideration in the targeting of asset transfers, as we demonstrate with simulations of alternative post-drought herd restocking project designs.

Keywords: ability, herd restocking, poverty traps, regression trees, shocks, subjective expectations.

1. Introduction

Contemporary policy debates are rife with discussion of "poverty traps".[1] Yet the supporting empirical evidence on the existence of poverty traps remains quite mixed. Some studies (e.g., Dercon 1998, Lybbert et al. 2004, Adato et al. 2006, Barrett et al. 2006) find support for the hypothesis while others (e.g., McKenzie and Woodruff 2003, Jalan and Ravallion 2004, Lokshin and Ravallion 2004, Antman and McKenzie 2005) find no evidence of a trap, as manifest by a threshold effect associated with multiple dynamic equilibria (with one such equilibrium below a poverty line).[2] However, a poverty trap can also result from a unique dynamic equilibrium below a poverty line, as might be consistent with a hypothesis of "convergence clubs" based on intrinsic characteristics such as time preferences, location or immutable skills or disabilities.[3] The convergence clubs and threshold-based multiple equilibrium explanations are not mutually exclusive. In principle, there might be groups within a population for whom there exists a unique equilibrium associated with persistent poverty, others who face multiple equilibria and thus face wealth dynamics conditioned by their starting positions, and still others who converge towards a unique equilibrium above the poverty line regardless of their starting conditions. This paper explores the possibility of such heterogeneous wealth dynamics.

The policy implications of the convergence club and threshold-based multiple equilibria mechanisms differ markedly. If poverty is a unique dynamic equilibrium because of immutable individual characteristics, ongoing social transfers may be the only

[1] See, for example, Sachs (2005) or United Nations Millennium Project (2005).

[2] See Azariadis and Stachurski (forthcoming) or Bowles et al. (2006) for good reviews of the theoretical and early empirical literature on poverty traps

[3] Baumol (1986), DeLong (1988) and Canova (2004) define and discuss the estimation of convergence clubs in macroeconomic growth data.

available remedy for an unacceptably low independent standard of living. But if poverty results from initial asset holdings insufficient to clear a critical minimum endowment threshold and thereby follow a positive accumulation path, then one-off asset transfers or changes to the productivity of existing assets can yield permanent increases in wealth and well-being and obviate the need for ongoing transfers. 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. Sorting out the mechanisms that underpin persistent poverty is therefore enormously important in practical terms, but also quite difficult methodologically.

The possibility of convergence clubs and/or multiple equilibria can be integrated as follows. Let y_{it} be a strictly non-negative measure of economic well-being for cross-sectional unit i in period t. In our empirical implementation, this will be household wealth. Household characteristics (*e.g.*, savings propensities, geographic location or intrinsic ability) may sort cross-sectional units into a distinct cohort or club c, where c=1,…,C ,and the parameters defining welfare dynamics in population may vary by club as assumed under convergence club models. In addition, there may be some critical threshold value, $\gamma^c \geq 0$, at which the welfare dynamics bifurcate, with one path, subscripted ℓ, leading to a low-level equilibrium and another, subscripted h, leading to a high-level equilibrium, as hypothesized by multiple equilibrium models. The union of the convergence club and multiple equilibria possibilities yields the following reduced form growth specification:

(1) $$y_{it} = \begin{cases} \alpha_\ell^c + g_\ell^c(y_{i0}) + \varepsilon_{it} \; if \; i \in c \; and \; y_{i0} < \gamma^c \\ \alpha_h^c + g_h^c(y_{i0}) + \varepsilon_{it} \; if \; i \in c \; and \; y_{i0} \geq \gamma^c \end{cases}$$

where $g^c(\cdot)$ is some potentially cohort-specific and highly non-linear function that describes welfare dynamics, mapping initial well-being (y_{i0}) into some future level t periods ahead and ε_{it} is a random component. Setting γ^c=0 yields a simplified version of Canova's (2004) method of optimally partitioning cross-sectional units into discrete clubs under the club convergence hypothesis. Similarly, setting $\alpha_j^c = \alpha_j \forall c$ and $g_j^c = g_j \forall c$ reduces this specification to a variant of Hansen's (2000) approach to the identification of multiple equilibrium thresholds. Both of those papers, indeed most of the literature on prospective poverty traps, offers empirical evidence at the macro level of growth using national-level real per capita income data. The methodological challenge is to unpack possible cohort-level cross-sectional variation in welfare dynamics while simultaneously allowing for the possibility of threshold effects.

If one further allows for differences in expected growth conditional on states of nature, that is $E[y_{ist}] = \alpha_{se}^c + g_{se}^c(y_{i0})$, for state s and equilibrium $e \in \{h, \ell\}$, then there exists one more dimension in which analysts need to allow for prospectively important variation. The recent literature on poverty traps emphasizes the importance of risk in the presence of multiple equilibria because shocks can cause agents to move from a high level equilibrium's basin of attraction onto a path converging instead toward a low level equilibrium (Carter and Barrett 2006). It may be that all agents follow a path dynamic that converges towards a high level equilibrium when they face favorable states of nature and that low-level equilibria only arise because shocks routinely knock some backwards, preventing self-insurance sufficient to lock-in one's accumulated gains (Dercon 1998). In that case, risk can be a source of persistent poverty not only because it induces ex ante risk management that causes the poor to choose lower expected return portfolios

(Rosenzweig and Binswanger 1993) but because differential ability to cope ex post with shocks may distinguish high performers from their less fortunate counterparts. Thus, variation in welfare dynamics across states of nature may be central to understanding how both individual-level characteristics and initial conditions affect expected welfare dynamics.

This paper explores these issues empirically. We unpack and extend the results of Lybbert et al. (2004), who analyzed wealth dynamics among Boran pastoralists, a poor population in southern Ethiopia. Cattle are the Boran's major (in many cases, the only non-human) asset and herd evolution is characterized by boom-and-bust cycles determined by drought and biological reproduction. Using 17-year herd history data, Lybbert et al. find herd dynamics that follow an S-shaped curve with two stable dynamic equilibria (at roughly 1 and 35-40 cattle), separated by an unstable dynamic equilibrium, a threshold at 15-20 cattle. The authors conjecture 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. Those with smaller herds are forced to stay near their base camps, where pasture conditions soon get degraded, leading to a collapse of herd size towards the low-level stable equilibrium, while those with bigger herds can migrate in search of adequate water and pasture, enabling them to sustain far larger herds. We collected new data among the same population so as to explore the role of shocks and household-specific ability in shaping wealth dynamics.

The next section briefly explains the data. In section 3, we use data on pastoralists' expectations of herd size one year ahead, given different values of initial herd size, to simulate long-run equilibria that correspond closely with those identified in

Lybbert et al. (2004). Pastoralists appear to perceive the dynamics reflected in herd history data. We disaggregate these dynamics as a function of respondents' expected rainfall states and find that multiple equilibria arise exclusively in adverse states of nature. Under favorable rainfall regimes, respondents' subjective perceptions suggest a smooth asset growth process towards a unique, high-level dynamic equilibrium. Given manifest variation in expected herd dynamics under adverse states of nature, section 4 explores the hypothesis that herder-specific ability, which we derive using stochastic frontier estimation methods, conditions wealth dynamics. This appears true in both the herders' expectations data and in herd history data. In Section 5 we apply this approach to the analysis of the (expected) evolution of the wealth of a sample of herders in this region. We find evidence that the incorporation of ability does make a difference in terms of expected wealth and inequality in this system. Section 6 concludes, stressing 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.

2. Data

We employ three data sets. The first is that used by Lybbert et al. (2004), originally collected by and described in Desta (1999), reflecting 17 years of herd histories for 55 Boran pastoralist households drawn from four communities (*woredas)* in southern Ethiopia (Arero, Mega, Negelle and Yabello). Because 16 of the sample households were formed within the 17 year period, this is an uneven panel of data, with 833 total observations. The data were collected using a stratified random sampling design, using detailed interviews held with entire extended families whose collective recall permitted the construction of reliable panel data on herd histories, including mortality, marketing, gifts and loans, slaughtering and calving.[4]

The second consists of household survey data collected from 120 randomly selected Boran pastoralist households in the same four *woredas* of southern Ethiopia, although the respondent households differ from those Desta surveyed. These data were collected every three months, March 2000-June 2002, and then annually each September-October starting in 2003.[5] The data include rich detail on household composition, educational attainment (although very few respondents are literate or attended any school), migration histories, changes in herds, shocks, etc.

The third data set consists of subjective expectations of herd dynamics we elicited from the PARIMA survey households in 2004. The use of elicited expectations to study decision-making was recently reviewed by Manski (2004). Although the efficacy of elicited expectations for testing economic hypotheses has been well established, most such studies have taken place in high-income countries. Important exceptions are Delavande (2004), on the efficacy of contraceptive methods in Ghana, and Luseno et al. (2003) and Lybbert et al. (forthcoming) on pastoralists' rainfall expectations in East Africa. Given the paucity of studies of low-income country respondents' subjective expectations, it is worth explaining in some detail how we elicited these data.

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[4] Prior studies have confirmed the reliability of herd history recall data collected among African pastoralists (Grandin 1983, Assefa 1990, Ensminger 1992).

[5] The data were collected by the Pastoral Risk Management (PARIMA) project of the USAID Global Livestock Collaborative Research Support Program. Barrett et al. (2004) describe the location, survey methods and available variables.

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).[6] Respondents were then asked their expectations for rainfall next year (choosing between good, normal or bad[7]) and to assume a cattle herd of standard composition for the region (in terms of age and sex of the animals). 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, 20 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. 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.

3. Expected herd dynamics

[6] The intervals are [1,5), [5, 15), [15, 40) and [40, 60].

[7] Published rainfall forecasts, such as those disseminated by the regional Drought Monitoring Centre and government and nongovernmental organization extension officers, use precisely this sort of trinomial rainfall forecast, so it is familiar to respondents (Luseno et al. 2003, Lybbert et al. forthcoming). The data were collected well into the rainy season, hence these are not uninformed priors.

Figure 1 presents the scatter plot and kernel regression[8] relating expected herd size one year ahead (*herd1*) and initial herd size (*herd0*), conditional on ever having had a herd with a similar size for our sample of 441observations.[9] The solid. 45-degree line from the origin represents the dynamic equilibria where herd sizes are equal across periods. Three points emerge immediately from comparing pastoralists' subjective expectations of one year-ahead herd dynamics (figure 1) with the dynamics revealed by Desta/Lybbert et al.'s herd history data (the dashed line in figure 2). First, both 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. This would seem to suggest a different story from the one described by herd history data and detailed studies of the system (Coppock 1994). Finally, there is considerable dispersion in pastoralists' expectations of herd dynamics conditional on a given starting herd size. If one interprets this variation as reflecting pastoralist-specific herding abilities – assuming each pastoralist accurately perceives his or her own herd dynamics given his or her individual aptitude for herding – then this suggests that ability plays a significant role in wealth dynamics.

[8] We use the Nadaraya-Watson nonparametric regression, with the Epanechnikov kernel and bandwidth of 4.545. The value of bandwidth was selected using Silverman's (1986) rule of thumb, as determined by the "bounds for Stata" package (Beresteanu and Manski 2000). We apply the same bandwidth choice procedure in the remainder of this paper.

[9] 23 of the 464 total observations (116 respondents with four different starting values each) do not include a herd size prediction, either because respondents were unwilling to make predictions about rainfall or because they were unable to distribute the stones across the board. The latter problem 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, in 285 cases (64.6%) the respondents had prior personal experience managing a herd of comparable size.

These casual comparisons invite more careful analysis, especially as regards the intersection of rainfall conditions and herder ability. The pattern exhibited in the actual herd history data (figure 2) is the result of a mixture of environmental conditions over a period of 17 years. Meanwhile, the data on herders' subjective assessments of herd dynamics (figure 1) represent only the year-ahead expectation under necessarily more limited rainfall variability regimes.[10] Put differently, the dashed line in figure 2 reflects herd dynamics conditional on rainfall across a varied mixture of states of nature while figure 1 reflects the union of the conditional dynamics with a more limited mixing.

Figures 3a and 3b disaggregate herders' subjective herd dynamics, now conditioning on rainfall expectations. The difference is striking. The relation between expected and initial herd size is nonlinear and suggests multiple equilibria only in the case of bad rainfall conditions. Under good or normal climatic conditions (and perhaps unsurprisingly), herders expect herds to grow no matter the initial herd size. The dispersion around the expected values is also much bigger under conditions of bad rainfall than in a good or normal year. Herders exhibit far more heterogeneous beliefs about their ability to deal with adverse states of nature than with favorable ones. If we are correct in attributing this feature of the data to individual ability, then such differences seem to matter most when times are tough.

In order to simulate pastoralists' long run expectations of herd dynamics, we need data on the expected behavior under more extreme conditions, namely severe drought and very good years. To obtain such information, we used a second questionnaire similar to

[10] For example, Kamara, Swallow and Kirk (2003) 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.

the one described above except that we defined rainfall conditions in advance.[11] This instrument was fielded in only one of the four sites (Dida Hara). The results largely correspond with those already reported, showing an almost linear relation between expected and initial herd sizes in very good years and a highly nonlinear relation in cases of severe drought.[12]

In order to generate herders' subjective expectations of herd dynamics under a mixture of states of nature – corresponding to the solid line in figure 2, depicting ten year herd transitions in the Desta/Lybbert et al. data – we need to integrate information on herd growth expectations (i.e., the relation between *herd1* and *herd0*) conditional on rainfall regimes with rainfall data. We therefore simulate using the elicited expectations data previously described and monthly rainfall data for the 4 sites over the period 1991-2001.[13] Since we must predict out-of-sample in simulating herd evolution for large values of initial herd size, we had to estimate the parametric relation between *herd1* and *herd0*. Conditional on each of the four rainfall scenarios (drought, poor rainfall, normal/good rainfall, 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 on each individual. We thus estimate

(2) $$h_{ir} = f(h_{ir}) + \alpha_i + \varepsilon_{ir}$$

[11] 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.
[12] To conserve space, we omit graphics reflecting these data and nonparametric regressions, although plots corresponding to figures 1 and 3 are available upon request.
[13] 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.

where $f(h_{ir})$ is a polynomial function of initial herd size.[14] Table 1 presents the estimates, which reflect the results displayed visually in figures 1 and 3: unambiguous, effectively linear expected growth under normal/good/very good rainfall conditions, but a nonlinear estimated relation between *herd1* and *herd0* only under conditions of poor rainfall (and drought), and with considerable dispersion so that the precision of those estimates is far less than under favorable rainfall regimes. We then used these estimation results to simulate the expected evolution of herd sizes, properly calibrated to impose basic biological rules for livestock.[15] Figure 4 presents the basic structure of the simulation procedure we used.

Figure 5 presents the mean of 10-year ahead herd size and its smoothed plot[16] for 500 replicates of this simulation with initial herd sizes between 1 and 60. The results are remarkably similar to the dynamics revealed by the herd history data (solid line in figure 2), both in the general shape of the curve and in the location of the different equilibria. While the one year ahead transitions predicted by the two data sets (figure 1 and the dashed line in figure 2) did not match because of the fundamentally different underlying states of nature, once one takes into account historical rainfall patterns and simulates the

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[14] Besides the assumptions on the functional form of f(*), we also assumed that $\varepsilon_{ei} \sim N(0,\sigma^2)$. 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, which are available upon request. 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.
The estimates of these last models estimated on the subsample of the observations on which the respondent has prior experience managing a herd with a similar size were not statistically different from the ones obtained when using the full sample. The same is not true when we estimate these models under conditions of bad rainfall or drought. We present the unconditioned models when rainfall is good or very good and the conditioned ones when rainfall is bad or drought occurs.

[15] More precisely, we do not allow for negative herds and impose that biological growth under good rainfall conditions is delayed in 2 years, i.e., enough for cows to reproduce. We also constrain the predicted values for initial herd sizes above 52 (poor rainfall) and 46 (drought) to be linear, with a slope of 0.1292 and 0.0419, preventing unbelievable predictions due to the parameter estimates at the boundaries of our sample.

[16] The smoothed plot was obtained using an Epanechnikov kernel with bandwidth of 6.930.

longer-term, decadal herd dynamics, it appears that Boran pastoralists have a remarkably accurate understanding of the nature of how their herds evolve, including the implied existence of poverty traps. That is, they expect that someone with a small herd – below approximately five cattle – will not accumulate wealth, but will instead collapse towards a destitute, sedentarized equilibrium with just one animal.

In Table 2 we use these simulation results to quantify the probability of moving between equilibria. In a strict, formal interpretation of the concept of a poverty trap, where initial conditions totally determine future wealth and the system is non-ergodic, these probabilities should be zero. This strict standard finds no support in our results. For example, a herder starting with a herd size between 1 and 4 cattle has a strictly positive probability of holding a herd between 15 and 39 cattle one decade later. However, that probability is extremely low (less than 1%), suggesting that, in this context, the idea of a poverty trap is associated with the notion of very slow, stochastic convergence towards higher levels of welfare, a weaker but widely used interpretation of the concept (Azariadis and Stachurski forthcoming).

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, in the sense of very slow, probabilistic convergence to higher levels of welfare. However, these dynamics seem entirely the result of an asymmetry 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. Our data also show that, even in bad years, not all herders expect their herds to shrink. The considerable interhousehold dispersion of beliefs about herd dynamics under adverse states of nature suggests that herder-specific characteristics, perhaps especially unobserved husbandry skills and related talents we summarize as "ability", may likewise play a central role in conditioning wealth dynamics among these Ethiopian herders. The next section investigates this hypothesis via two different methods.

4. Ability and expected herd dynamics

Herding 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, etc. Not everyone learns and practices these diverse skills equally well. One would naturally expect more skilled herders to enjoy faster herd growth and to be less subject to adverse shocks to herd size than less skilled herders. Put differently, the herd dynamics explored in Lybbert et al. (2004) and in the previous section may ignore salient differences in herder ability.

We explore the impact of differences in herding ability upon herd dynamics by using the PARIMA panel data on pastoralist households to estimate herder ability using stochastic parametric frontier estimation methods for panel data (Kumbhakar and Lovell 2000). More precisely, we estimate the herd growth frontier conditional on household attributes and initial period herd size using a composed error term that includes a symmetric random component reflecting standard sampling and measurement error, ψ, and a one-sided term reflecting observation-specific but time invariant inefficiency, $\phi \geq 0$, which we assume follows a truncated normal distribution, $N^{+}(\mu,\sigma^{2}_{\mu})$:

(3) $$h_{it} = f(h_{i\,t\text{-}1}) + \beta X_{it} - \phi_i + \psi_{it}$$

Since these households have been surveyed since 2000, we can take advantage of multiple observations for each herder to compute consistent herder-specific mean efficiency measures, i.e., each pastoralist's proximity to the herd growth frontier that provide at least a coarse proxy for herder-specific ability that is not otherwise directly observable.[17]

Table 3 presents estimates of the herd growth frontier based on 2000-1, 2001-2 and 2002-3 annual observations for the 113 households for which we have complete data on each of the covariates.[18] Table 4 defines these variables and presents the descriptive statistics. Notice that we use an exogenous switching regressions formulation to incorporate the possibility of two different growth paths, depending on whether the herder is above or below the 15 cattle threshold identified by Lybbert et al. (2004). The results indicate statistically significant (p-value = 0.053) differences in the asset dynamics above and below the threshold, with expected herd growth (collapse) above (below) the threshold. The estimated frontier is piecewise quadratic in *herd0-herd1* space, as higher order polynomial terms of lagged herd size have no statistically significant effect.[19]

[17] An earlier version of this paper used the data on expected herd growth, described in the previous section, to estimate the growth frontier. The results were qualitatively identical. However, two strong assumptions underpin the use of expectations data rather than actual herd history data: that one's ability classification is not conditional on rainfall conditions and that pastoralists incorporate accurate self-assessment of their own herding ability into their expectations of herd dynamics. The latter point was of special concern, as one could easily conflate optimism for ability in expectations data.

[18] 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.

[19] We also ran 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 the biology of 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

Household labor and land endowments have no effect at the margin on expected herd growth, signaling that these are not limiting in this environment for most households. Male-headed households enjoy significantly higher herd growth rates, which may partly capture household composition effects (with male-headed households having more men able to herd, 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 (for 2001-2, the year of recovery after the severe 1999-2000 drought), the latter result reinforcing our earlier finding about state-dependent growth.

Using the predicted value of each herder's estimated technical inefficiency, we then divide our sample into three sub-samples: low ability (those in the 4th quartile of the inefficiency estimates, above 15.38), high ability (those in the 1st quartile, below 14.29) and a residual medium ability category (the 2nd and 3rd quartiles). The distribution of the inefficiency estimates (with cattle as the units) is presented in figure 6,[20] allowing a visual analysis of the diversity within each sub-sample. The observations are concentrated within a limited range of inefficiency estimates, in particularly suggesting that the classes of high and medium efficiency may be quite similar.

For each of these classes we re-estimated equation (2), obtaining estimates of the parametric models that relate expected and initial herd size[21] for each sub-sample. After calibration of these models we performed the same simulations as above. Figure 7 shows

this variable is statistically insignificantly 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.

[20] Estimated using the Epanechnikov kernel, with a bandwidth of 0.24697.

[21] These 12 parametric models (4 states of nature x 3 ability classes) are qualitatively similar to the ones presented in Table 1. To conserve space, we omit them here but they are available from the authors upon request.

the smoothed plot of the mean of 10-year ahead herd size obtained for 500 replicates with initial herd sizes between 1 and 60 for each of the three ability classes.[22] 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-degree line in figure 6). Thus, low ability herders are expected to converge towards a low-level dynamic asset equilibrium at only 1 or 2 head of cattle, just as Lybbert et al. (2004) found unconditional on ability. Those that are not considered to be low-ability likewise exhibit S-shaped expected herd dynamics. However, they face multiple dynamic equilibria, with a nearly identical threshold (i.e., unstable dynamic equilibrium) at 12-17 cattle, similar to the threshold Lybbert et al. (2004) estimated in the herd history data. The high ability herders clearing the threshold enjoy a much higher upper equilibrium, however, at 54-55 cattle, as opposed to the medium ability herders' upper equilibrium of 32-33 head. The implication, reflected in figure 7, is that S-shaped herd dynamics characteristic of a poverty trap are not a characteristic of all herders. In particular, 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 medium and high ability herders, who expect to accumulate wealth so long as they start with an adequate herd size. These results clearly raise important practical questions with respect to any asset redistribution or transfer policy, as ability is not easily established, at least not by outsiders such as the governmental and nongovernmental agencies that typically provide transfers and public safety net programs.[23]

[22] Obtained using an Epanechnikov kernel with bandwidth of 6.930.
[23] Santos and Barrett (2006) explore the effects of ability and multiple equilibria on private, interhousehold transfers among these pastoralist households.

Because of these critical policy implications, we sought to confirm this last result in the herd history data used by Lybbert et al. (2004). As before, we do that in two steps. First, we estimate a stochastic growth frontier, following equation (3), to obtain estimates of herder-specific, time-invariant inefficiency relative to the estimated growth frontier, and interpret these inefficiency estimates as a measurement of unobserved ability. Given the longer panel, here we use decadal (ten year) transitions, rather than the annual transitions estimated in the more detailed PARIMA data. But the limited variables in this dataset restrict the controls we can include to site fixed effects and the number, in the previous decade, of years of bad rainfall and of good rainfall. As a consequence the interpretation of estimated inefficiency as ability is considerably less clear than in our previous results. Nevertheless, as a check on the robustness of the previous result, we think it is useful. Finally, because we are interested in comparing our results with the ones from the previous section, we restrict the estimation of this efficiency frontier to herd sizes within the same range as found in the PARIMA data, below 100 cattle.[24] Table 5 presents the estimation results.

The first observation on these results is the statistical insignificance of the explanatory variables. The effect of past herd sizes (here, with a lag of 10 years) is better expressed through a cubic function and we cannot find evidence of a threshold at an initial herd size of 15 cattle, as we found in the PARIMA data analyzed above. These results can be explained both by the lack of detailed information on other covariates available in the PARIMA data and by the much bigger lag being explained. As a consequence, the inefficiency terms are clearly different, stressing the differences

[24] The smaller maximum herd sizes in the PARIMA data than in the Desta/Lybbert data reflect declining median herd sizes as well, reflecting what most observers perceive as deepening poverty in the region.

between the two samples. Not only is their average much bigger (68.5 cattle versus 14.7 in Table 3), they also explain a much bigger part of the total variability (r^2=0.869 versus 0.229 in Table 3). Figure 8 graphs the empirical probability density function.[25]

With these estimates of herder-specific ability, we now explore the possibility of heterogeneous wealth dynamics within this sample using regression trees. This approach was used by Durlauf and Johnson (1995) and more recently by Tan (2005) to study economic growth in national-level data. Regression trees is a non-parametric technique introduced by Breiman et al. (1984) that allows the identification of an *a priori* unknown number of sample splits in order to maximize the fit of piecewise linear estimate of a regression function. At each split, the estimator defines increasingly homogeneous subsets, without the need to determine exogenously the threshold variables and values that mark such divisions. Given the lack of theory on how to select such variables, this approach has the double advantage of eliminating much of the arbitrariness in the analysis and of providing results that are structurally interpretable, in the sense that they reveal the relative importance of particular determinants of the relation being explained. Although the results have been shown to be consistent (Breiman et al., 1984), the limitation remains that there is no asymptotic theory to test the statistical significance of the number of splits identified.[26]. In what follows we'll use the *Generalized, Unbiased Interaction Detection and Estimation* (GUIDE) algorithm, explained briefly in the Appendix and at length in Loh (2002).

[25] Estimated using the Epanechnikov kernel, with a bandwidth of 6.9621.
[26] Other approaches, such as the use of mixture models (Bloom, Canning and Sevilla 2000) can, in principle, overcome such problem but, given their computational cost, usually at the cost of reducing the number of admissible splits. Note also that the validity of the theory underlying the identification of thresholds through sample splitting proposed in Hansen (2000) is unclear when we consider more than one split of the original sample, as noticed by the author (p.588).

The result of this procedure is the regression tree shown in figure 9. Empty circles indicate the splitting criteria while numbered circles represent terminal nodes that contain different subsamples. At each splitting point, the tree indicates the threshold variable and its value. Observations with a value smaller than the threshold value follow the left branch from the node; those with a greater value follow the right branch. Consistent with our findings to this point, the first splitting variable is herder ability, which divides the sample into 164 observations on 24 lower ability herders (a much larger subsample than the lower quartile we arbitrarily imposed earlier) and 70 observations on 21 higher ability herders. Within the subsample of lower ability herders, there does not appear to be any threshold in the herd growth function, consistent with our earlier findings using other data from this region. Within the subsample of higher ability herders, however, a further split occurs, at the relatively high herd size of 66 head of cattle. The sample splitting generated by the regression trees method thus reinforces the finding of a unique equilibrium for lower ability herders and multiple equilibria for the rest.

Our estimates of the herd growth models associated with each terminal node appear in Table 6 and are graphed in figure 10.[27] Expected herd dynamics appear highly nonlinear in each regime. For the lower ability herders, however, the unique dynamic equilibrium occurs at a herd size of zero, qualitatively consistent with the earlier evidence of expected collapse into destitution. Interpretation of the higher ability herders' expected wealth dynamics is somewhat complicated by inevitable extreme behaviors in the tails of each subsample, due to the low-order polynomial, parametric model being fitted. But this too is qualitatively quite similar to our previous result. In particular, there appear multiple

[27] The (perhaps counter-intuitive) lack of smoothness of these growth paths is a general result of the regression trees approach, given that splitting the data implicitly assumes that small changes in one variable lead to significant changes in behavior.

stable equilbria, in this case at 18-20 animals and around the sample splitting point of 66 head for those within the range of herd sizes comparable to our earlier results.

5. Expected growth and inequality among the Borana

We now apply this simulation approach to analyze the expected evolution of wealth and inequality in our sample of respondents. We use the same approach as above on the subsample of 97 households that had cattle in 2003.[28] Table 7 presents the results for expected average herd size 10 years ahead and for expected inequality, based on 500 runs of our simulation procedure, first when we disregard the effect of herder ability (column b), then when we incorporate it (column c).

The results are simple to interpret. When we take into consideration the role individual heterogeneity plays in shaping wealth dynamics, we should expect both an increase in average herd size and a large increase in inequality over time, as low ability herders collapse into destitution. If we simulate the evolution of the wealth of this population with a simpler approach that neglects such differences, then still expect an increase in inequality (although somewhat smaller), but with a decrease in average wealth.

Finally, we explore the effectiveness of herd restocking in this system, as this is perhaps the most common form of post-drought assistance provided to pastoralists by

[28] From our sample of 120 respondents, 5 were not interviewed in 2003 and 18 had no cattle. Given that we did not elicited the expectations about herd evolution for this situation and that, to the best of our knowledge there are no reliable estimates of the rate of re-entry into pastoralism for herders who lose all their cattle, we dropped them from the simulation. Among those with no cattle in 2003, 5 households (or 27%) were classified as of being of low ability, 11 (61%) as being of medium ability and the other 2 (11%) as being of high ability.

donors and governments in the region. We simulate the effect of three different scenarios. In Scenario 1, all herds below 5 cattle (the Boran-defined poverty line) are given animals to boost their herd to 5 head. In aggregate, that corresponds to a transfer of 36 cattle to 17 beneficiaries. In Scenario 2, we simulate the effects of transferring (approximately) the same number of cattle – so as to compare mechanisms under a constant budget – but now targeted not to the poorest first but rather in order to maximize expected herd growth from the transfer, assuming there exists no effective mechanism to elicit herder ability. Scenario 2 involves a fictive transfer of 35 cattle to 13 beneficaries. 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 of 36 cattle flow to 9 high ability herders.

The main difference between these scenarios is evident in Figure 11, where we draw the expected herd growth associated with the transfer of 1 cattle. Given expected herd dynamics over the decade following the hypothesized transfer, the transfer is expected to generate herd growth, net of the 1 cattle transfer, only for recipients with ex ante herd size between 7 and 22 head. Those with the smallest (or largest) herds are expected to lose some of their post-transfer herd over the ensuing decade, signaling negative medium-to-long term growth returns on livestock transfers to the poorest (or wealthiest) herders. The expected herd gain from a 1 cattle transfer is maximized for an ex ante herd size of 13 cattle, a significantly larger herd than is typically of restocking program participants since such interventions are typically target following some wealth-sensitive variant of Scenario 1.

Table 8 presents the results of a comparison among these three different scenarios for targeting herd restocking transfers. A tradeoff arises between the number of beneficiaries, the size of the average transfer and the ex ante wealth of beneficiaries, with Scenario 1 providing fewer animals to more and poorer recipients, Scenario 3 providing more animals to fewer and wealthier beneficiaries, and Scenario 2 lying between these two. But, as one would expect based on the growth dynamics in the system, restocking targeted to the lower levels of wealth (specifically, those below 5 cattle) fails to promote growth among the poor. After 10 years, beneficiaries enjoy an expected gain of 1.35 cattle, but from an average transfer of 2.12 cattle. This implies a -4.4% compound annual return on investment in transfer resources, given expected herd losses below the critical herd size threshold. The growth-promoting impacts of herd restocking become more satisfactory in the other two scenarios. Under scenario 2, the average net returns to this policy after 10 years are 17% (1.6% annually). These rise dramatically to 122% (8.3% annually), under scenario 3, showing that the growth payoff to identification of a reliable mechanism for identifying herding ability is potentially considerable since ability seems to matter a great deal to wealth dynamics in this system.

6. Conclusions

Using unique data on household-level expectations of herd growth and long-term herd histories, as well as some innovative empirical methods for eliciting subjective herd growth distributions, we find that southern Ethiopian pastoralists appear to understand the nonstationary herd dynamics that herd history data suggest characterize their system. Moreover, their responses enable us to unpack the herd history data, revealing that multiple dynamic equilibria arise purely due to adverse shocks associated with low rainfall years and for pastoralists of intermediate or high herding ability. Lower ability herders appear to converge towards a unique, low-level equilibrium herd size. Thus, the data suggest that even among a seemingly homogeneous a population as pastoralists 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 and multiple dynamic equilibria for a subset of those clubs.

The policy consequences of these results are important. First, there indeed appear to exist poverty traps among this population, corroborating Lybbert et al.'s (2004) findings. Second, the mechanisms that trap people in long-term poverty seem to vary within the population. For those of low herding ability, livestock transfers – e.g., through post-drought restocking projects – seem an unwise investment, although this remains the primary intervention offer to help pastoralists recover from drought in the region. Identifying herders' unobserved ability is indisputably tricky, and may require community-based targeting methods to take advantage of local information unavailable to central governments and external donors and nongovernmental organizations (Alderman 2002). For higher ability herders, our results suggest a need for safety net programs that safeguard minimum herd sizes – e.g., through water point improvements, preventive and curative veterinary treatments, supplemental feed deliveries – or provide restocking to at least the critical threshold necessary to resume herd growth.

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Figure 1: Herd dynamics, based on respondent subjective expectations (all cases)

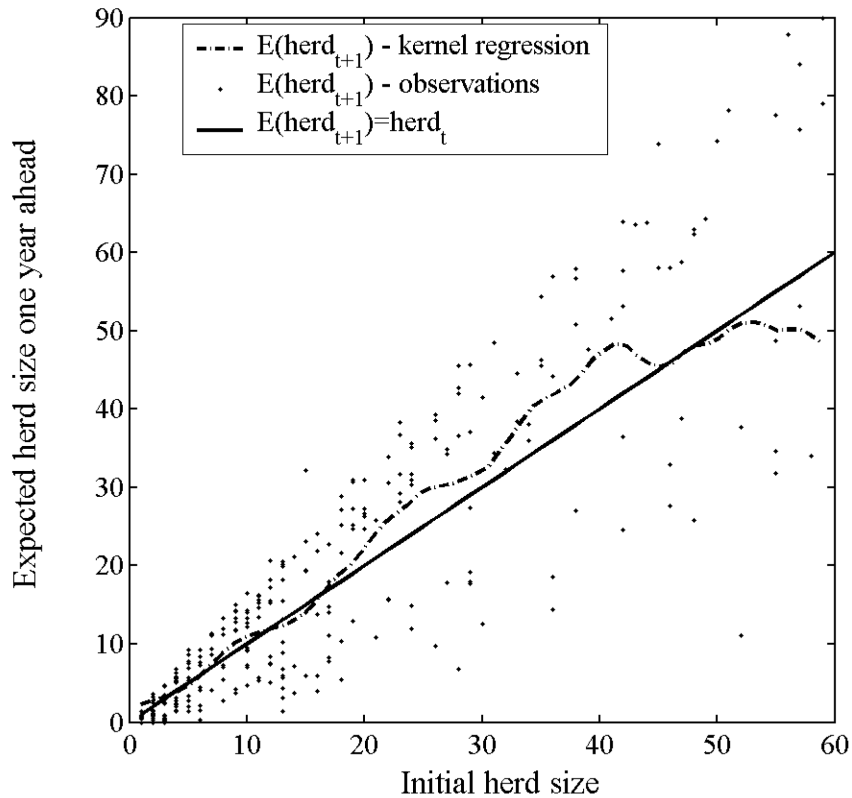
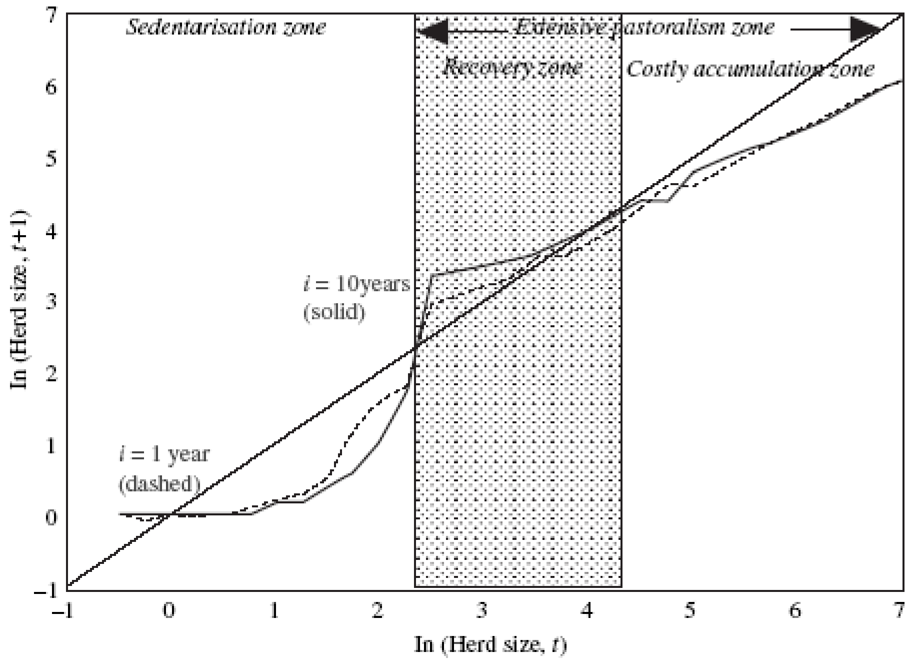


Figure 2: Herd dynamics in southern Ethiopia, based on herd history data

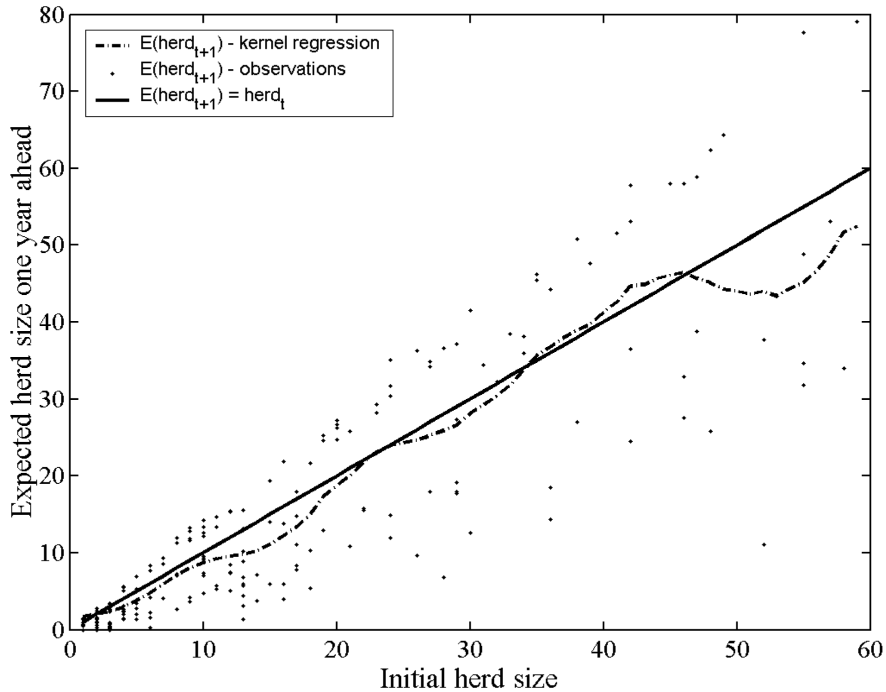
(reprinted from Lybbert et al. (2004))



Nadaraya-Watson estimates using Epanechnikov kernel with bandwidth (h = 1.5)

Figure 3: Expected herd dynamics conditional on rainfall conditions

a) Bad rainfall conditions



b) Good/normal rainfall conditions

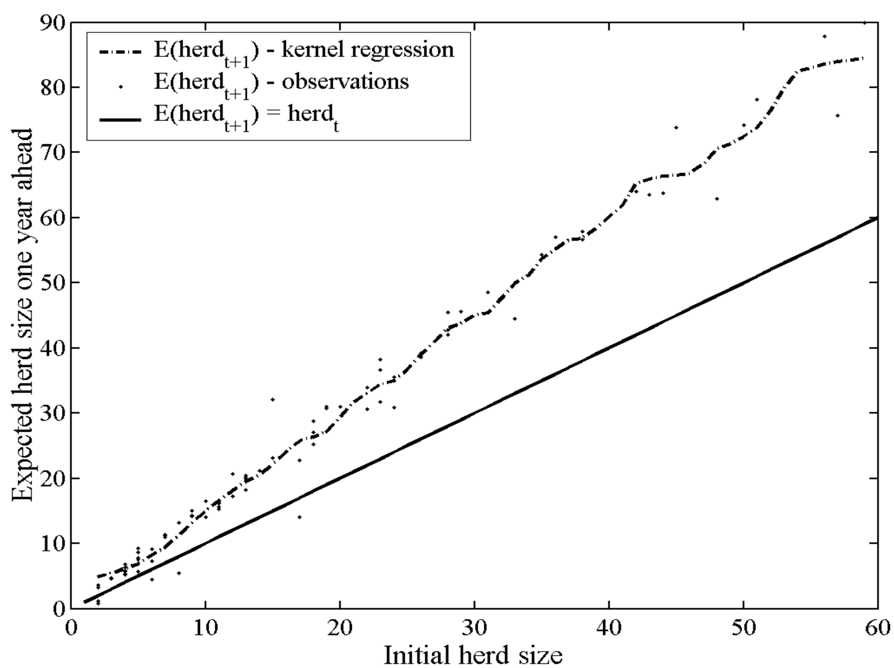


Figure 4: Simulation method schematic

Time Period	t-1		T		t+1
	herd t	→	Rainfall draw		
			↓ call appropriate growth model		
			[$herd1$= f ($herd0 \mid$ rainfall)]		
			predict next period's herd ↓		
			herd t+1	→	repeat as in period t

Figure 5: Simulated expected herd dynamics

based on estimated state-conditional dynamics and stochastic rainfall

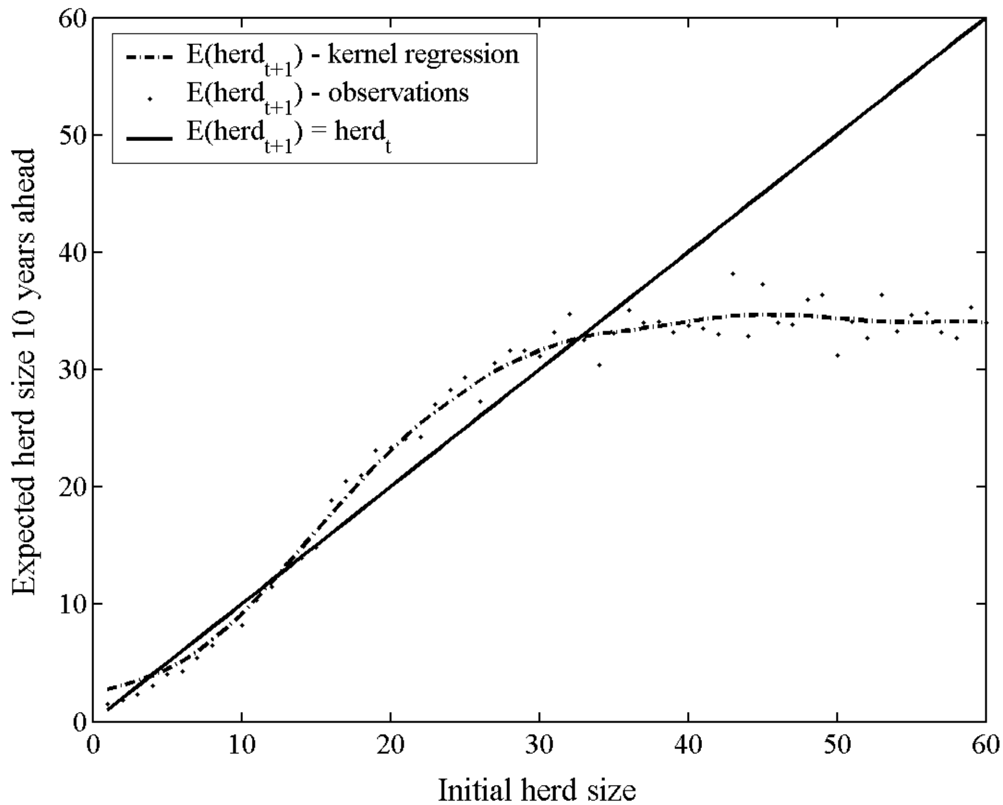
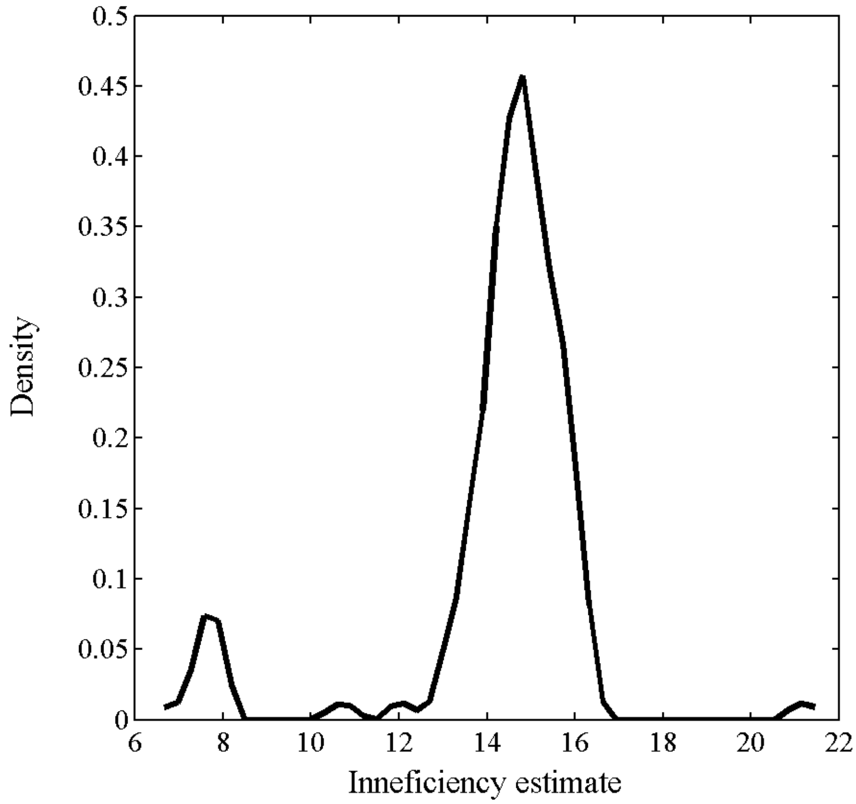


Figure 6: Empirical density function of inefficiency estimates.



Empirical density estimates obtained using an Epanechnikov kernel with bandwidth 0.2469. The value of bandwidth was selected using Silverman's rule of thumb.

Figure 7: Expected herd dynamics: the effects of herder ability

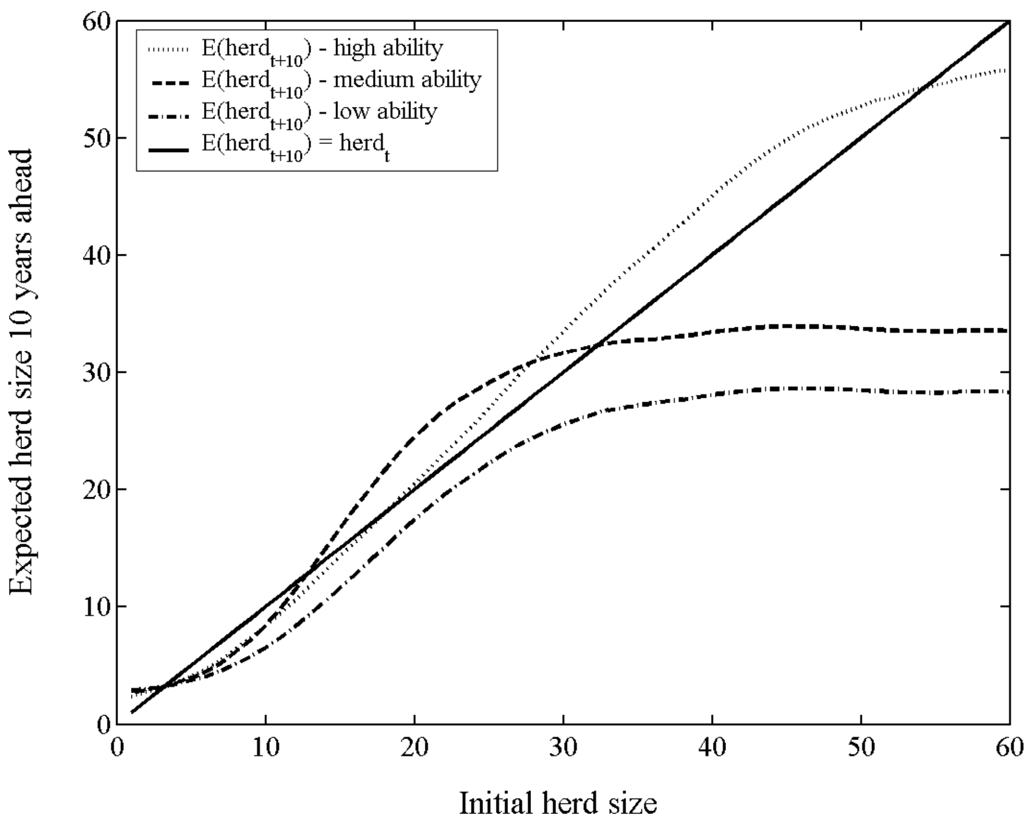
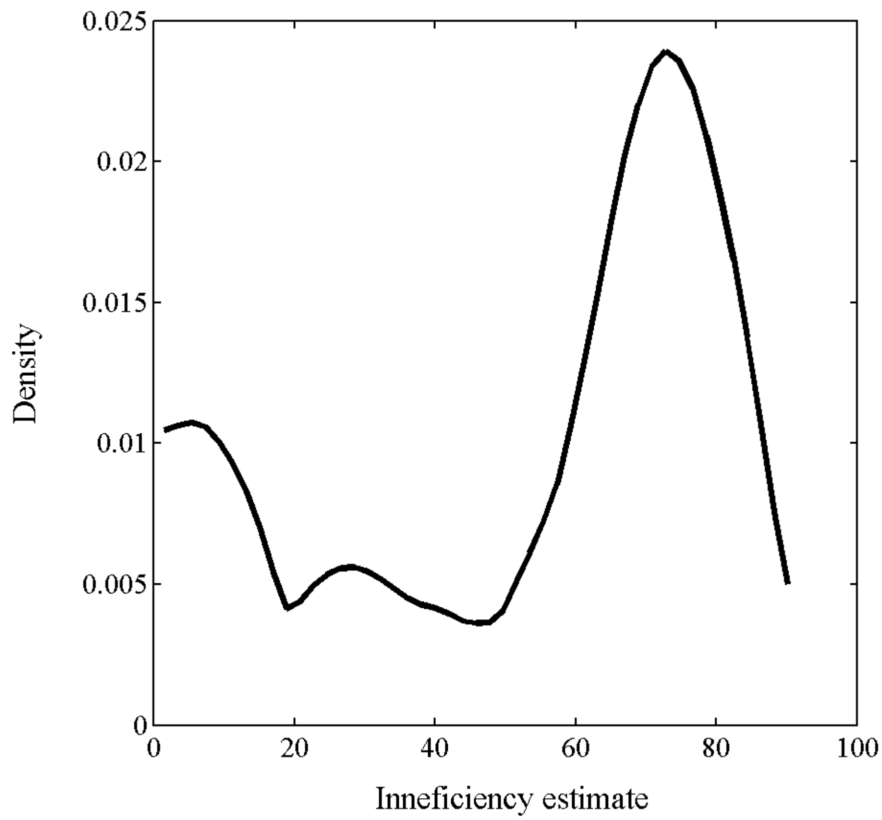
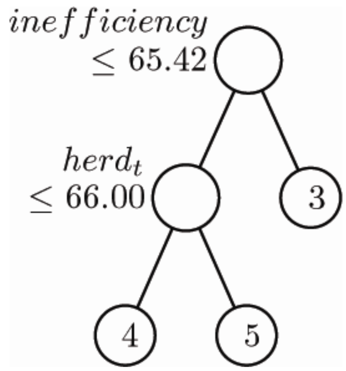


Figure 8: Empirical density function of inefficiency estimates.



Empirical density estimates obtained using an Epanechnikov kernel with bandwidth 6.962. The value of bandwidth was selected using Silverman's rule of thumb

Figure 9: Real herd dynamics: regression tree due to ability and initial herd size



Piecewise-multiple linear least square GUIDE model.
At each intermediate node, a case goes to the left
child node if and only if the condition is satisfied.

Figure 10: Predicted herd dynamics, conditional on ability and initial herd size

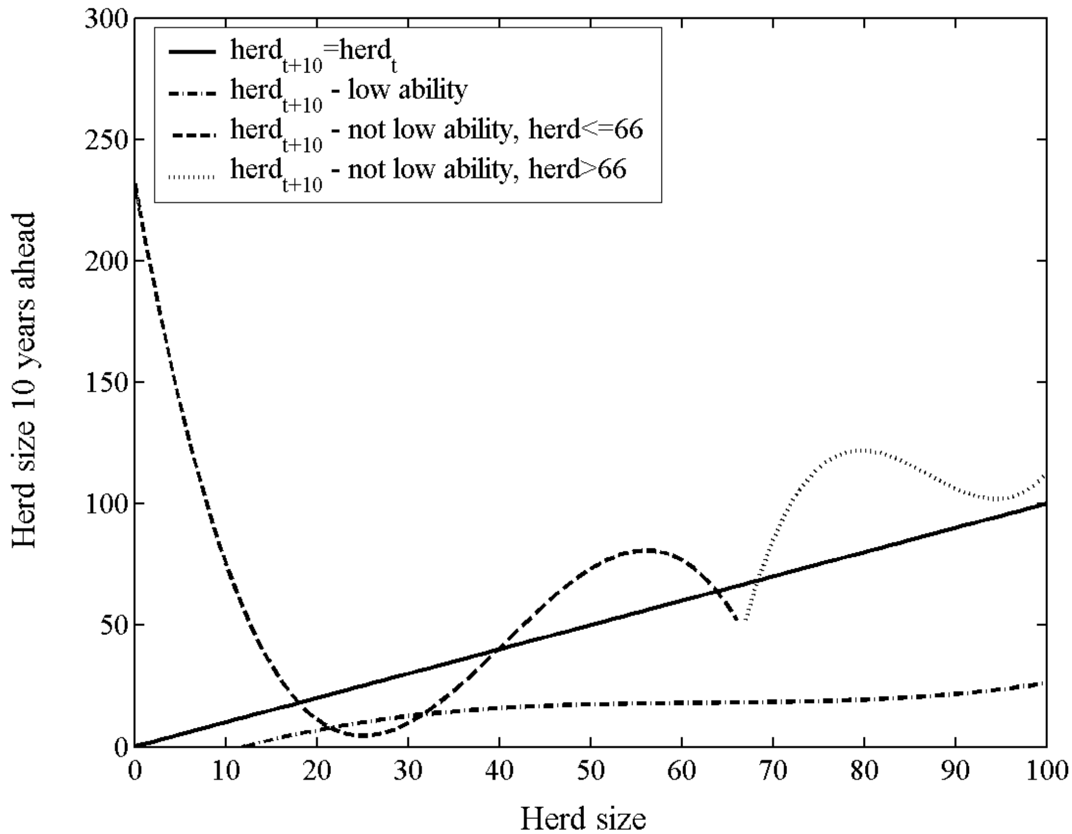


Figure 11: Expected gains from the transfer of 1 cattle

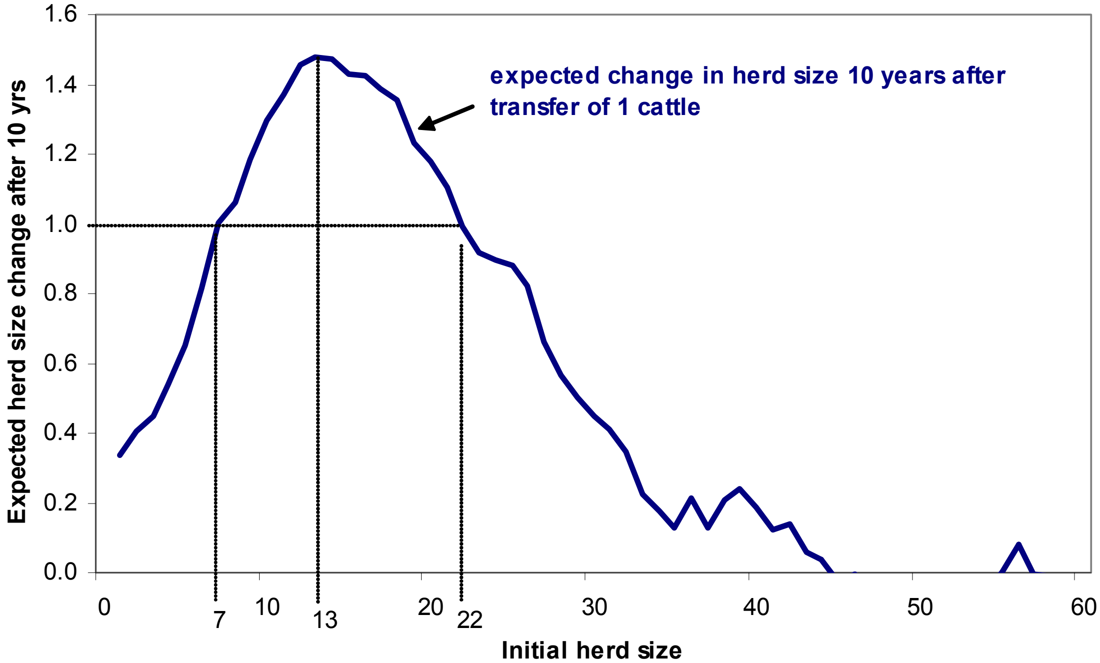


Table 1: Fixed Effects Estimates of Expected Herd Dynamics Conditional on Rainfall

Rainfall	Very good	Good/normal	Bad	Drought
herd0	1.293	1.477	0.655	0.264
	[0.000]	[0.000]	[0.035]	[0.159]
herd0^2			0.016	0.005
			[0.167]	[0.535]
herd0^3			-0.00019	-0.00011
			[0.161]	[0.323]
Constant	0.897	0.179	0.382	-0.834
	[0.053]	[0.668]	[0.781]	[0.711]
r^2	0.986	0.984	0.792	0.6082
Number of Observations	61	96	192	60

Note: Robust p-values within brackets.

Table 2: Herd Size Transition Matrix (10 year period)

h_t \ h_{t+10}	0-4	5-14	15-39	40-60
1-4	0.838	0.153	0.009	0.000
5-14	0.558	0.287	0.133	0.023
15-39	0.200	0.293	0.257	0.250
40-60	0.130	0.243	0.300	0.331

Table 3: Stochastic Parametric Herd Growth Frontier Estimates

	Point Estimate [p-value]
herd size at t-1*above threshold	1.022
	[0.000]
herd size at t-1 squared * above threshold	-0.000
	[0.689]
herd size at t-1* below threshold	0.890
	[0.004]
herd size at t-1 squared * below threshold	-0.009
	[0.681]
no cattle at t-1	-1.126
	[0.366]
labor * above threshold	-0.089
	[0.611]
labor * below threshold	0.099
	[0.427]
Land	0.022
	[0.885]
sex	1.333
	[0.057]
Experience	0.137
	[0.052]
experience squared	-0.002
	[0.174]
Migrant	-0.605
	[0.544]
2000-01	-0.740
	[0.164]
2001-02	1.553
	[0.003]
Dida Hara	1.870
	[0.092]
Qorate	0.026
	[0.983]
Wachille	0.827
	[0.465]
Constant	13.012
	[0.947]
μ	14.671
σ^2_μ	4.331
r^2	0.230
H_0: cattle above threshold = cattle below threshold (prob > F)	0.053

Note: robust p-values within brackets.

Table 4: Explanatory variables: definition and descriptive statistics

Variable	Definition	Mean (standard deviation)
herd size at t-1*above threshold	Herd size in the previous period if greater than 15, 0 otherwise	3.95 (3.99)
herd size at t-1* below threshold	Herd size in the previous period if smaller or equal to 15, 0 otherwise	4.17 (12.08)
no cattle at t-1	Dummy variable, equal to 1 if the respondent has no cattle in the previous period, 0 otherwise	0.185 (0.389)
labor * above threshold	Family size, if herd size in the previous period is greater than 15, 0 otherwise	3.44 (3.38)
labor * below threshold	Family size, if herd size in the previous period is smaller or equal than 15, 0 otherwise	0.87 (2.67)
Land	Land cropped in June 2000	1.12 (2.25)
sex	Dummy variable, equal to 1 if the respondent is male	0.639 (481)
Experience	Number of years between start of herd management	20.26 (14.07)
Migrant	Dummy variable, equal to 1 if the respondent migrated to the are where currently lived	0.210 (0.408)
Dida Hara	Dummy variable, equal to 1 if the respondent lives in Dida Hara	0.25 (0.43)
Qorate	Dummy variable, equal to 1 if the respondent lives in Qorate	0.25 (0.43)
Wachille	Dummy variable, equal to 1 if the respondent lives in Wachille	0.25 (0.43)

Table 5: Stochastic Parametric Herd Growth Frontier Estimates

Dependent variable: $Herd_t$	Point estimate [p-value]
$Herd_{t-10}$	0.141
	[0.779]
$Herd_{t-10}^2$	0.001
	[0.914]
$Herd_{t-10}^3$	-0.000
	[0.985]
Good rainfall	0.005
	[0.997]
Bad rainfall	-1.907
	[0.178]
Mega	0.613
	[0.963]
Arero	-5.009
	[0.713]
Negelle	-13.120
	[0.294]
Constant	206.316
	[0.976]
μ	68.511
Σ^2_μ	795.561
r^2	0.869

Note: robust p-values within brackets.

Table 6: Herd dynamics

Terminal node	Inefficiency > 65.42	Inefficiency $\leq$ 65.42 & $Herd_{t-10} \leq 66$	Inefficiency $\leq$ 65.42 & $Herd_{t-10} > 66$
Variable	Point estimate [p-value]	Point estimate [p-value]	Point estimate [p-value]
$Herd_{t-10}$	2.162	-6.739	268.360
	[0.000]	[0.007]	[0.020]
$Herd_{t-10}^2$	-0.0043	0.246	-3.074
	[0.001]	[0.002]	[0.027]
$Herd_{t-10}^3$	0.00027	-0.00231	0.0116
	[0.000]	[0.001]	[0.036]
Yabello	1.263	0.145	53.630
	[0.573]	[0.136]	[0.000]
Mega	4.495	-4.217	48.427
	[0.084]	[0.570]	[0.000]
Arero	1.388	-1.468	
	[0.584]	[0.016]	
Low rain	2.036	2.607	-18.317
	[0.007]	[0.208]	[0.002]
High rain	0.741	-1.337	-20.183
	[0.278]	[0.534]	[0.497]
Constant	-1.905	74.395	-7604.675
	[0.000]	[0.014]	[0.016]
Number of observations in subsample	164	41	29
r^2	0.28	0.76	0.71

Table 7: Expected evolution of wealth and inequality among the Borana.

	2003 (a)	2013 (disregarding ability) (b)	2013 (considering ability) (c)
Average herd size	12.76 (1.49)	10.47 (3.59)	14.59 (8.11)
Gini coefficient on herd size	0.46 (0.05)	0.66 (0.04)	0.71 (0.07)

Note: values in column (a) reflect the situation among the 97 respondents in the PARIMA sample that had cattle in 2003. Values in columns (b) and (c) are the expected values of the statistics for 500 runs of our simulation procedure. Values within parentheses are standard errors. The standard deviation for the Gini coefficient was computed using the algorithm described in Karagiannis and Kovacevic (2000).

Table 8: Expected effects of restocking under different targeting assumptions

Scenario		Number	Average Transfer	Average herd size (2003)	Expected herd size (2013)		Expected gains from transfer
					w/ transfer	w/out transfer	
1	Beneficiaries	17	2.12	2.88	4.06	2.71	1.35
	Non- Beneficiaries	80	0	14.86	12.05	12.05	-
2	Beneficiaries	13	2.69	12.54	14.63	11.48	3.15
	Non- Beneficiaries	84	0	12.80	10.25	10.25	-
3	Beneficiaries	9	4.00	13.22	24.15	15.26	8.89
	Non- Beneficiaries	88	0	12.72	14.54	14.54	-

Appendix: Regression trees analysis

This Appendix describes the construction of a regression tree using **G**eneralized, **U**nbiased, **I**nteraction **D**etection and **E**stimation (GUIDE). Loh (2002) is the central reference, while Loh (2005) explains how to use the program, which is freely downloadable from www.stat.wisc.edu/~loh/, and how to interpret the output.

We start by considering four categories of variables, as a function of their type (numerical(N)/ categorical(C)) and their role in the model (fit the model(F)/ split the tree(S)/ both):

	Fit	Split	Fit + Split
Numerical	F	S	N
Categorical	F *	C	N *

* in these cases, the variable is converted to a dummy variable. We use the same designation regardless of the role.

The algorithm proceeds in three steps: 1) choice of the splitting variable at each node of the tree; 2) choice of the splitting value and finally, 3) cost-complexity pruning. Steps 1) and 2) construct two mutually exclusive subsets at each node, starting with the set of all observations and stopping when the number of observations in the subsets falls below a predetermined (chosen) value. To avoid over-fitting the data, the tree is pruned back using a cost-complexity algorithm.

The choice of the split variable proceeds as follows:

1) obtain the residuals from the regression on the N and F variables;
2) for each numerical variables used to split the sample (either S or N), divide the data into 4 groups at the sample quartiles; construct a 2x4 contingency table with the signs of the residuals (positive/ non-positive) as rows and the groups as columns; count the number of observations in each cell and compute the χ^2 statistic and its p-value from the χ^2_3 distribution;

3) do the same for each categorical variable used to split the sample (either C or N), taking the categories of the variable as the columns; omit those columns with zero column totals;

4) to detect interactions:

   4.1) between pairs of variables, divide the space formed by them into 4 quadrants by splitting each in two at the sample median; construct a 2x4 contingency table (with residuals as rows and each quadrant as columns); compute the χ^2 statistic and its p-value;

   4.2) do the same for each S variable;

   4.3) use the value pairs of the C variables to divide the sample space; construct a 2 x (c1 x c2) contingency table, where c1 and c2 are the number of unique values of each variable; compute the χ^2 statistic and its p-value, omitting those columns with zero column totals;

   4.4) compute the χ^2 statistic and its p-value for each pair (N, C) from a contingency table with 2 x (2 x c1) dimensions, omitting those columns with zero column totals;

   4.5) do the same for each pair (S, C);

   4.6) do the same for each pair (S, N), following 4.4);

5) if the smallest p-value comes from one of the sets generated by steps 2) or 3), the associated variable is selected to split the node;

6) if the smallest p-value comes from one of the sets generated by step 4), then use the following rules to select which, from among the interaction variables, is the splitting variable:

   6.1) if only one of these variables is a N-variable, choose the other one;

   6.2) if neither is a N-variable, choose the one with the smallest p-value, as computed from step 3);

   6.3) if both are N-variables, split the node along the sample mean of each variable and choose the variable whose split yields the smaller total SSE.

After this step, the split value for that variable has to be determined. This is done using the next algorithm:

1) define the partitions $P_1(v)$ and $P_2(v)$ as:

   $P_1(v) = \{(y, X) \mid x_j \leq v\}$

   $P_2(v) = \{(y, X) \mid x_j > v\}$

where $x_j \in X_j$ and X_j is the chosen split variable;

2) regress y on X separately for each partition and obtain the residuals of these regressions (r_1 and r_2, respectively);
3) choose v to be the value of the split variable that minimizes the sum of squared residuals:

   $$1/n_1 * r_1^2 + 1/n_2 * r_2^2.$$

   where n_1 and n_2 are the number of observations in each partition.

Finally, once the most extensive tree is constructed, the algorithm "prunes" it to avoid over-fitting the data. This is done using cost-complexity pruning, where a penalty is put on overly complex trees: formally, the cost complexity criterion is expressed by

$$\text{(A.1)} \qquad C_\alpha (T_b) = \sum_{n=1\ldots b} \sum_{(xi,\, yi) \in n} (y_i - \beta_n x_i)^2 + \alpha * b$$

where α is the penalty parameter ($0 \leq \alpha \leq \infty$), T_b represents a tree with b nodes. The objective of the algorithm is to identify the tree that minimizes C_α. It proceeds in two steps: the construction of the optimal tree for each value of α (denote it by $T^*(\alpha)$) and the choice of the optimal α (denote it by α^*). Denote by T_0 the tree originated when splits were costless (that is, $\alpha = 0$).

1) Start with T_0 and increase α.
2) Remove any terminal splits in T_0 whose elimination reduces the value of equation (A1), producing a new tree. This is done by merging the observations in these terminal nodes in a new terminal node.
3) Increase α by a chosen increment.
4) Repeat Steps 2) and 3) until the nodes of tree have a unique element (by analogy with our previous notation, denote the resulting tree by T_∞).
5) For each $T^*(\alpha)$, produce a V-fold cross validated estimate of the squared sum of residuals (SSR) in equation (A1).

6) Choose $T^*(\alpha)$ that minimizes the SSR.

Breiman et al. (1984) show that each of the trees in the (finite) sequence between T_0 and T_∞ is unique and it must contain $T^*(\alpha^*)$. The concept of V-fold cross-validation is explained in detail in Hastie et al. (2001, section 7.10).