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Heterogeneous wealth dynamics: The role of risk and ability

Paulo Santos
Monash University

Christopher B. Barrett
Cornell University

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Poverty traps commonplace in policy debates today.

But are there really poverty traps?

Do people perceive such dynamics accurately?

If poverty traps exist, what sort, why and for whom?

Multiple dynamic equilibria w/threshold effects?

Conditional/club convergence based on immutable characteristics, w/unique low-level eqn?

Might populations exhibit heterogeneous dynamics?

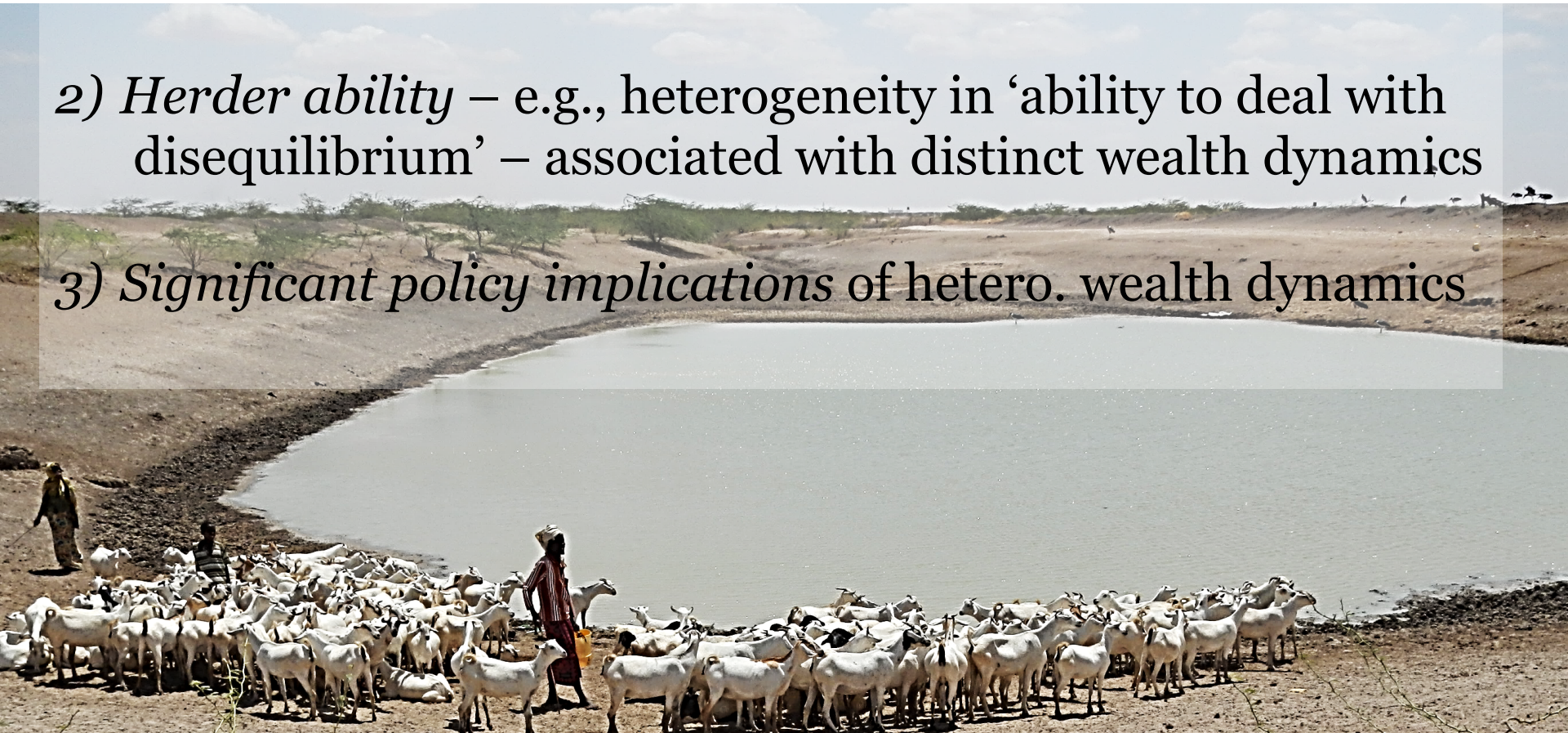
Can we identify heterogeneous wealth dynamics?

What **policy implications** of heterogeneous wealth dynamics?



What we find, studying southern Ethiopian pastoralists:

- 1) Nonlinear wealth dynamics that result in multiple dynamic equilibria only arise in *adverse states of nature*.
- 2) *Herder ability* – e.g., heterogeneity in ‘ability to deal with disequilibrium’ – associated with distinct wealth dynamics
- 3) *Significant policy implications* of hetero. wealth dynamics





Generalizing the two distinct poverty trap mechanisms:

$$y_{ist} = \begin{cases} \alpha_{s\ell}^c + g_{s\ell}^c(y_{i0}) + \varepsilon_{ist\ell}^c & \text{if } i \in c \text{ and } y_{i0} < \gamma_s^c \\ \alpha_{sh}^c + g_{sh}^c(y_{i0}) + \varepsilon_{isth}^c & \text{if } i \in c \text{ and } y_{i0} \geq \gamma_s^c \end{cases}$$

where y is a measure of well-being (e.g., assets)

i indexes individuals, s states of nature, t time periods and
 c cohorts/clubs

h is the high equilibrium BA, ℓ is the low equilibrium BA

γ^c is a cohort-specific threshold

Note:

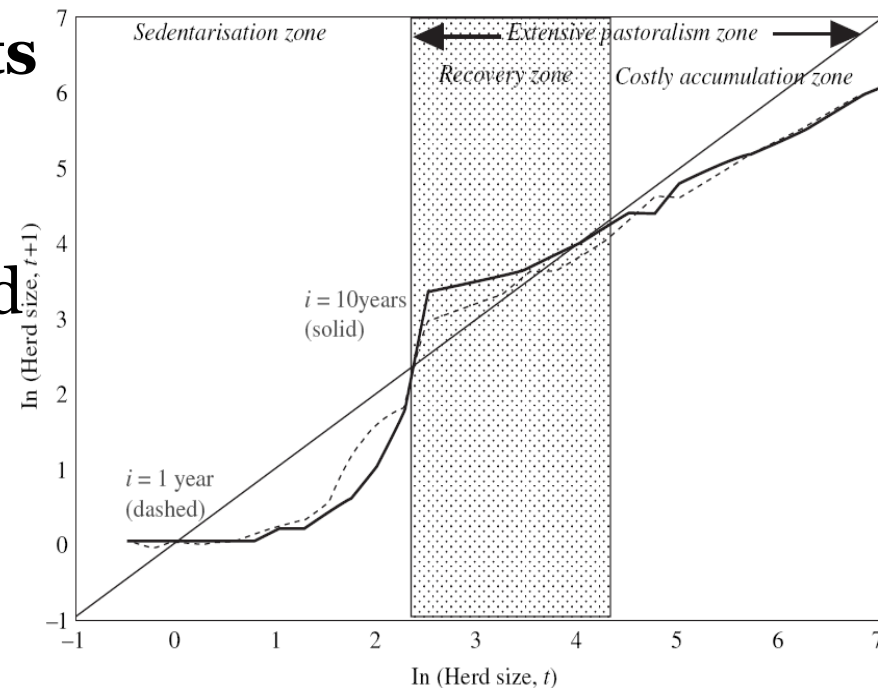
$\gamma^c=0$ and $g(\cdot)$ concave implies unique dynamic eqn

$\alpha^c=\alpha$ and $g^c(\cdot)=g(\cdot)$ imply common path dynamics for all



Southern Ethiopian pastoralists

- Simple pastoralist system
- Droughts major system shock
- Prior studies found S-shaped herd dynamics and multiple dynamic wealth equla (Lybbert et al. 2004 *EJ*, Santos & Barrett 2011 *JDE*).



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



Unusual data: can unpack wealth dynamics

Scalar-valued asset (livestock herd ... TLU), with hh panel and state-conditional growth expectations

Quarterly/annual hh panel, 2000-3 on 120 households in same *woreda* as Lybbert et al. (2004 *EJ*). Kenyan subsample also exhibits S-shaped herd dynamics (Barrett et al. 2006 *JDS*).

Subjective herd growth expectations, 2004 (n=288)

- randomly selected herd size within 4 herd size intervals ([1,5),[5,15),[15,40), [40,60] head of cattle)
- asked herders rainfall expectations for next year (A/N/B) and herd size distributions, given four random start values
- established if respondent ever managed a herd that size



Table 1: PARIMA data: definition and descriptive statistics

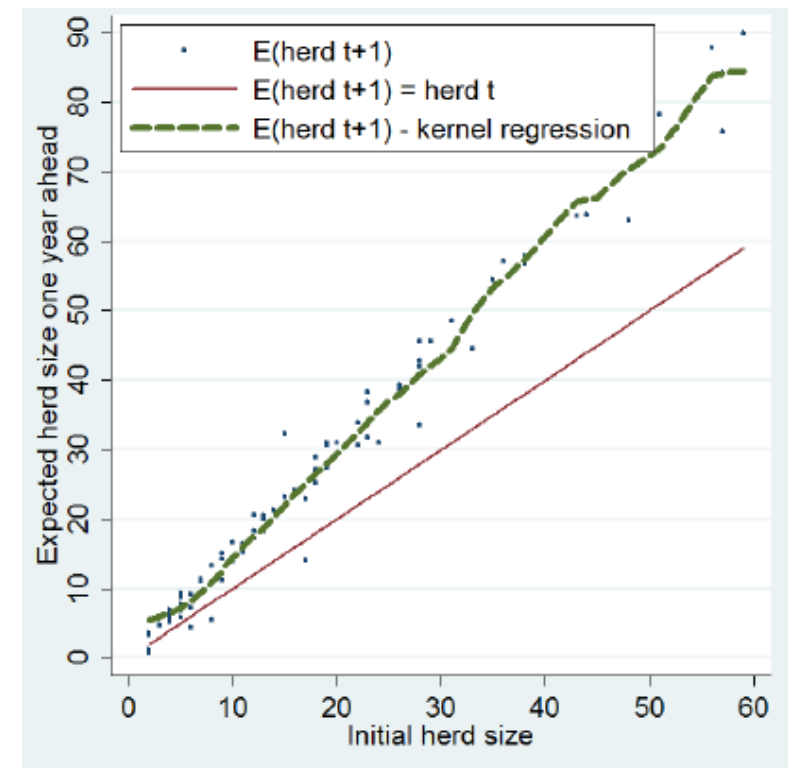
Variable	Definition	Mean	Std. Err.
herd size at t	herd size at t	9.18	12.87
herd size at t-1	herd size at t-1	8.12	11.35
no cattle at t-1	=1 if owns no cattle at t-1, 0 otherwise	0.19	0.39
herd below threshold at t-1	=1 if $0 < \text{herd size at t-1} < 15$, 0 otherwise	0.68	0.47
herd above threshold 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
Dida Hara	=1 if lives in Dida Hara	0.25	0.43
Dillo	=1 if lives in Dillo	0.25	0.43
Qorate	=1 if lives in Qorate	0.25	0.43
Wachille	=1 if lives in Wachille	0.25	0.43



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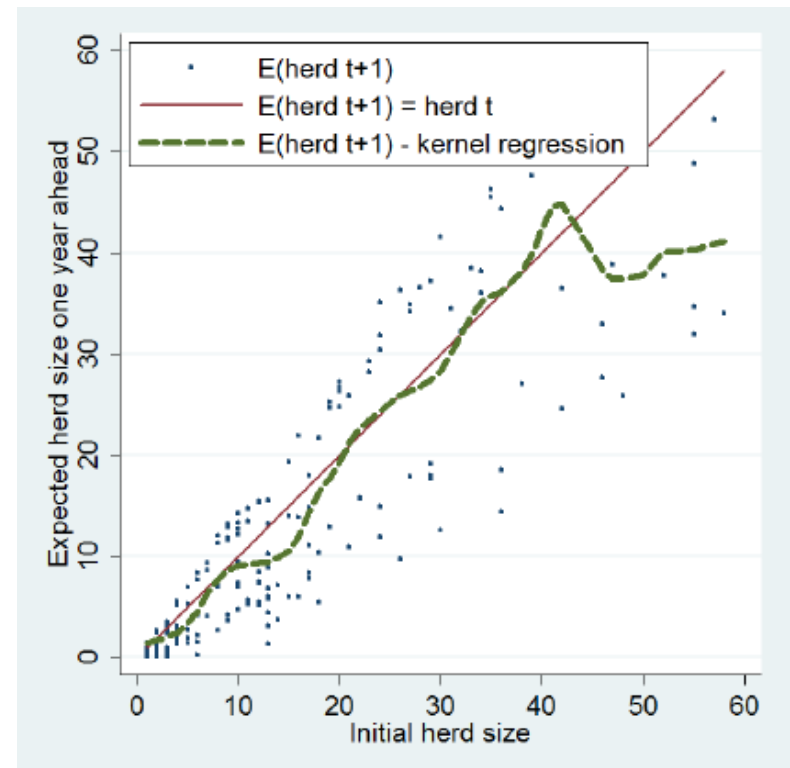
State-conditional herd growth

Under normal/good rainfall, virtually universal expectations of near-linear growth, with minimal dispersion among herders.





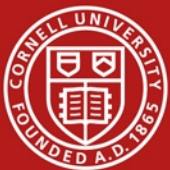
But with low rainfall, considerable dispersion, and highly nonlinear herd dynamics ... some suggestion that multiple equilibria poverty trap arises due to drought risk. Insurance and risk management ability become important differentiators.





Observed herd dynamics are a mixture of draws from state-conditional herd growth distributions. So simulate unconditional herd dynamics using data on (i) weather distributions and (ii) state-conditional growth functions. Then differentiate by herding ability and re-estimate.

1. Estimate parametric state-conditional growth functions.
2. Check that the observed mixtures match observed herd growth. Then predict transition probabilities.
3. Simulate dynamics w/climate change (B&S 2014 *EcolEcon*)
4. Estimate herder-specific ability and re-estimate unconditional herd growth functions conditional on ability.



1. Estimate parametric rainfall-conditional herd growth function:

$$h_{1ir} = f(h_{0ir}) + \alpha_i + \varepsilon_{ir}$$

where $f()$ is polynomial and r indexes rainfall state.

Table 4: Estimates of Expected Herd Dynamics Conditional on Rainfall

Variable	Very Good	Good	Bad	Very bad
herd ₀	1.293 (0.000)	1.477 (0.019)	0.528 (0.224)	0.246 (0.246)
herd ₀ ²			0.026 (0.010)	0.009 (0.010)
herd ₀ ³			-0.00039 (0.0001)	-.00017 (0.0001)
constant	0.897 (0.448)	0.179 (0.416)	0.513 (1.185)	-0.575 (1.083)
N	61	96	192	61
R ²	0.986	0.994	0.792	0.589

Note: Values within parenthesis are robust standard errors

Results replicate earlier figures (as they should).



2. Check if unconditional dynamics implied by estimated model match observed herd dynamics

Simulate unconditional herd dynamics using simple method:

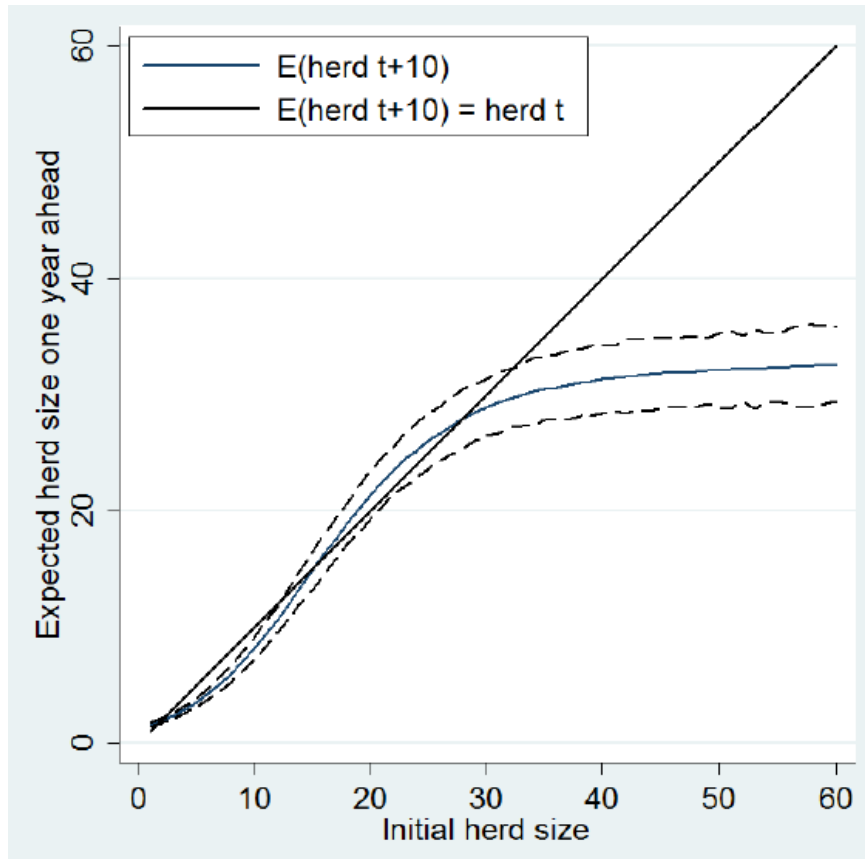
t-1	t	t+1
predict herd _t (herd ₀ given)	→ rainfall draw ↓ call $h_{t+1}=f(h_t \mid \text{rainfall})$ ↓ predict $h_{t+1} \rightarrow$	repeat as in t

Simulate using 500 replicates for each starting value to simulate 10-year ahead herd size transitions

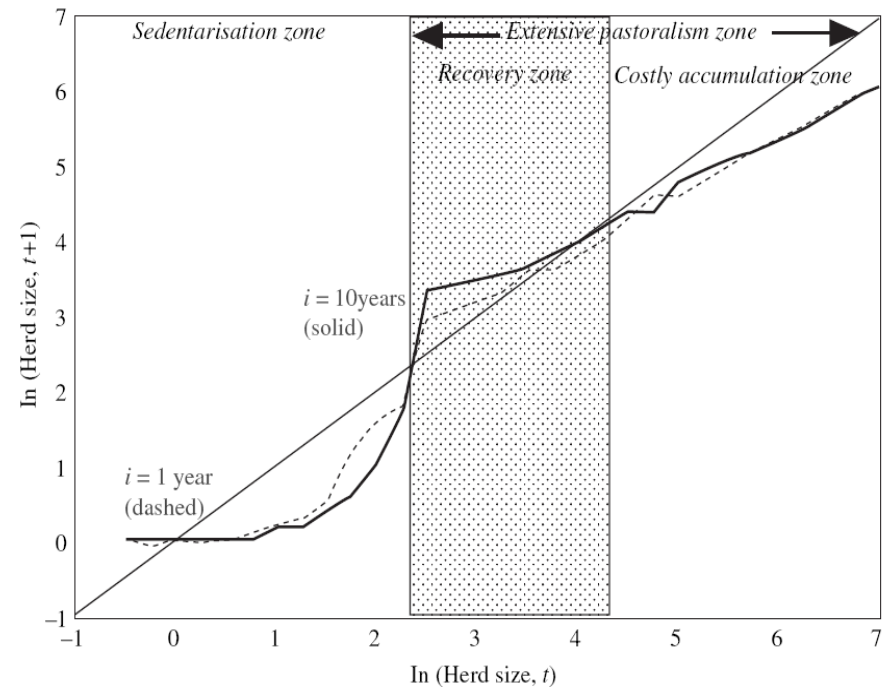


Expected herd dynamics with stochastic weather

Result:



Compared w/observed:



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

For coarse methods, very strong correspondence (equilibria and shape the same). Herders seem to understand the system.



Implied 10-year herd transition probability matrix is:

Table 5: Estimated herd size ten year transition matrix

herd_{t+10} herd_t	0-4	5-14	15-39	>40
1-4	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

Not non-ergodic distributions, but very clearly different probabilities of outcomes based on initial conditions.

Looks like a poverty trap w/ a herd size threshold ~ 15 TLU.



4. Estimate herder-specific ability and then re-simulate.

Exploit the household panel data to generalize the earlier parametric growth function using stochastic frontier estimation methods:

$$h_{it} = f(h_{it-1}) + \beta X_{it-1} - \phi_i + \psi_{it}$$

where $\phi_i \geq 0$ is a one-sided, herder-specific, time-invariant inefficiency estimate. Use this as proxy for herder ability.

Let $f()$ be an exogenous switching specification:

$$f_{it} = \begin{cases} f^L(h_{it-1}) & \text{if } h_{it-1} < 15 \\ f^H(h_{it-1}) & \text{if } h_{it-1} \geq 15 \end{cases}$$



Estimation concerns:

- Lagged herd size endogenous, so inefficiency estimates almost surely inconsistent.
- Misspecification will be conflated with inefficiency

Neither a problem if we just use ordinal groupings:
high vs. low ability cohorts.

[Robustness check with nonparametric DEA yields qualitatively identical results.]

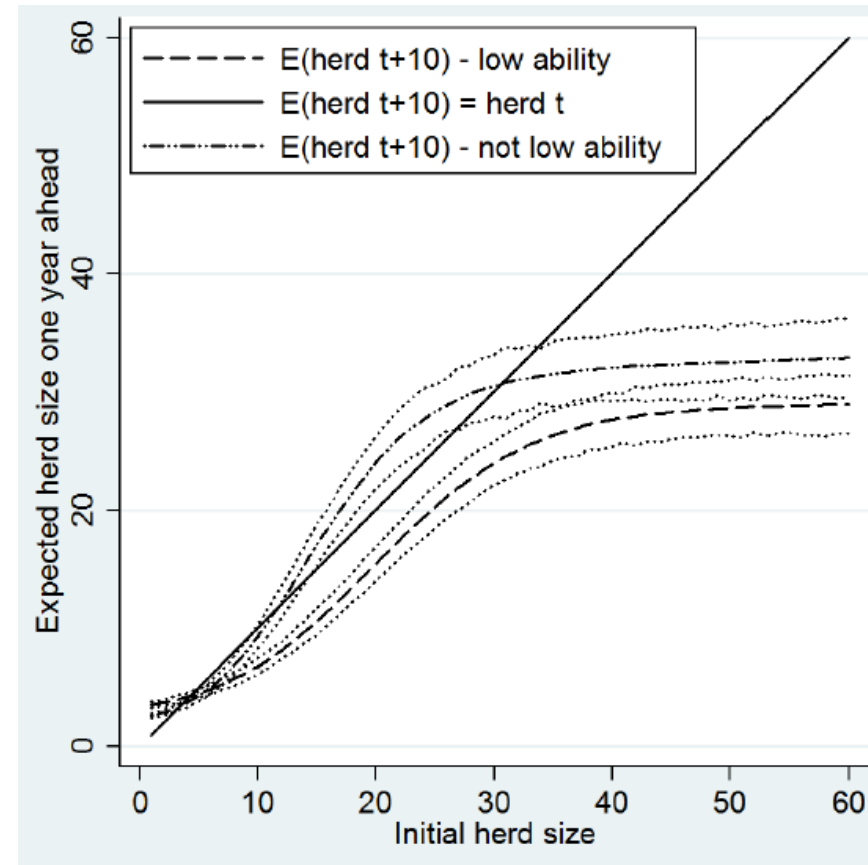




Now divide sample into two: lower ability subsample (4th quartile of the φ_i dist'n) and the rest. [Results robust to other partitionings of inefficiency dist'n.] Re-estimate herd growth models for each sub-sample. [Results qualitatively identical to earlier results.] Re-simulate.

Results show two different herd dynamics:

- Low ability herders have just one low-level equilibrium
- Higher ability herders face multiple dynamic herd equilibria





Use these disaggregated estimates to simulate evolution of herd sizes. What difference does ability make?

Incorporating ability leads to:

- (i) directionally different aggregate growth estimate
- (ii) greater growth in inequality

Table 7: Expected evolution of wealth and inequality among the Boran

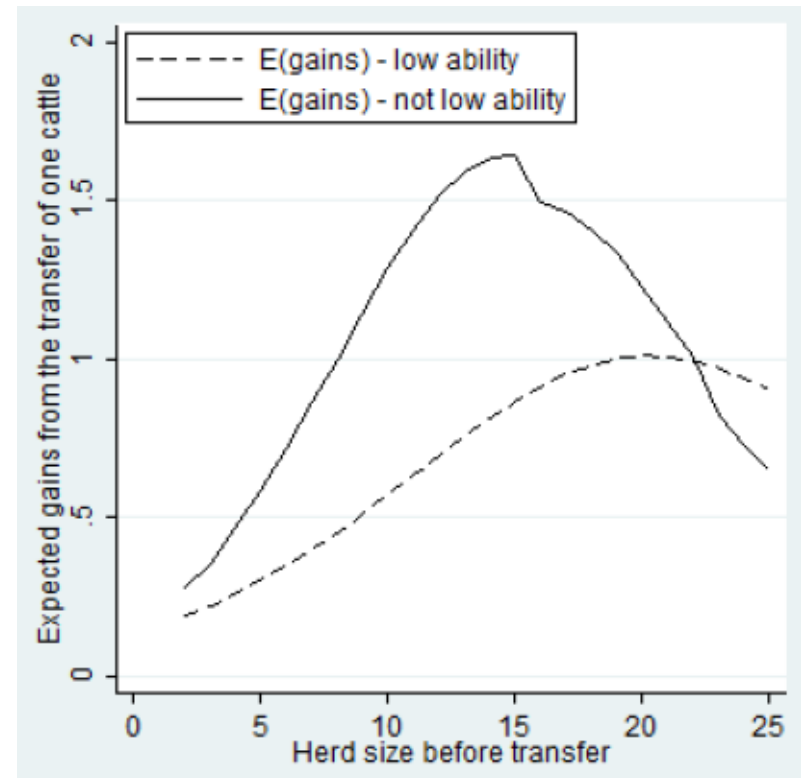
	t=0	t=10 (disregarding ability)	t=10 (considering ability)
	(a)	(b)	(c)
Average herd size	12.76 (1.49)	9.61 (3.34)	15.85 (8.89)
Gini coefficient on herd size	0.46 (0.05)	0.66 (0.04)	0.71 (0.07)



In this region, perhaps the most common post-drought policy intervention (pre-insurance) was herd restocking.

With heterogeneous ability, targeting becomes critical because expected returns vary based on recipient ability.

Only higher ability herders w/ initial herds of 9-22 TLU grow herds following restocking.





Target the poorest ... but poverty is correlated with both ability and herd size. If we could target those with adequate herd size (or adequate herd size and ability), could substantially increase ROI from herd restocking.

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	4.46	3.63	0.86
	Non-Beneficiaries	80	0	14.86	18.45	18.45	0
2	Beneficiaries	23	2	10	12.20	9.34	2.86
	Non-Beneficiaries	74	0	13.62	17.88	17.88	0
3	Beneficiaries	18	1.94	10.05	13.40	10.09	3.3
	Non-Beneficiaries	79	0	13.38	17.16	17.16	0

Targeting method

ROI pa

Naïve

-4.4%

Herd size

3.6%

Herd size and ability

5.4%



Even in a simple system, wealth dynamics appear heterogeneous

- Two different sorts of poverty traps at play
- Weather shocks give rise to one sort of poverty trap for herders of average or better ability
- Low ability generates a different sort of poverty trap
- This matters for policy since the mechanism behind growth dynamics matters to the impact of interventions.
 - Risk management may be as/more valuable than transfers
 - Targeting of social protection matters a lot

Thank you for your time and interest!

