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Risk and intertemporal substitution: Livestock portfolios and off-take among Kenyan pastoralists

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ABSTRACT

Most decisions involve variability in two dimensions: uncertainty across states of nature and fluctuations over time. The stakes involved in tradeoffs between these variability dimensions are especially high for the poor who have difficulty managing and recovering from shocks. We assume Epstein and Zin recursive preferences and estimate risk aversion and intertemporal substitution as distinct preferences using data from Kenyan herders. Results suggest that the assumption implicit in additive expected utility models that relative risk aversion (RRA) is the inverse of the elasticity of intertemporal substitution (EIS) is flawed. Specifically, our RRA and EIS estimates are consistent with a preference for the early resolution of uncertainty, which we believe is driven importantly by the instrumental value of early uncertainty resolution. This same preference pattern is consistent with asset smoothing in response to a dynamic asset threshold.

1. Introduction

Most decisions in life involve variability in two dimensions: uncertainty across states of nature and fluctuations over time. Classic savings and investment dilemmas, for which there are well-established analytical frameworks, epitomize the complex interplay between state and time variability, but even trivial decisions often hinge on basic tradeoffs between these dimensions. While this two dimensional variability is a central feature of human existence, the stakes are perhaps never greater than for the poor in poor countries who are exposed to extreme volatility in welfare outcomes and often lack access to capital and institutions necessary to manage and recover from these fluctuations. The presence of poverty traps may further complicate tradeoffs between state and time variability. Near a dynamic asset threshold the poor may be extremely risk averse to uncertainty across states and yet willingly increase consumption variability over time to protect their assets from this threshold. Asset pricing and equity premium questions have prompted economists in finance and macroeconomics to discern between risk and intertemporal substitution preferences among investors in rich countries (e.g., Attanasio and Weber, 1989; Campbell, 1996; Schwartz and Torous, 1999; Vissing-Jorgensen and Attanasio, 2003). There has been no attempt as yet to distinguish between the two preferences among a poor and vulnerable population, a void we aim to fill.

Time-additive Expected Utility (EU) models, which remain the default for modeling intertemporal decisions, attribute willingness both to insure across states and to smooth consumption across dates to the concavity of the utility function. In this framework, risk aversion and resistance to intertemporal substitution are but different manifestations of the same primal preference. This assumption restricts the two most common measures of these preferences—the coefficient of Relative Risk Aversion (RRA) and the Elasticity of Intertemporal Substitution (EIS)—to be simple inverses of each other and quite literally two sides of the same coin. While it may seem logical for RRA and EIS to be inversely related in some settings, there are reasons to believe this may not be a sensible restriction in the setting we are studying. According to the standard interpretation, deviations from this inverse restriction relate to the timing of uncertainty resolution (Kreps and Porteus, 1978). As a complement to this perspective, we argue that when asset accumulation and

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preservation is critical to future income production, individuals may be both relatively risk averse (higher RRA) and have a relatively high tolerance for consumption variability over time as reflected in the EIS (higher EIS).

Risk and intertemporal variability have long played a central role in economists' understanding of decision making among the poor. Recent empirical work has shed valuable light on the topic. Risk sharing and consumption smoothing have figured prominently in this literature (e.g., Dercon, 2004; Fafchamps and Lund, 2003; Kazianga and Udry, 2006; Townsend, 1994). While much of this work relies on reduced-form estimation, some notable and relevant exceptions take a structural approach. Rosenzweig and Wolpin (1993) estimate a structural dynamic model of agricultural investment to study consumption smoothing. They estimate an average coefficient of RRA of 0.96, but assume time-additive EU preferences so that EIS = 1/RRA = 1.04. Atkeson and Ogaki (1996) use the same data and same restriction to estimate EIS for the poor as 0.50 and for the rich as 0.80. In a cross-country comparison, Ogaki and Atkeson (1997) estimate the average EIS since 1960 as 0.27 for India and 0.40 for the United States. Such EIS differences could theoretically generate poverty traps in which the poor with low EIS fail to invest in high return activities (Bliss, 2006), but the pervasive inverse restriction makes a low EIS-induced poverty trap indistinguishable from a high RRA-induced trap. Fafchamps (1993) makes a step away from the inverse restriction by using a dynamic formulation to study sequential labor decisions among farmers in Burkina Faso. In his formulation, RRA and EIS appear as distinct parameters, but to estimate the model he arbitrarily sets RRA at 0.50. His point estimates for EIS range from 0.04 to 1.14, but are statistically indistinguishable from either zero or 1/RRA = 2. Although Fafchamps breaks from the inverse relationship imposed by time-additive EU, he is ultimately unable to estimate EIS and RRA separately.

More recent work in development economics clearly suggests that the distinction between variability across states and dates can matter enormously for the poor, especially if underlying asset dynamics are characterized by dynamic thresholds and poverty traps (e.g., Barrett et al., 2006; Hoddinott, 2006; Lybbert et al., 2004). In such cases, individuals may willingly and rationally destabilize consumption in order to smooth assets and avoid irreversible asset losses[1] (Carter and Barrett, 2006; Zimmerman and Carter, 2003). While fully exploring how poverty dynamics relate to the distinction between RRA and EIS preferences is beyond the scope of this paper, we draw our motivation from the intuition that the presence of poverty traps fundamentally alters tradeoffs between state and time variability. These potentially altered tradeoffs are relevant to the pastoral systems we study as they have been characterized by asset smoothing (Barrett et al., 2006; McPeak, 2004) and non-convex herd dynamics (Lybbert et al., 2004). Evidence that pastoralists in this setting perceive these non-convex dynamics (Santos and Barrett, 2006b) suggests that their tradeoffs between state and time variability may indeed be shaped accordingly.

This paper makes three interrelated contributions. First and most importantly, this empirical analysis represents, to our knowledge, the first estimation of Epstein and Zin (1991, hereafter EZ) preferences among a poor population for whom assets are not financial investments. Our context involves Kenyan pastoralists investing in large and small livestock rather than stocks and bonds and requires a modified empirical approach. Livestock risk and return in this context is highly seasonal and idiosyncratic (Lybbert et al., 2004), which necessitates a household-specific approach to estimating expected livestock returns. Our results illustrate what can be gained by allowing RRA and EIS to be estimated independently, and what may be lost by using a model that restricts them to be inverses of each other. Second, by estimating RRA and EIS as distinct preferences, we are able to explore precisely how they differ. We apply the common interpretation of this difference (Kreps and Porteus, 1978) to provide the first empirical test for a Preference for Early Resolution of Uncertainty (PERU) among a poor and vulnerable population for which the timing of uncertainty resolution may be especially important. We find strong evidence against this restriction and in favor of PERU. Given our research context, poverty dynamics and asset smoothing provide an insightful complementary interpretation of the difference between RRA and EIS. Although we do not provide a full, formal treatment of the linkages between PERU and asset smoothing—which is the subject of ongoing research—we hope in this paper to stimulate new thinking about how we model vulnerability and intertemporal decision making among the poor. Finally, this paper uses cross site differences to indirectly investigate whether our estimates of RRA and EIS result from underlying preferences or from structural features that are difficult to observe and model explicitly. We exploit differences in production and marketing conditions to interpret to what extent our findings reflect preferences and to what extent they reflect underlying constraints. Although these contrasts do not allows us to precisely decompose the role of preferences and constraints in our estimates, we present findings that suggest our estimated preferences are shaped in part by structural features.

2. Risk, intertemporal substitution and uncertainty resolution

EIS captures an individual's willingness to move consumption *between time periods*, typically in response to changes in the expected rate of return on an asset base from which consumption is drawn, and exists with or without uncertainty. RRA, on the other hand, captures an individual's willingness to move consumption *between states of nature* and exists with or without multiple periods (Schwartz and Torous, 1999). Thus, EIS reflects preferences about consumption variability across time, while RRA reflects preferences about variability across states of nature.[2] More concretely, in our empirical application, EIS corresponds to the individual's tolerance for consumption variability over time, largely reflecting the degree to which they sell livestock to buffer fluctuations in milk produced by the herd, while RRA corresponds to the individual's tolerance for an asset portfolio containing a higher share of high risk high return assets (goats and sheep) compared to lower risk lower return assets (camels and cattle). In this section, we describe the prevailing interpretation of the difference between these preferences as an indication of PERU. Using this familiar perspective as a point of departure, we then explore an asset smoothing interpretation of differences between RRA and EIS.

The pervasive time-additive EU assumption forces an inverse relationship between EIS and RRA. While in many contexts it might be reasonable for a risk averse individual to like neither variation across states of nature nor consumption variability across time, this inverse relationship also implies individuals are indifferent about the timing of the uncertainty resolution (Kreps and Porteus, 1978)—i.e., uncertainty resolved a week from now is indistinguishable from uncertainty resolved a year from now. There are, however, good reasons why individuals may care about the timing of uncertainty resolution. First, early resolution often confers an *instrumental* benefit by allowing individuals to refine future plans and to make adjustments. Second, individuals may have primitive preferences that assign *inherent* value to early or late resolution of uncertainty.

[1] As quoted in Zimmerman and Carter (2003): "…the reduction of food consumption tends to be an early response to the threat of entitlement failure, apparently motivated, at least partly, by the preservation of productive assets. (Drèze and Sen, 1989)".

[2] These distinctions apply equally to EIS and higher order risk preference measures such as prudence ($-u'''/u''$), cautiousness, and temperance, which all involve derivatives of the contemporaneous utility function and are well-defined even in single period models.

These preferences have been explored in experimental settings, where they are commonly linked to anxiety or hope depending on whether individuals prefer early or late resolution, respectively (e.g., Chew and Ho, 1994; Lovallo and Kahneman, 2000). If an individual has locked in his plans and can make no adjustments, early resolution has no instrumental value, but could still have inherent value to the individual. In our setting, both inherent and instrumental value may be important. Instrumentally, a herder can decide to move his herd to a different grazing area upon receipt of information. If this information is correct and his reaction is timely, such early resolution of uncertainty could make the difference between maintaining a productive herd and suffering painful asset losses. Based on emotions such as regret, anxiety and hope and their daily struggle to survive, herders may also harbor an inherent value for early resolution even if they cannot use the information to alter herd migration decisions.

Economists' efforts to detect PERU empirically hinge importantly on this distinction between inherent and instrumental value of early resolution. Since the instrumental value depends on the structure of a given context, a structural model could in principle capture the instrumental value of early resolution—but only if one knows enough about resolution timing and intervening planning and adjustment opportunities to model early resolution as a structural feature of the model (Dreze and Modigliani, 1972; Mossin, 1969; Spence and Zeckhauser, 1972).[3] An alternative means of testing for PERU is to embed the value of early resolution into preferences. This is precisely what Kreps and Porteus (1978) preferences do. Specifically, this preference specification allows individuals to value early resolution both instrumentally and inherently, but cannot discern between the two since the full value of early resolution implied by observable behavior is attributed to preferences.[4] In contrast, time-additive EU preferences disallow any inherent value of resolution timing and can only capture its instrumental value if one has the wherewithal to take the structural approach. While the structural approach may describe the decision problem more completely and may therefore be preferable to the preference approach, empirical implementation of the structural approach may simply be impossible due to the mismatch between the intertemporal structure of uncertainty resolution and the temporal resolution of data on relevant decision making. Experimental approaches may (partially) remedy this problem, but observational field data will nearly always suffer from this mismatch. This is true in our case, so we take the preference approach in this paper and attribute both the instrumental and inherent value of resolution timing to herder preferences.

The Kreps and Porteus (1978) preference structure relies on a recursive formulation that preserves preference consistency via a "temporal consistency" axiom while allowing for non-indifference about the timing of uncertainty resolution. This structure specifies intertemporal utility recursively over current period consumption (K_0) and uncertain future consumption ($\tilde{K}_1$). Following the notation and exposition of Gollier (2001), this structure is defined as

$$U\left(K_0,\tilde{K}_1\right) = u_0(K_0) + u_1\left(v^{-1}\left(Ev\left(\tilde{K}_1\right)\right)\right) = u_0(K_0) + u_1\left(w\left(\tilde{K}_1\right)\right) \quad (1)$$

where v is a monotonically increasing utility function and w is the certainty equivalent function defined as $v\left(w\left(\tilde{K}_1\right)\right) = Ev\left(\tilde{K}_1\right)$. Preference parameters EIS and RRA are distinct in this formulation because they relate to different functions. The concavity of v determines risk aversion but not EIS. The concavity of u_0 and u_1 determine EIS but not risk aversion since the function w has effectively removed all uncertainty. EZ use convenient power functions to define these functions as $\beta u_0(K) = u_1(K) = \frac{K^{1-\alpha}}{1-\alpha}$ and $v(K) = \frac{K^{1-\gamma}}{1-\gamma}$, where α indicates the relative resistance to intertemporal substitution such that $1/\alpha = \sigma$ is EIS, and γ is the coefficient of RRA. Time-additive EU is a special case that obtains when $\alpha = \gamma = 1/\sigma$ such that the concavity of these functions is identical and preferences over state and time variability are one-and-the-same. This requires, in other words, that risk aversion and desire to smooth consumption move in the same direction. Violation of this restriction implies non-indifference to the timing of uncertainty resolution. In particular, $\gamma > \alpha = 1/\sigma$ implies PERU (see Gollier, 2001 p.300) [5] and suggests that individuals are more risk averse than they are concerned about smoothing consumption.

This implication offers an intriguing link to the recent asset smoothing literature: PERU implies that risk aversion and desire to smooth *assets* move in the same direction. From this perspective, the possibility that agents concurrently smooth income and assets makes the standard inverse assumption fundamentally flawed. Such an agent would simultaneously demonstrate a high RRA and a high EIS, which implies that the PERU test for $\gamma > 1/\sigma$ is also consistent with asset smoothing. While this pattern of preferences is therefore indistinguishable from PERU, the interpretation is different. What appears to be a high tolerance for consumption variability (high EIS) instead reflects a deliberate strategy to protect asset stocks against irreversible losses—a reasonable strategy if assets determine future consumption. In contrast to the PERU perspective, which attributes $\gamma > 1/\sigma$ to the inherent and instrumental value of early resolution of uncertainty, the asset smoothing perspective attributes this pattern to preferences that are conditioned on optimal responses to structural constraints and dynamics.

Just as estimates of PERU include both instrumental and inherent value of early resolution of uncertainty, the inability to capture the full spatial–temporal structure of a context attributes structural features to estimates of RRA and EIS. While we generally interpret RRA as the outcome of an individual's selection of payoffs and probabilities that optimally balance expected income and variability of income, structural constraints that cannot be fully captured with observational data can confound this interpretation. In our livestock setting, we could potentially attribute a preference for largestock (camels and cattle) over smallstock (goats and sheep) to risk aversion because largestock are generally lower risk lower return and smallstock are higher risk higher return. However, structural differences in production environment can also shape the risk profile of livestock as assets as we illustrate below by comparing livestock risks and returns across our two study sites. In recognition of this we will describe these differences and estimate key parameters for the two areas separately. Similarly, we typically interpret an EIS estimate assuming individuals have ways to draw down or store up wealth in order to adjust consumption levels across time periods. The nomadic pastoralists in our setting make these consumption-wealth adjustments largely through milk and animal transactions. Given limitations to milk storage and thin local milk markets, high fluctuations in milk consumption over time may reflect the lack of a mechanism to conserve milk income into wealth that can be stored over time. The means by which herders can buffer these milk fluctuations is largely though decisions to slaughter or sell animals, steps that confront the herder with the decision to balance current period consumption

[3] Such a structural approach is akin to removing (some of) the concavity of the utility function by attributing it to structural features such as credit market imperfections or dynamic thresholds rather than to primitive preferences that exhibit decreasing marginal utility of consumption (Lybbert and Barrett, 2007; Masson, 1972).

[4] While instrumental reasons for PERU are "completely orthogonal" to inherent reasons for PERU because the former has structural roots and the latter has preference roots (Gollier, 2001 p.300), Kreps and Porteus (1978) preferences capture both in the same way that the concavity of the utility function (and hence risk preferences) will reflect any structural features that are not explicitly incorporated in the structure of the problem (e.g., Masson, 1972).

[5] Others have referred to this same relationship between risk aversion and intertemporal substitution (i.e., more risk averse than resistant to intertemporal substitution) as "correlation aversion" (Bommier, 2003) and "intertemporal risk aversion" (Traeger, 2007).

against the objective of asset accumulation in the context of stochastic asset shocks.

From the asset smoothing perspective, structural features can drive a wedge *between* EIS and RRA estimates as well. Near a dynamic asset threshold, optimal intertemporal behavior requires adjustments in consumption and investment decisions. A pastoralist whose herd size looms just above a critical herd size threshold will simultaneously prefer less uncertainty across states (Lybbert and Barrett, 2007; Lybbert and Barrett, 2011) and smoother asset holdings—and, hence, more consumption variability—over time. In our context, this would be evident in deliberate suppression of consumption in the current period (e.g., limiting consumption to the flow of milk from the herd by not selling animals to buy food) and trading smallstock for largestock to reduce aggregate risk in order to limit the odds of falling below the dynamic herd threshold in the near future. Such a herder would appear then to have both relatively high RRA and relatively high EIS. Although this preference pattern is not possible in conventional time additive models, we argue that it is possible or even probable among some herders in our study site.

3. Model

In deriving our model, we use the EZ recursive preference specification and follow the empirical approach derived by Campbell (1996) and modified by Vissing-Jorgensen and Attanasio (2003). They consider consumption and the allocation between stocks and bonds. We analogously consider consumption in the form of herd off-take and the allocation between small and large livestock. Herders in our sample derive nearly all of their household consumption from their livestock—either directly in the form of milk consumption or indirectly via income earned through off-take and milk sales. Herd growth and total milk production in this setting are highly stochastic. The model we derive in this section uses herders' allocation between small and large livestock, their consumption off-take from these herds, and their expected rates of return for small and large livestock to provide distinct estimates of RRA and EIS. The differences between smallstock and largestock in this pastoral setting are central to this empirical approach. As described in McPeak (2004, 2005), smallstock (goats and sheep) are managed very differently than largestock (cattle and camels). Relative to largestock, smallstock can reproduce quickly thanks to short pregnancies and lactation periods, but are less robust to extended periods of drought-related stress. Smallstock are easier to sell than largestock, in part because they are less lumpy. Largestock may be difficult to cash out, but they produce a much steadier dividend stream in the form of milk production. Whereas high return and high risk smallstock are like junk bonds and penny stocks, largestock are more like large capitalization mutual funds.

EZ recursive preferences for herder household *j* are captured in the intertemporal utility function

$$U_{jt} = \left\{K_{jt}^{1-\alpha} + \beta\left[E_{jt}\left(\tilde{U}_{j,t+1}^{1-\gamma}\right)\right]^{(1-\alpha)/(1-\gamma)}\right\}^{1/(1-\alpha)} \tag{2}$$

where K_{jt} is the value at prevailing period t prices of herd off-take in the form of livestock sales, slaughter, transfers out of the herd, and total milk produced by the herd that is allocated to household consumption; ~ indicates a random variable; E_{jt} denotes the household-specific expectation conditioned on information available at time t; and β is the time discount factor

Since their wealth is largely—if not exclusively—held in livestock form, each herder's budget constraint is closely tied to the equation of motion for herd size, which is a function of the herd growth rate. For convenience, we represent livestock and off-take in value units and herd growth rates as rates of return. Assuming that seasonal milk production is consumed or marketed within the season, that herders only accumulate wealth in livestock form, and that the opportunity cost of milk diverted to human consumption (in terms of foregone herd growth) is reflected by market prices for milk,[6] herd wealth for household j in period $t+1$ is given by

$$\begin{aligned}\tilde{H}_{j,t+1} &= \left(H_{jt}-K_{jt}\right)\tilde{R}_{Tot,j,t+1} \\ &= \left(H_{jt}-K_{jt}\right)\left[\omega_{Sjt}\tilde{R}_{Sj,t+1} + \left(1-\omega_{Sjt}\right)\tilde{R}_{Lj,t+1}\right]\end{aligned} \tag{3}$$

where $\tilde{R}_{ij,t+1}$ is gross herd return in period $t+1$ for $i = Tot$ (total herd), $i = S$ (small livestock), and $i = L$ (large livestock), and ω_{ijt} is the proportion of the total herd in small and large livestock in time t. Gross return on the herd reflects market prices and captures (i) appreciation in the total value of the herd (akin to capital gains) due to changes in herd size births,[7] deaths,[8] and in-transfers[9] or in livestock prices and (ii) the value of per period milk production (akin to dividends), which is highly seasonal and stochastic.

Subject to the equation of motion for herd wealth in Eq. (3), the optimal value of intertemporal utility can then be defined as a Bellman equation of the form

$$J\left(H_{jt}\right) \equiv \max_{K_{jt},\,\omega_{Sjt}}\left\{K_{jt}^{1-\alpha} + \beta\left[E_{jt}\left(J\left(\tilde{H}_{j,t+1}\right)^{1-\gamma}\right)\right]^{(1-\alpha)/(1-\gamma)}\right\}^{1/(1-\alpha)} \tag{4}$$

which includes K_{jt} and ω_{Sjt} as control variables ($\omega_{Ljt} = 1-\omega_{Sjt}$). For N assets, EZ derive N Euler equations from maximization of this Bellman equation. In our case, these two Euler equations are

$$E_{jt}\left[\left(\beta\left(\frac{\tilde{K}_{j,t+1}}{K_{jt}}\right)^{-\alpha}\right)^{\theta}\tilde{R}_{Tot,j,t+1}{}^{\theta-1}\tilde{R}_{ij,t+1}\right] = 1 \quad i = \{S, L\} \tag{5}$$

where $\theta = (1-\gamma)/(1-\alpha)$. These Euler equations should hold for all agents who have a non-zero position in the respective assets (see Vissing-Jorgensen, 2002). All the herders in our sample have both largestock and smallstock, making both equations in Eq. (5) uniformly relevant. Campbell (1996) uses a second-order Taylor approximation of these Euler equations to generate two equations in log-linear form.[10] The first equation is

$$E_{jt}\Delta k_{j,t+1} = \delta + (1/\alpha)E_{jt}r_{Tot,j,t+1} = \delta + \sigma E_{jt}r_{Tot,j,t+1} \tag{6}$$

where $\Delta k_{j,t+1} = \ln\left(\frac{K_{j,t+1}}{K_{jt}}\right)$, $r_{Tot,j,t+1} = \ln(R_{Tot,j,t+1})$ and σ is EIS.[11] The second Euler equation approximation is needed to extract the coefficient of RRA, which is embedded in the intercept δ in Eq. (6).

[6] Without this simplifying assumption one would have to model explicitly the impact of human milk consumption on herd growth. In addition to complicating the analysis throughout, this would require data on total milk production, including milk consumed by suckling animals, which is impossible to observe directly. To more fully evaluate this assumption, two features are worth noting. First, given prevailing market prices during the time of the study (Eq. (3) is in value terms), one goat was worth roughly 44 l of milk. Second, by valuing every liter allocated to human consumption at the same market value, we are effectively imposing a linear approximation on the inherently non-linear relationship between milk offtake and herd growth. We leave for future research a complete exploration of this assumption and alternatives to it.

[7] In addition to births, herd appreciation captures the capitalized value of the milk consumed by suckling animals (i.e., not consumed by humans).

[8] In the survey, we distinguished between livestock that were edible at death and those that were inedible. The vast majority of livestock that died were inedible. The meat value of the few that were reported as edible is accounted as part of the herd return, but is not included in the off-take choice variable.

[9] From a herder's perspective, out-transfers are clearly a control variable and therefore included in the control variable K_{jt}. In-transfers, on the other hand, are based on others' decisions to transfer animals and are more exogenous, so they are included in gross herd return. Results are qualitatively robust to this assumption.

[10] Alternatively, assuming joint log-normality of portfolio return and off-take yields the same equations.

[11] Henceforth, we focus on σ (EIS) rather than $\alpha = 1/\sigma$ (relative resistance to intertemporal substitution) since these preferences are typically represented in the literature as EIS.

This second equation exploits differences in the first and second moments of the conditional return on small and large livestock to identify the RRA coefficient and is given by

$$E_{jt}r_{Sj,t+1}-E_{jt}r_{Lj,t+1}+\frac{Var_{SS}-Var_{LL}}{2}=\theta\frac{Cov_{S-L,K}}{\sigma}+(1-\theta)Cov_{S-L,Tot} \quad (7)$$

where θ is a function of both σ and γ and the *Var* and *Cov* terms are second moments defined as

$$\begin{aligned} Var_{ii} &= Var\left(r_{ij,t+1}-E_{jt}r_{ij,t+1}\right) \\ Cov_{S-L,K} &= Cov\left[\left(r_{Sj,t+1}-E_{jt}r_{S,j,t+1}\right)-\left(r_{Lj,t+1}-E_{jt}r_{Lj,t+1}\right),k_{j,t+1}-E_{jt}k_{j,t+1}\right] \\ Cov_{S-L,Tot} &= Cov\left[\left(r_{Sj,t+1}-E_{jt}r_{Sj,t+1}\right)-\left(r_{Lj,t+1}-E_{jt}r_{Lj,t+1}\right),r_{Tot,j,t+1}-E_{jt}r_{Tot,j,t+1}\right] \end{aligned} \quad (8)$$

Household-specific conditional expectations at time t for $r_{ij,t+1}$ and $k_{j,t+1}=\ln(K_{j,t+1})$ are given by

$$\begin{aligned} E_{jt}r_{ij,t+1} &= f_i\left(\mathbf{x}_{it}^r,\mathbf{y}_{jt}^r,\mathbf{z}_t^r,\mathbf{d}\right) \\ E_{jt}k_{j,t+1} &= g_i\left(\mathbf{x}_{it}^k,\mathbf{y}_{jt}^k,\mathbf{z}_t^k,\mathbf{d}\right) \end{aligned} \quad (9)$$

where **x**, **y** and **z** are vectors of household, village and season variables, respectively, and d is a vector of time-invariant household dummies that control for household fixed effects in livestock portfolio returns due to differences in herding ability for example (Santos and Barrett, 2006a). Following Vissing-Jorgensen and Attanasio (2003), we take unconditional expectations and solve this equation for θ as:

$$\theta=\frac{Er_{Sj,t+1}-Er_{Lj,t+1}+\frac{Var_{SS}-Var_{LL}}{2}-Cov_{S-L,Tot}}{\frac{Cov_{S-L,K}}{\sigma}-Cov_{S-L,Tot}} \quad (10)$$

With an estimate of σ and θ from Eqs. (6) to (10), respectively, we can then estimate the coefficient of RRA as $\gamma=1-\theta(1-1/\sigma)$. While RRA remains a function of EIS, it is also a function of the other terms in Eq. (10). In this formulation, the time-additive EU special case holds when $\theta=1$, which provides a simple, testable null hypothesis of the standard EIS = 1/RRA restriction. Specifically, rejecting the null in favor of the alternative that $\theta<1$ would be consistent with both PERU and dynamic asset smoothing as described in the previous section.

4. Data

This study uses longitudinal data gathered from 88 households in the Chalbi and Dukana areas of Marsabit District in northern Kenya, a region that has been described as the most arid in east Africa (FAO, 1971). These two sites, roughly 100 km apart, differ in some important ways for the purposes of this study as described in the Range Management Handbook of Kenya (Schwartz et al., 1991). For Chalbi, forage biomass production estimates are 850 kg/ha/year for the herb layer and 350 kg/ha/year for the shrub layer. Livestock production in the Chalbi basin is very risky due to extended periods of drought, but water points are relatively abundant in this area.[12] Mean rainfall is around 150 mm per year and is generally distributed bi-modally, although the second rainy season often fails.

The towns of the Chalbi area are market centers that have some permanent residents and are also used by nomadic herders who are currently using rangelands within walking distance of a particular town. This study focused on herders in the rangelands surrounding the towns of North Horr and Kalacha. The average household in the Chalbi sample had a one-way walk of 5.1 h to get to a town where there was a market to sell livestock and livestock products. Chalbi herders sold the equivalent of just over one goat a month on average, and in 20% of all three month periods recorded, sold no animals (McPeak, 2004). In Chalbi, 55% of total household income[13] is from home consumed milk; 21% is from household consumption of animals they own; 20% is obtained from the sale of animals; 3% is from milk sales; and 1% is from hide and skin sales, remittances, and gifts (McPeak and Doss, 2006).

In contrast, the Dukana area, still very arid in absolute terms, receives more rainfall and is less risky in terms of rainfall patterns for herders, but has fewer water points. Forage biomass production estimates are 1350 kg/ha/year for the herblayer and 600 kg/ha/year for the shrublayer. Mean annual rainfall is around 300 mm and is bi-modal with a more reliable second rainy season than Chalbi. Livestock production in the Dukana area is less risky than in the Chalbi area in terms of rainfall patterns[14](Schwartz et al., 1991). The towns in the Dukana area are also market centers; this study focused on herders in the rangelands surrounding the towns of Dukana and Sabarei. The average household in the Dukana sample had a one-way walk of 8.3 h to get to a town where there was a market to sell livestock and livestock products. Dukana herders sold the equivalent of one goat every three months on average, and in over half of all three month seasons (53%) sold no animals at all (McPeak, 2004). In Dukana, 82% of household income is from home consumed milk; 9% is from livestock sales; 8% is from home consumption of slaughtered animals; 1% is from milk sales; and less than 1% is from hides and skin sales, remittances, and gifts (McPeak and Doss, 2006).

The Gabra, the pastoralists who occupy both sites in our study area, are nomadic herders who raise mixed herds of camels, cattle, goats, and sheep and who rely almost exclusively on these herds for their livelihoods as reflected in the income patterns noted above. Recall that in both areas, home produced and consumed milk is the largest component of total income. Animals are milked twice a day. As a general rule half the teats of an udder are left for the nursing offspring and the other half is taken for human consumption.[15] Most of this milk will be consumed within a day of being milked. Any milk that is not consumed by the household is sold in local towns (see McPeak and Doss, 2006) or on rare occasions stored in the form of fermented milk or ghee.

Given the nomadic nature of the production system in this environment, we used a transect sampling methodology: enumerators walked a transect between towns in each study area and interviewed the herders they encountered along the way. The questionnaire was fielded in 1997 and was retrospective in nature, recording information for four time periods per year for each of the years 1993–1997. Within a year, the four time periods correspond to the bimodal rainfall pattern of the area: the long rains, a dry season, the short rains, and a second dry season. Each period is roughly three months in length. Recall was aided by construction of livestock family trees for camels and cattle, placing dates on the season and year of significant events such as the birth and death of animals (for more on this method see Grandin, 1983; Turner, 2003). The recall was also designed to take account of the fact that 1992 was a year of severe drought and herd losses, so that herders were asked to describe their position coming out of the drought, which provided a significant and shared benchmark.

Respondents were asked to report several variables for each time period: ages of household members; household size; starting period household herd size and species composition; sales from the

[12] The expected maximum length of a drought in the Chalbi basin is 16–20 months in a given 30 year period.

[13] For total income, local market prices are applied to home produced and consumed commodities.

[14] The expected maximum length of a drought in the Dukana basin is 8–18 months in a given 30 year period.

[15] While herders sometimes deviate from this 'half of the udder' rule depending on the season, their animals and household needs, they generally follow this herd management rule. This implies that neither total milk production nor milk for human consumption are control variables in this setting like they are in less stochastic, more controlled dairy production settings.

household herd including characteristics and price per animal sold; slaughters from the household herd including characteristics of animals slaughtered; transfers into and out of the herd and characteristics of animals transferred; average milk production from the herd per day for human consumption and total milk sales per period; and other sources of household income. Household size was converted into an adult equivalent scale following the method outlined by Martin (1985).[16] Variables recording herd size are converted to total livestock units (TLU), following the method of Schwartz et al. (1991).[17] Households were also asked their subjective perceptions of seasonal pasture availability. These perceptions were elicited on a scale of one (very low) to five (very high) with three being average using questions about three pasture dimensions: (1) overall pasture availability assessed by the relative ease of satisfying animals, (2) relative level of feed production, and (3) relative stocking pressure. Each of these questions was asked for the area within a five hour radius of the largest town in their area and the area beyond this circle.[18]

The average seasonal price received for male goats per period is constructed as the age corrected average of all sales recorded in the data set. Male goats are the most commonly sold animal in the area and can thus serve as a relative indicator for price per animal per period in general. We use this price throughout for the price per TLU. Prices are not deflated over time as there was no change in the four year period for the price for the main item bought by households (maize stayed at 20 shillings per kilo) or milk sold by households (20 shillings per liter) and the price per male goat shows no significant change over time. We use total seasonal (three month) rainfall, which is the average of weather stations in two Chalbi towns (Kalacha and North Horr), and Normalized Difference Vegetation Index (NDVI) data taken from satellite images to account for pasture quality and fodder availability.[19] Finally, we use seasonal dummy variables to indicate whether the period was expected to be a long rains season, a short rains season, or one of the dry seasons in between.

As evident in the top panel of Fig. 1, Chalbi has higher average herd sizes than Dukana for all periods. Chalbi herds grew faster following the drought losses of 1992, but also suffered losses of nearly half its herd in the second half of 1996 (see McPeak, 2004; 2005 for analysis of this collapse). The middle panel of Fig. 1 shows the seasonal NDVI by site. Since the impact of pasture quality on herd health and growth is cumulative, this panel also shows the cumulative NDVI for each site since 1991. The lower panel shows the average of rainfall levels recorded in North Horr and Kalacha in the Chalbi area, as well as a subjective livestock feed index based on the recall of our herder households. The figure confirms the explanation provided by Chalbi herders for the livestock losses in 1996. The cumulative effect of the poor short rains of 1995 (1.8 mm in North Horr), the lower than average long rains in 1996 (71.2 mm in North Horr), and the poor short rains of 1996 (42.8 mm in North Horr) lead to a severe decline in pasture availability in the Chalbi area in late 1996. By the time the extent of the decline was realized, herds were already severely weakened and many animals died en route to areas that had sufficient pasture such as the Dukana rangelands (see the feed index in Fig. 1).

Further evidence of differences between these sites is shown in Table 1 and Fig. 2. The rates of return in this table and figure are net return versions of the gross return described above. Off-take rates are calculated in value terms as a percentage the total value of the herd. The collapse and subsequent recovery in Chalbi is clearly apparent. Off-take is higher and more volatile in Chalbi than in Dukana. Unconditional probability distributions of net return, estimated using an Epanechnikov kernel, are shown in Fig. 3. Dukana seems to have a more stable large livestock return, but may be more risky for small stock. These rates of return are of course quite variable across seasons.

5. Estimation and results

To implement the empirical strategy of our model, we first estimate the return and off-take functions in Eq. (9) and use these results to predict $Er_{ij,t+1}$ and $Ek_{j,t+1}$. We then use these household-specific predicted values to estimate the variance and covariance terms required to estimate Eq. (10) and recover RRA. We specify the herd return functions for $i = \{Tot, S, L\}$ as

$$\begin{aligned} R_{ijzt} = {} & \phi_{j0} + \phi_1 LongRains_t + \phi_2 ShortRains_t + \phi_3 DrySeason_t \\ & + \phi_4 Rain_{t-1} + \phi_5 Rain^2_{t-1} + \phi_6 NDVI_{z,t-1} + \phi_7 NDVI^2_{z,t-1} \\ & + \phi_8 NDVI_{z,t-2} + \phi_9 NDVI^2_{z,t-2} + \phi_{10} sd(NDVI)_{z,t-1} \\ & + \phi_{11} sd(NDVI) \times NDVI_{z,t-1} + \phi_{12} cum(NDVI)_{z,t-1} \\ & + \phi_{13} cum(NDVI)^2_{z,t-1} + \phi_{14} AvgTLU_{z,t-1} + \phi_{15} NDVI \\ & \times AvgTLU_{z,t-1} + \phi_{16} TLU_{ijt} + \phi_{17} TLU^2_{ijt} + \phi_{18} \omega_{Sj,t-1} \\ & + \phi_{19} Dist_{z,t-1} + \phi_{20} Feed^2_{z,t-1} + \varepsilon_{ijt}, \end{aligned} \tag{11}$$

and the off-take function as

$$\begin{aligned} K_{jzt} = {} & \phi_{K j0} + \phi_{K1} LongRains_t + \phi_{K2} ShortRains_t + \phi_{K3} DrySeason_t \\ & + \phi_{K4} Rain_{t-1} + \phi_{K5} Rain^2_{t-1} + \phi_{K6} NDVI_{z,t-1} + \phi_{K7} NDVI^2_{z,t-1} \\ & + \phi_{K8} TLU_{Tot,jt} + \phi_{K9} TLU^2_{Tot,jt} + \phi_{K10} TLU_{Tot,jt} / Adult_{jt} + \phi_{K11} Dist_{jt} + \varepsilon_{jt} \end{aligned} \tag{12}$$

where subscripts indicate household j, site z, and season t. R_{ijzt} represents seasonal gross herd return, and off-take K_{jt} is the value at prevailing period t prices of net herd off-take in the form of livestock sales, slaughter, transfers out of the herd, and milk consumed or sold by the household. *LongRains*, *ShortRains*, and *DrySeason*[20] are dummy variables that identifies season t. $Dist_{t-1}$ is the walking distance in hours from base camp to town in season $t-1$. $Rain_{,t-1}$ is total rainfall received (mm) during season $t-1$. $NDVI_{z,t-1}$ is the average NDVI for site z in season $t-1$, $sd(NDVI)$ captures the intraseasonal spatial variance of the NDVI in site z and indicates, in part, the returns to transhumance (taking advantage of differences in rangeland quality across a site that are captured by higher variability across sites within a given season), and the interaction between the two reflects the fact that returns to transhumance might be especially high when average rangeland quality is low. Cumulative NDVI is given by $cum(NDVI)$ and captures the cumulative effects of rangeland quality. $AvgTLU_{z,t-1}$ is the average herd size in site z for season $t-1$ and is an indicator of stocking density. The pressure on the rangeland is indicated by the

[16] The adult equivalent weighting scheme used in this study assigns a value of one to individuals of both sexes older than 15, a value of .6 to individuals 6–14 years old, a value of .3 to children ages 2–5, a value of .1 for children under 2.

[17] One livestock unit = 10 sheep or goats = 1 head of cattle = 0.7 camels. This differs slightly from the scheme in Schwartz et al. as they weigh 11 goats equal to 1 TLU. As the total number of sheep and goats is the variable recorded in the data set, the composite measure of smallstock is assigned a weight of 1 animal = 0.1 TLU.

[18] This threshold produces a logical grouping of herders according to their access to and reliance upon towns, markets, etc. For any given household, their distance from town is computed as their average distance from town over the 1993–1997 window in contrast to the time-varying distance variable included in the return functions.

[19] The NDVI data was collected for each 8 km by 8 km pixel in a 96 km by 96 km block centered on the towns of the respective areas (144 pixels per site per dekad). For each pixel, data from the first dekad of July 1981 to December 2004 were used to construct a mean and variance for NDVI in that pixel over this entire period. We then used these summary statistics to calculate the average z score per dekad for each pixel. This data was then used to generate two variables per dekad; one is the mean z score across all 144 pixels, the second records the variation in the z values across the pixels. We then calculate two variables used in the regression analysis. One is the average seasonal NDVI, which is the average over nine dekads (roughly three months) of the per dekad NDVI average, and provides a sense of how 'green' things were in that season overall. The second records the variation in the spatial variation over the nine dekads. This reflects how much the spatial variation in 'greenness' changed within the period.

[20] This indicates the dry season that follows the long rains season. The dry season that follows the short rains season—the riskiest season is the reference season.

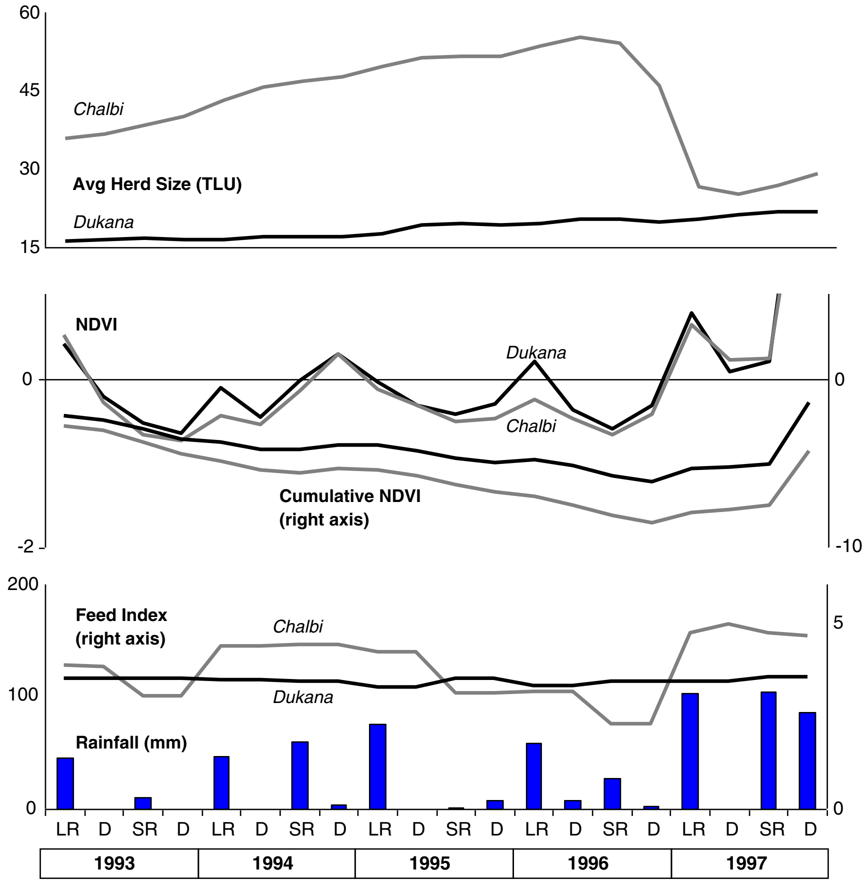

Fig. 1. Average herd size in Tropical Livestock Units by site (top), seasonal and cumulative average NDVI by site (middle), and subjective livestock feed index and seasonal rainfall (bottom).

interaction of this variable with the NDVI (i.e., stocking density may matter most when rangeland quality is low). TLU_{ijt} is the size of herd i for household j at the beginning of season t. $Adult_{jt}$ is the adult equivalent size of household j in season t, so that $TLU_{ijt}/Adult_{jt}$is an indicator of household wealth. We estimate these specifications using household fixed effects (i.e., the constant in these specifications is household-specific).

Since expected return and off-take based on the specifications in Eqs. (11) and (12) are central to our empirical approach, a few observations are worth making. First, our singular objective in estimating these equations is to predict R_{ijzt} and K_{jt} so we can estimate $E_{jt}r_{ijz,t+1}$ and $E_{jt}k_{jz,t+1}$ and the moments needed for Eq. (10). These conditional expectations are specific to household j and season t, so our goal is to estimate as accurately as possible the expectations of a herder for the coming season. We therefore care more about our ability to predict than we care about getting unbiased individual coefficient estimates. Among other potential endogeneity problems in these specifications, *TLU* is related to gross herd return (recall Eq. (3)) and is therefore endogenous. But potential bias in the coefficient on *TLU* is irrelevant for our purposes because we only care about predicting gross returns. *TLU* belongs in this prediction since herders likely take their herd size into account when formulating expectations about next season's rate of return.[21] Second, since these are *ex ante* conditional expectations, these equations include only explanatory variables that are known to households at the beginning of each season. With the exception of *TLU* and *Adult*, which are measured at the beginning of the period, and the season dummies, which follow a predictable schedule, explanatory variables are therefore lagged at least one period. Finally, given obvious differences between our two sites and between largestock- and smallstock-dominant herders within each site, we estimate these return and off-take functions separately by herder type within each site (still including household fixed effects). Estimating herders' expectations based on these relevant subgroups improves the accuracy of our estimated conditional expectations for herd return and off-take.[22] Note that we only split herders by herd composition in order to estimate more accurate

Table 1
Summary of unconditional seasonal return and off-take by site, 1993–97.

	Mean	Median	St. Dev	Min	Max
Chalbi					
Herd return	5.2%	5.9%	16.0%	−76.8%	94.9%
Largestock return	4.0%	2.1%	14.2%	−52.5%	93.4%
Smallstock return	9.5%	7.8%	31.5%	−89.1%	410.3%
Off-take	4.9%	4.1%	3.1%	0.0%	30.4%
Dukana					
Herd return	9.8%	8.2%	12.6%	−41.0%	99.7%
Largestock return	8.6%	3.6%	14.0%	−27.1%	95.8%
Smallstock return	16.4%	13.0%	36.3%	−92.1%	788.8%
Off-take	7.9%	7.2%	4.8%	0.0%	37.1%

[21] Our ultimate estimates of RRA and EIS are robust to excluding the *TLU* variables from these equations because the first and second moments of the resulting distributions of predicted returns and off-take change very little without these variables. For concerned readers, we offer a simple example (provided by Aaron Smith) to illustrate why potential endogeneity bias in a particular coefficient is irrelevant for our purposes. Suppose we wanted to model the effect of the turbulence expected by airline passengers on the probability that they are standing in the aisles. Whether the captain has turned on the fasten seatbelt light would certainly be an important part of passengers' expectations and would therefore improve our predictions of these expectations, even though the light is clearly endogenous.

[22] With enough seasonal observations for each herder household further improvements could be had by estimating these functions separately for each household.

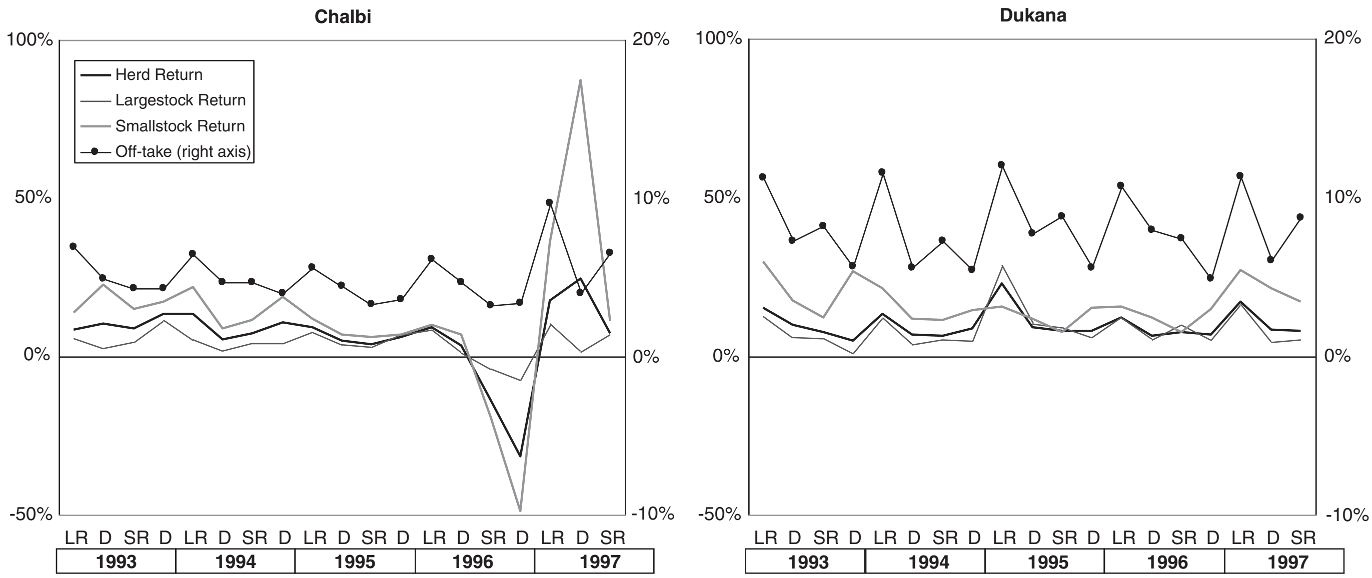

Fig. 2. Average seasonal return for herd, largestock and smallstock and average value of seasonal off-take as percentage of herd value by site.

return and off-take functions; we pool all herders within each site together when estimating RRA and EIS in Eqs. (6) and (10).

Estimation results for these return and off-take functions by herder type for Chalbi and Dukana are shown in Table 2. The fit of these equations is generally better in Chalbi than in Dukana. Household fixed effects tend to explain more variation in off-take than in return. While we are ultimately interested in predicted values (and hence fit), some of these estimates are nonetheless noteworthy. Expected return is obviously heavily conditioned on season, rainfall and NDVI, although these tend to matter more in Chalbi than in Dukana. Where the intraseasonal variability of NDVI matters, it increases expected return, but this effect is muted as NDVI increases, which is consistent with our priors that nomadic herders take advantage of variability in rangeland quality over space and that this is particularly valuable when average rangeland quality is low. Cumulative NDVI matters to returns in Chalbi, but not Dukana (see Fig. 2). We use predicted values from these return and off-take estimations to compute the moments in Eq. (10) (see Table 3).

To estimate EIS in Eq. (6), we must control for variables other than the total herd return that directly affect changes in off-take. As in Vissing-Jorgensen (2002), we include season dummies as control variables since herders' off-take decisions are influenced by season independent of return. For example, while milk consumption is higher during rainy seasons, livestock sales are generally lower because income from milk sales is higher and transport is relatively difficult during these seasons. Following Vissing-Jorgensen and Attanasio (2003), we replace expected values in Eq. (8) with their realized values, then specify the equation as

$$\Delta k_{jt} = \delta_0 + \delta_1 LongRains_t + \delta_2 ShortRains_t + \delta_3 DrySeason_t + \sigma r_{Tot,jt} + \varepsilon_{jt} \quad (13)$$

Note that since herd return is distinctly seasonal, including seasonal dummies as controls ensures that our estimate of σ is capturing only the portion of changes in off-take that are attributable to changes in herd return. Since the value of milk production affects both herd return and off-take, our estimate of interest, σ, may be biased due to potential endogeneity problem. Fortunately, we have several possible instruments to remedy this problem from our specification in Eq. (11). We estimate this equation via both OLS (assuming groupwise heteroskedasticity) and IV (assuming White heteroskedasticity) with the season dummies, rainfall, NDVI, and stocking density variables as instruments. We then estimate Eq. (13) and the moments and parameters in Eq. (10) for each site separately, but with conditional return and off-take expectations still estimated by herder type within each site. Since θ and γ are functions of

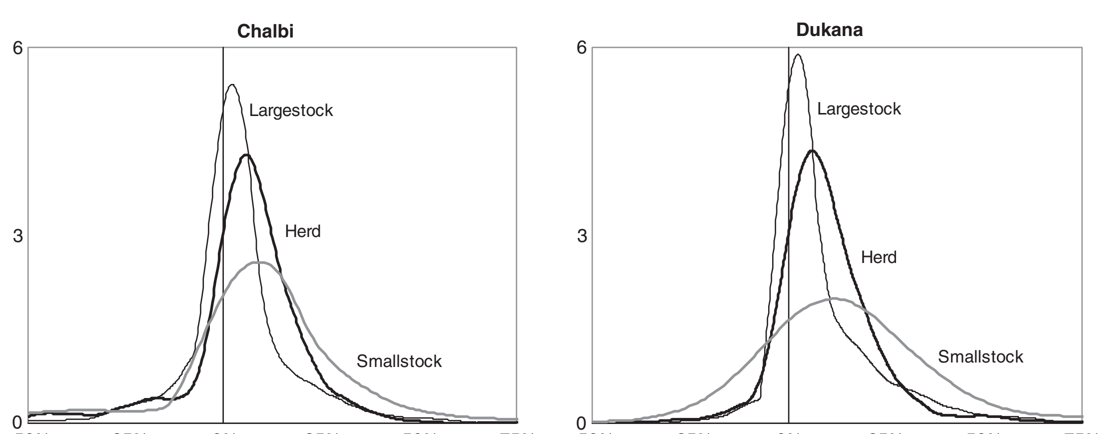

Fig. 3. Probability distributions of unconditional seasonal herd, largestock and smallstock return by site.

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Table 2
Estimated livestock return and off-take equations by site and herder type.

Dependent variable	Herd return				Largestock return				Smallstock return				Off-take			
Site	Chalbi		Dukana		Chalbi		Dukana		Chalbi		Dukana		Chalbi		Dukana	
Herder type§	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
Long rains$_t$ {0,1}	11.07 ***	13.56 ***	9.06 ***	6.94 ***	10.83 ***	6.40	12.20 ***	11.53 ***	13.88 *	15.29 **	5.92	0.19	7576 ***	12,744 ***	7317 ***	4778 ***
Short rains$_t$ {0,1}	−6.90 **	−11.73 ***	−1.75	−1.39	−4.28	−7.09 **	−2.47	−1.05	−10.49 *	−14.37 ***	−7.97	−4.25	−3166 **	−843	2367 ***	2350 ***
Dry 1 season$_t$ {0,1}	16.30 ***	31.54 ***	1.66	−0.37	9.59 **	5.79	1.74	1.73	21.84 **	34.70 ***	5.24	−2.50	5720 ***	6363 ***	2485 ***	1371 **
Rainfall (t−1)	−0.84 ***	−1.12 ***	−0.80 ***	−0.20	−0.33 *	0.01	−0.83 ***	−0.58 **	−1.90 ***	−1.96 ***	−0.18	−0.12	−125 *	−194 **	−66 **	−28
Rainfall2 (t−1)	0.009 ***	0.011 ***	0.010 ***	0.003	0.003	−0.001	0.010 ***	0.008 **	0.024 ***	0.022 ***	−0.001	0.002	0.94	1.93 **	0.56 **	0.17
NDVI (t−1)	203.5 ***	370.7 ***	39.5 *	25.6	126.9 ***	120.5 **	65.9 **	33.1	348.8 ***	485.5 ***	−120.2	−5.5	9780	478	4492 *	1372
NDVI^2 (t−1)	−31.50 **	−43.25 ***	22.90 **	3.40	−22.90 **	−19.09	22.28 *	17.13	−51.31 **	−55.47 ***	5.77	−0.03	−5372 *	610	−1546	−471
NDVI (t−2)	71.90 ***	132.34 ***	12.84	−7.32	68.95 ***	69.03 **	26.19 **	10.14	107.11 **	159.61 ***	56.65 *	−38.86 **				
NDVI^2 (t−2)	−52.62 ***	−99.62 ***	−5.63	4.77	−41.90 ***	−39.97 **	−9.87 **	−3.18	−88.04 ***	−125.43 ***	−27.65 *	19.85 **				
Std Dev NDVI (t−1)	48.34	66.16	380.35 **	52.77	67.65	33.10	432.28 **	229.32	194.72	238.11 **	317.66	−92.46				
Std Dev NDVI (t−1)× NDVI (t−1)	−145.8 **	−301.2 ***	−294.6 ***	−49.1	−104.3 *	−83.0	−318.6 **	−197.4	−316.6 **	−460.9 ***	−164.1	42.8				
Cumulative NDVI	30.52 **	68.14 ***	−0.48	4.82	14.64	2.65	−3.05	−3.15	60.20 **	99.50 ***	0.28	13.88				
Cumulative NDVI^2	1.82 **	4.36 ***	0.40	0.89	0.92	0.01	0.60	0.61	3.65 **	6.46 ***	−1.72	1.69				
Avg site TLU (t)	1.97 ***	3.35 ***	1.69	−0.02	0.90 **	0.60	2.59	2.12	3.57 ***	4.95 ***	−2.17	−5.34				
Avg TLU (t)×NDVI (t-1)	−2.75 ***	−5.13 ***	−3.56 **	−1.31	−1.81 ***	−1.77 **	−4.75 **	−2.78	−4.68 ***	−6.90 ***	4.97	0.78				
Total TLU (t)	−1.55 ***	−0.53 ***	−1.43 ***	−2.93 **									525 **	197	214	669 **
Total TLU2 (t)	0.01 ***	0.00 ***	0.02 ***	0.04									−1.7	−0.7	−0.9	−0.5
Large TLU (t)					−2.31 ***	−1.84 ***	−1.73 ***	−2.59 **								
Large TLU2 (t)					0.02 ***	0.01 **	0.02 ***	0.02								
Small TLU (t)									−3.74 ***	−0.30	−22.21 **	−9.40 ***				
Small TLU2 (t)									0.05 ***	0.00	1.22 **	0.28 ***				
Small livestock share (t−1)	3.91	−14.33 *	−31.24 ***	−11.63	11.85	14.63	8.47	17.78	−63.63	−97.25 ***	−204.50 ***	−27.93	−8925 *	−1130	−5544 **	1505
Distance base to town (t−1)	0.25 **	0.16	−0.07	−0.28 ***	0.23	0.42 *	0.02	−0.20 **	0.24	0.18	−0.21	−0.33 **	−26	454 *	11	−25
TLU/Adult equivalent (t)													118	319	912	−908 **
N=	300	309	432	450	300	309	432	450	300	309	432	450	337	346	480	500
R2 with HH fixed effects† only =	0.06	0.07	0.04	0.08	0.05	0.05	0.04	0.05	0.10	0.13	0.05	0.10	0.29	0.62	0.14	0.20
R^2=	0.55	0.67	0.33	0.26	0.30	0.20	0.35	0.25	0.52	0.68	0.25	0.31	0.47	0.72	0.49	0.51

*** (**) [*] denotes signifcance at 1% (10%) [15%] level based on groupwise heteroskedastic standard errors.
§ Smallstock (largestock) dominant herders include all herders whose average smallstock herd share is above (below) the site-specific median smallstock share.
† All specifications include household fixed effects. These coefficients are not displayed.

Table 3
Estimated moments from predicted conditional return and off-take.

	$E[r_{Sj,t+1}]$	$E[r_{Lj,t+1}]$	Var_{SS}	Var_{LL}	$Cov_{S-L,Tot}$	$Cov_{S-L,K}$
Chalbi	4.4%	2.8%	0.034	0.015	0.009	−0.006
Dukana	11.6%	7.4%	0.050	0.010	0.006	0.010

estimated moments and parameters (see Eq. (10)), we use bootstrapping to estimate standard errors on these estimates.

Estimation results for the preference parameters in our recursive utility approach are shown in Table 4 and suggest that estimated variability preferences are substantially different between pastoralists in our two sites. While Chalbi herders appear to be averse to consumption variability over time with estimated EIS similar to estimates from other settings (Atkeson and Ogaki, 1996), they are much less averse (or even statistically neutral) to atemporal risk. A more recent field experiment to gauge the willingness to pay for index-based livestock insurance similarly found that Chalbi pastoralists were statistically risk neutral (Chantarat et al., 2009). Dukana herders, on the other hand, appear to be extremely risk averse, but not averse to intertemporal consumption variability. Although the differences in EIS and RRA between these sites are stark, in both sites the estimate of RRA is greater than 1/EIS. Thus, we uniformly reject the null hypothesis that $\theta = 1$ in favor of the alternative that $\theta < 1$, which is strong evidence against the implicit assumption of time-additive EU. As discussed above, this preference pattern is also consistent with both PERU and/or dynamic asset smoothing.

To interpret these results in our pastoralist context, recall from Section 2 the initial discussion of residual structure being attributed to preferences. We first discuss our interpretation of the RRA and EIS estimates based on structural features of this pastoral setting and then explore the PERU and asset smoothing perspectives on the θ estimates. We speculate that the difference in RRA estimates between these sites may stem from a few notable structural differences. Dukana has a higher risk and return profile for smallstock than is found in Chalbi as noted in Table 1, with the higher risk possibly reflecting the fact there are fewer watering points in Dukana which could predispose Dukana herders to allocate more of their herd to largestock and makes them appear relatively more risk averse. Another possibility is that the towns in the Chalbi basin are also larger than those of Dukana, implying that alternative income opportunities are more abundant in Chalbi than in Dukana. Although these options are not highly attractive or remunerative, they offer greater possibility for survival in the event of herd loss in Chalbi than in Dukana and may explain the latter herders' extreme risk aversion. Similar structural differences could possible undergird different EIS estimates in these sites. Dukana herders have to travel further on average to access livestock and milk markets making it more costly for them to smooth consumption than it is for Chalbi herders, which may partially explain the substantially higher EIS estimates in Dukana.

While further research would be needed to adequately explain these differences, we note that our estimates of θ are consistent with either PERU or dynamic asset smoothing (or both). We view these as complementary perspectives on this result, both of which may hinge on structural features. Kreps and Porteus (1978) preferences allow for PERU to emerge for either instrumental or inherent reasons, but cannot distinguish between the two. Thus, PERU among our herders may arise from either the instrumental value of early resolution or its inherent value or both. If we interpret θ from this perspective, it seems safe to attribute much of herders' PERU to the instrumental value of early resolution, especially given the flexibility inherent in their migratory livelihoods. With fewer watering points, migration mistakes during the dry season—such as moving one's herd to a watering hole that is drier than expected—are more costly for Dukana herders since it is more difficult to recover from the mistake by moving to the next closest watering point. This would confer greater instrumental value to the early resolution of uncertainty and might provide an alternative explanation for our relatively large estimates of θ for Dukana herders.

From an asset smoothing perspective, the θ estimates are consistent with optimal responses to a dynamic asset threshold. To be more precise, these results are consistent with an asset smoothing response *above* such a threshold. In a similar pastoral setting across the border in southern Ethiopia, herders whose herds fall below a critical threshold tend to exit the nomadic pastoral system, settle down and adopt in low return cultivation strategies (Lybbert et al., 2004). If such a threshold exists in our setting as well,[23] we would expect most of the herders in our sample to be above the threshold—even if they are not too far above—because our sampling frame randomly selected pastoralists into the sample. Thus, by construction our sample does not include herders who may have exited the pastoral system as a result of previous shocks. The differences in our estimates between Dukana and Chalbi can be interpreted as providing further evidence of asset smoothing above a critical herd threshold. The magnitude of the optimal response to a threshold is directly proportional to one's current distance from the threshold. If we interpret θ as an indication of the degree of asset smoothing, this estimate will therefore increase with proximity to a threshold herd size. Average herd sizes in Chalbi are more than double those in Dukana (see Fig. 1), suggesting that Dukana herders may be closer on average to any looming dynamic thresholds and offering another possible explanation for the differences in the results across the sites. Finally, note that this asset smoothing perspective and the PERU interpretation are not mutually exclusive. All of our herders could genuinely prefer early resolution of uncertainty. In addition to this wedge between RRA and 1/EIS, herders might also smooth assets in proportion to their proximity to a critical herd threshold, which—if data limitations prevent us from explicitly modeling the full structure of the problem—would drive yet another wedge between the two.

6. Conclusion

Economists working in finance and macroeconomics have long recognized the value of allowing preferences over state and time variability to be distinct. In this paper, we argue that the techniques they have developed for studying risk aversion and intertemporal substitution preferences among financial investors in rich countries can shed light on the interplay of these preferences among the poor. This strikes us as an important methodological extension since the tradeoffs between state and time dimensions can involve substantial stakes in human welfare terms for the poor in poor countries who are vulnerable and have difficulty managing and recovering from these fluctuations. In such a context, the time-additive EU assumption that state and time variability preferences are identical seems especially restrictive from both a conceptual and an empirical point of view. To move beyond this restriction, we use Epstein and Zin (1991) recursive preferences to distinguish between risk aversion and intertemporal substitution among poor and vulnerable herders in Kenya.

Once we disentangle relative risk aversion (RRA) and the elasticity of intertemporal substitution (EIS) in the case of our Kenyan herders, we find evidence that the effort taken to separate these effects is merited. Our RRA and EIS estimates reflect different ways in which individuals confront uncertain outcomes and allow for the possibility that one can be both risk averse and tolerant of high consumption variability over time. This pattern of preferences, which is nearly universally disallowed by assumption, is consistent with a strong Preference for Early Resolution of Uncertainty (PERU). Our results

[23] Note that our herd history data is too short to directly estimate livestock accumulation dynamics. By comparison to our data, which span five years, Lybbert et al. (2004) use 17 years of herd history data.

Table 4
EIS, RRA and θ estimates with heteroskedastic standard errors (.) and bootstrapped standard errors {.}.

	Chalbi				Dukana			
	OLS		IV		OLS		IV	
Constant	−0.059	(0.07)	−0.047	(0.09)	−0.92***	(0.10)	−0.94***	(0.21)
Long rains$_t$ {0,1}	0.58***	(0.10)	0.55***	(0.10)	1.58***	(0.14)	1.54***	(0.27)
Short rains$_t$ {0,1}	−0.25***	(0.09)	−0.26**	(0.11)	1.13***	(0.12)	1.13***	(0.13)
Dry 1 season$_t$ {0,1}	−0.29***	(0.09)	−0.30***	(0.09)	−0.028	(0.13)	−0.030	(0.13)
σ = EIS	0.66***	(0.18)	0.86**	(0.40)	2.84***	(0.45)	3.27	(2.83)
γ = RRA	0.54	{0.88}	0.84	{1.05}	13.47***	{3.06}	12.50*	{7.76}
θ (PERU iff < 1)	−0.90^^^	{0.77}	−1.02^^^	{0.79}	−19.25^^^	{7.12}	−16.55^^	{12.84}
Herder random effects	Yes		No		Yes		No	
N	628		628		882		882	

*** (**) [*] denotes different than 0 at 1% (10%) [15%] significance level.
^^^ (^^) [^] denotes rejection of H0: $\theta=0$ in favor of H1: $\theta=0$ at 1% (10%) [15%] significance level.

clearly fit this pattern. The analysis is novel since it is based on the first test of PERU in a poor population exposed to significant welfare vulnerability and for whom the timing of uncertainty resolution may be especially important. While PERU has been tested in experimental, finance and other settings, it is particularly intriguing in the present context since it is also consistent with an asset smoothing response to a critical herd threshold.

We interpret our preference estimates as reflecting both innate preferences and residual structural features. Observational field data generally lack the resolution necessary to fully capture spatial–temporal structure, and we may consequently attribute residual structural features to preference estimates. An empirical approach that assumes recursive intertemporal preferences while also capturing the full structure herders' optimization problem would enable us to identify herders' inherent valuation of early resolution of uncertainty, but such an approach far outstrips what observational data (including ours) can provide. Our PERU estimates therefore include herders' instrumental and inherent valuation of early resolution of uncertainty. Systematic differences between herders in our two research sites suggest that PERU in this context is driven importantly by the instrumental value of uncertainty resolution. Structural features may similarly explain why Dukana herders appear to be more risk averse and less concerned about smoothing consumption than their Chalbi counterparts. We explore an asset smoothing perspective on these preference estimates that hinges even more fundamentally on residual structure being captured in preferences: asset smoothing implies that herders would appear simultaneously and in proportion to their proximity to a critical threshold to have high RRA and high EIS. Again, the differences between Dukana and Chalbi are consistent with this asset smoothing interpretation.

We emphasize that the familiar PERU interpretation and the nascent asset smoothing interpretation we explore are mutually compatible and potentially complementary perspectives. From either perspective or both, our results suggest that distinguishing between state and time variability preferences may be particularly important for vulnerable populations that face asset dynamics. We leave to future work the full and formal treatment of these intriguing perspectives and the attendant implications for how we model intertemporal decision making in development economics. As a practical matter, understanding the variability preferences of these vulnerable populations—including their instrumental valuation of early resolution of uncertainty and preference for smoothing assets over consumption—could have direct policy relevance for interventions that aim to improve forecasts, forecast dissemination, information and communication infrastructure, or to reduce the welfare effects of asset losses and risks.

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