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Resource Risk and the Origins of Inequality: Evidence from a Pastoralist Economy

Abstract

Resource risk is a core ingredient of models of wealth inequality in modern economies, but remains understudied in explanations of inequality in early human and small-scale societies that can inform us about the origins of inequality. Resource risk generates variation in resources and leads to wealth inequality via savings decisions, given the available production and storage technology and the institutional arrangements that govern property rights and insurance. We examine whether this mechanism can explain wealth inequality in a pastoralist economy where wealth is held in livestock, production and storage technology resembles that of early human societies and there is virtually no financial market penetration. Our analysis uses original survey data from traditional Turkana pastoralist communities in Kenya to measure wealth inequality and relevant shocks to resources and to inform a model of wealth accumulation under resource risk. The data reveal substantial wealth inequality and resource risk, including via shocks to the growth rate of livestock holdings, which depends on droughts. Asset accumulation decisions also show that livestock is not used as a buffer stock with respect to shocks to livestock. The wealth accumulation model accurately reproduces the empirical wealth distribution while also predicting the pattern of asset accumulation decisions in response to different shocks to resources observed in the data. These results demonstrate that resource risk and the economic decision making it implies explain the wealth inequality observed in the Turkana pastoralist economy we study. Our findings highlight the role of the resource risk mechanism as a driver of inequality in a small-scale economy, suggesting its importance in the origins of inequality in early human societies.

JEL-Codes: E210, N300, O150, D310.

Keywords: origins of inequality, risk exposure, small-scale economy, Turkana pastoralists.

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1 Introduction

Analysis of factors driving inequality in early human societies and in economies that have changed little over time can improve our understanding of the origins of inequality, and thus of fundamental characteristics of economies that tend to generate inequality. This motivation has led to an extensive research literature that combines studies using archaeological evidence from prehistoric societies and studies of historical or contemporary agrarian, pastoralist and hunter-gatherer communities with similar institutions and production technology to those of early human societies (see, e.g. analysis and reviews in Bar-Yosef (2001), Barker (2006), Borgerhoff Mulder *et al.* (2009), Halstead (2014), Scheidel (2017), Bogaard *et al.* (2019), Bowles and Choi (2020) and Dow and Reed (2023)). In this literature, the emergence of farming and agriculture in early human societies is generally associated with increases in inequality relative to that of earlier hunter-gatherer societies. Indeed, it is argued that the technological revolution of farming and agriculture created increased opportunities to accumulate wealth. In particular, farming and agriculture provided enhanced storage opportunities, in the form of livestock, grain storage and land, as well as more clearly defined private property rights. In turn, this allowed individuals to more effectively move resources over time by accumulating assets with the aim of increasing future consumption and wealth and protecting consumption from negative shocks. In this new environment, a reasonable conjecture is that resource risk should contribute to increased levels of wealth inequality. Specifically, when it is not possible to completely insure against idiosyncratic shocks, these lead to variation in resources, which is propagated over time to generate wealth inequality because savings decisions are a function of these resources. We refer to this logic as the resource risk mechanism.

The resource risk mechanism is an important ingredient of economic analysis of wealth inequality, both in industrialised economies and in small-scale societies, be they prehistoric or contemporary. It underpins quantitative analysis of wealth inequality under incomplete insurance markets in industrialised economies, following the contributions of Bewley (1986), Huggett (1993) and Aiyagari (1994). Models founded on the resource risk mechanism, implementing it via a multitude of channels to account for the complexities of modern economies, have been successful in explaining multiple aspects of wealth inequality (see e.g. Krueger *et al.* (2016), Benhabib and Bisin (2018) and Hubmer *et al.* (2021) for reviews).[1] The logic of the resource risk mechanism has also been included in comparisons of wealth inequality between small-scale contemporary and prehistoric societies, respectively, in e.g. Borgerhoff Mulder *et al.* (2009) and Bogaard *et al.* (2019).[2] However, despite the extensive literature that builds on the resource risk mechanism to study wealth inequality quantitatively in modern economies, the extent to which it explains observed wealth inequality in pre-modern economies is poorly understood. For example, in explaining variation in wealth inequality between societies, Borgerhoff Mulder *et al.* (2009) and Bogaard *et al.* (2019) assume stochastic idiosyncratic variation in resources and inputs to production as a source of inequality, but focus their analysis on the importance of cultural incentives and production and storage technologies for the generation and propagation of wealth over time. Therefore, quantitative evidence that shows that resource risk is important for wealth inequality in a pastoralist economy that maintains relevant features of early human societies would support its role as a driver of the emergence of wealth inequality.

We examine the extent to which resource risk explains wealth inequality in Turkana pastoralist communities that maintain critical characteristics of early human economies. Pastoralism is the most common form of livelihood in Turkana, Kenya's largest county by land area, where about

[1] Complexities of modern economies that are accounted for in this literature relate to e.g. production and its relationship with diverse and risky human and physical capital inputs, opportunity and preferences to improve productivity and participate in income-generating activity, and market and social insurance.

[2] See also e.g. studies in Halstead and O'Shea (1989), Halstead (2014), Scheidel (2017), and Fochesato *et al.* (2021) for the role of resource risk in shaping individual choices and societal and economic characteristics of small-scale and prehistoric communities.

85% of the population of 1 million lives in arid and semi-arid rural areas. Within Turkana county, the communities that we study were chosen in consultation with local partners as communities that maintain a traditional pastoralist lifestyle and husbandry practices, with infrastructure and institutional arrangements that remain as close as possible to those of early pastoralists. Specifically, these communities rely strongly on herding (primarily goats and sheep), have very limited access to essential services and infrastructure such as roads, education, healthcare, veterinary facilities and financial services, and limited opportunity for income generation that does not depend on livestock. Livestock, which is privately owned, is the main form of wealth held in these communities and constitutes the capital stock of the household business of herding; in contrast, pasture is a common resource. Resource risk mainly takes the form of shocks to livestock and to human inputs to production; although it depends on droughts, it affects households differentially, creating variation in resources. Within the community, social norms provide for support to mitigate extreme adversity (e.g. that poses a threat to survival), but this does not extend to broader insurance against negative shocks to resources; there is no comprehensive *ex post* risk sharing aiming to reduce inequality nor a central authority that collects resources for redistribution (see e.g. Anderson and Broch-Due (1999) for an anthropological analysis of Turkana and social relationships within these communities). Despite hardships, the societal arrangements that underpin Turkana pastoralist communities have proved resilient over time (e.g. Kratli and Schareika (2010)). Indeed, despite being extremely risk-exposed and having little or no access to many of the benefits of more complex societies, Turkana pastoralists do not consider themselves to be *poor* (Anderson and Broch-Due (1999)).

Our analysis is based on quantitative data we collected during 2018 via a survey of 1,347 pastoralist households (with data on 9,179 individuals) covering the years 2017 and 2018, complemented by findings drawn from in-depth interviews with key informants and focus group discussions with households conducted in early 2020. Crucially, our survey data provide quantitative information relating to a drought year (2017) and a non-drought year (2018); our sample is also sufficiently large to allow us to estimate the skewed distributions of wealth and shocks. We collected data from traditional rural communities located further from townships and, at the time of sampling, had little exposure to financial or labour markets. Indeed, our data confirm that no households were involved in crop cultivation and only 13 households had a member who received waged income; 27 households reported having savings and 7 had debt to banks or other financial institutions. We collected detailed information on wealth, which effectively consists of livestock, on returns to livestock and decisions to acquire or de-accumulate livestock, and on demographic and other household characteristics.

Our dataset reveals high wealth inequality and idiosyncratic variation in shocks among Turkana households. For example, we find a Gini coefficient of wealth inequality of around 0.55, in line with evidence from other pastoralist communities in e.g. Borgerhoff Mulder *et al.* (2009, 2010). There is substantial variation across households in terms of the natural growth of livestock holdings (i.e., due to births, deaths and theft), reflecting risk to returns to the asset. The implied risk is similar e.g. to that of returns to non-financial wealth reported for Norway (Fagereng *et al.* 2020). We also find variation in shocks that reduce human time input into production. Furthermore, only a small proportion of households generate income from market activities. Comparison between the distributions of both wealth and shocks to livestock between 2017 and 2018 shows that these were severely affected by the drought in 2017, which reduced mean livestock numbers and herd growth rate, and increased their variation across households, primarily by increasing the concentration on the left tail. Analysis of data on acquisitions and de-accumulation of livestock further reveal that households use these processes with the aim to maintain herd size in response to shocks to livestock holdings; in particular, we find that net acquisition of livestock increases when households receive negative shocks to the natural growth of their herd and decreases when they receive positive shocks. In other words, livestock holdings are not used as a buffer to respond to livestock shocks. On the other hand, there is some evidence that livestock serves a more traditional buffer role for shocks to human time input into production, although the relationship is weaker.

To quantify the impact of resource risk on wealth inequality, we use our survey data to inform a quantitative model analysis. In the model, agents make savings decisions subject to idiosyncratic and aggregate-level uncertainty, given the existing technological constraints and societal and institutional arrangements that determine production, storage and insurance against shocks to resources. Using the survey data, we estimate stochastic processes that capture household-specific resource risk as a function of aggregate risk (namely droughts) and use these processes as inputs to the model. To obtain our results, we generate the time series of cross-sectional distributions of wealth under the history of droughts between 1920 and 2018. We find that the model-generated wealth distributions provide an excellent fit to the data and that model-predicted net livestock acquisitions in response to different types of shocks match the empirical patterns. These findings imply that household savings decisions under risk exposure can explain the observed distribution of wealth. By demonstrating the power of the basic resource risk mechanism to explain inequality, our findings provide additional validation to different strands of research that have relied on elements of this mechanism to explain and model wealth inequality across a range of societies (e.g. Bewley (1986), Aiyagari (1994), Huggett (1993), Borgerhoff Mulder *et al.* (2009), Krueger *et al.* (2016), Benhabib and Bisin (2018) and Bogaard *et al.* (2019), Hubmer *et al.* (2021)). They also suggest that variation in resource risk can contribute to explaining differences in inequality over time or between economies. We find that the largest contribution to wealth inequality comes from household-specific shocks to the growth rate of livestock holdings, in effect, the return to the asset in this economy. This finding regarding the importance for wealth inequality of asset return risk is consistent with research that highlights the importance of risk to returns to assets (Benhabib *et al.* (2015, 2017), Benhabib and Bisin (2018), and Stachurski and Toda (2019)).

Our study relates to existing research that has examined, quantitatively, resource risk, individual and community response mechanisms and their implications, in small-scale contemporary economies. The study populations in this literature include: agrarian or agro-pastoralist economies where livestock is a key — but risky — asset used in production and as storage for savings (e.g. Rosenzweig and Wolpin (1993), Udry (1995), Fafchamps *et al.* (1998), Lim and Townsend (1998)); pastoralists for whom livestock is typically the only asset for production and storage, and for whom droughts have substantial and wide-ranging implications (McPeak (2004, 2006), McPeak *et al.* (2011), McGuirk and Nunn (2022)); and small-scale rural settlements where informal co-insurance community-level arrangements are found to be important in mitigating income risk (Townsend (1994), Kinnan and Townsend (2012), Samphantharak and Townsend (2018)). Compared with this literature, we ask a different research question, namely whether resource risk, when accounting for (limited) community-level co-insurance, generates observed wealth inequality in a pastoralist society that preserves production technology of early human societies and in which financial and insurance markets of modern societies are virtually non-existent. Our analysis nonetheless contributes to the literature on savings under risk in contexts with very limited mitigation options, which has been a central element in a large part of the literature on agrarian and pastoralist economies. In particular, previous work has generated mixed results regarding the use of livestock as a buffer against income shocks. We find that in both the model and the data, livestock is not used as a buffer to smooth income shocks that arise as a result of shocks to the asset, namely livestock; however, the model reveals that livestock is used as a buffer against other income shocks.

The rest of the paper is organised as follows. Section 2 summarises findings from our survey data regarding inequality, resource risk, savings decisions and co-insurance options among Turkana pastoralists. Section 3 presents the model that links shocks to resources to wealth inequality via savings decisions. In Section 4, we describe how we use the data to approximate the stochastic processes determining shocks to resources. We analyse results in Section 5, discuss implications in the context of existing research in Section 6 and conclude in Section 7. We provide further details relating to the data and methods in the Appendix.

2 Data and empirical results

To analyse livestock and resource risk in Turkana, we collected data via a survey of 1,347 pastoralist households (providing data on 9,179 individuals) in Turkana County, Kenya, during November-December 2018. The study site, comprising the sublocations Loperot, Kalapata and Napusimoru, located within the Kalapata and Lokichar wards in rural Turkana County, was selected because traditional pastoralist lifestyles are maintained in this area. We supplemented this dataset with interviews and focus group discussions in the area corresponding to our survey data, conducted in January-February of 2020, with the aim of obtaining detailed information on (co-)insurance and risk mitigation, environmental factors, herding practices and income generation streams.[3] In particular, we organised 11 key informant interviews, 31 household interviews and three focus group discussions (involving 16 participants across the focus groups) in Kangakipur, Loperot and Napusimoru, in Turkana South. Our survey dataset includes information on individual-level and household-level characteristics: household composition and demographic variables (including age, gender, and education of household members); productive (or 'work') and non-productive time for each household member, including waged work outside of the household (for 2017 and 2018); detailed livestock numbers (of goats, sheep, etc.), livestock population dynamics (births, deaths, theft) and livestock acquisition or reduction via household decisions (for 2017 and 2018); information on important durable goods (e.g. vehicles); other economic activities and potential sources of income (e.g. running a business, selling items at a market, etc.); access to financial markets; and the home location of the household (i.e. the location of the 'boma' or livestock enclosure, typically with huts). Details of the survey and data are provided in Appendix A. We use this dataset to analyse variation between households in terms of wealth and resource risk.

2.1 The importance of livestock in Turkana and livestock inequality

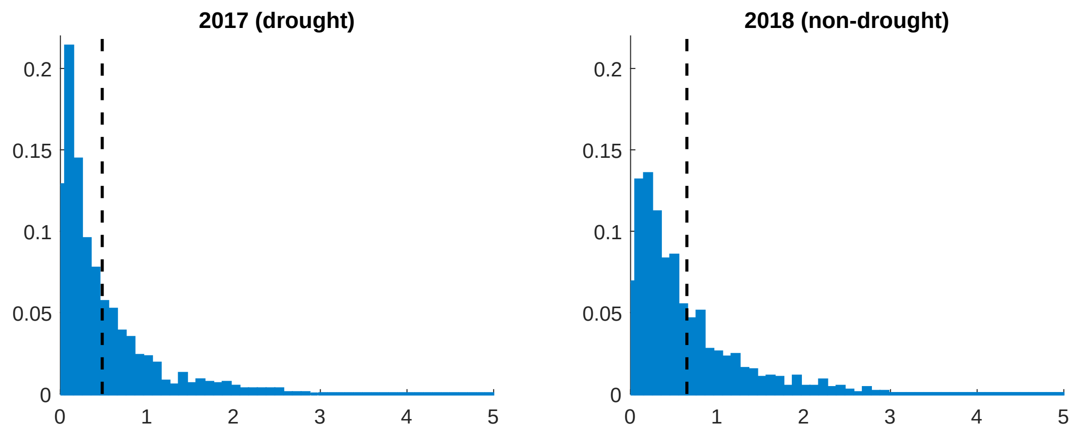
For the Turkana pastoralist communities that we study, livestock is paramount and functions, in effect, as the sole asset. Livestock provides returns in the form of milk (a dividend of the asset) and new animals (asset growth); it is also used as the principal means to transfer resources between periods. Livestock is the main preoccupation of the pastoralists and serves as the *de facto* unit upon which transactions are based. It is also the good that is most closely linked with the quality of life, as well as with differences in wealth between households. Goats are the most common species of livestock owned by Turkana households (on average, 22 goats per household in 2018), and there are also smaller numbers of sheep (on average, around 5) and of camels (on average, around 2), and very small numbers of cattle and donkeys (see Appendix A.4 for detailed information). We measure holdings in livestock units (LU) using conversion coefficients for the different livestock species from FAO (2011) which express livestock in units relative to 1 US breed cow (weighing 455kg). We report findings at the household level in livestock units per capita (i.e. per household member).

In Figure 1, we plot the empirical wealth distributions of household-level livestock ownership, measured in livestock units per capita, separately for 2017 and 2018. To do this, for each household, we convert livestock numbers into livestock units, aggregate across species and then normalise by converting to per capita terms by dividing by the number of household members (see Appendices A.3 and A.4 for details of sample selection and robustness using additional measures of wealth). We also show in Table 1 summary statistics of the distributions of wealth. In summary, the extent of overall inequality observed in our sample from Turkana is substantial. This is consistent with a series of studies (e.g. Sutter (1987) and research summarised in Borgerhoff Mulder *et al.* (2009, 2010)) which also document non-trivial wealth inequality in pastoralist communities; wealth inequality measured in our sample is within the range reported in these studies. Although the

[3]The work reported here is part of a larger ongoing research and engagement programme focusing on risk exposure, inequality, and mitigating options in Turkana.

wealth inequality shown in Figure 1 and Table 1 is lower than in a typical developed country (e.g. Davies *et al.* 2011), the magnitude is comparable.

Figure 1: Empirical wealth distributions in Turkana



Note: Wealth is measured in livestock units per capita at the household level. Vertical dashed lines indicate the mean. To avoid potential identification, the bins above 3 LU are grouped-averaged.

Table 1: Livestock ownership statistics in 2017 and 2018

	2017	2018
mean*	0.483	0.650
	[0.446, 0.520]	[0.608, 0.693]
Gini*	0.576	0.525
	[0.555, 0.597]	[0.506, 0.544]
Poverty*	0.116	0.062
	[0.098 0.133]	[0.049, 0.075]
Q1*	0.014	0.023
	[0.011, 0.017]	[0.020, 0.026]
Q2*	0.055	0.070
	[0.050, 0.060]	[0.065, 0.075]
Q3	0.113	0.128
	[0.104, 0.121]	[0.121, 0.135]
Q4	0.220	0.223
	[0.208, 0.233]	[0.213, 0.234]
Q5	0.598	0.556
	[0.574, 0.621]	[0.536, 0.576]
Top10%	0.410	0.371
	[0.383, 0.437]	[0.349, 0.393]

Notes: Wealth is measured in livestock units per capita at the household level. Poverty is defined as the proportion of households that own less than 0.05 LU per member. Q1 to Q5 denote the share of the total value held by each of the five quintiles of the distribution. Parentheses show the 95% confidence intervals calculated using a bootstrap with 1000 replications, with an asterisk (*) denoting that the confidence intervals do not overlap.

2.2 Effects of droughts on livestock

A striking observation from Figure 1 and Table 1 is the difference in the wealth distribution between the two years. In particular, relative to 2018, the concentration at lower livestock ownership levels seen in Figure 1 is substantially higher during 2017, which was a year of drought. Indeed, as can be seen in Table 1, average livestock ownership was significantly lower during the drought year, while poverty and inequality measures were substantially higher. Regarding poverty, we focus our analysis on a measure of poverty that reflects a critical threshold for Turkana pastoralists. Specifically, we define extreme poverty as the proportion of households whose end-of-year livestock is less than 0.05 livestock units per capita; this corresponds to about three goats per household for the median household size of six members. Given the dependency of pastoralists on their livestock, livestock numbers of this scale imply a very low potential to generate resources that captures critical poverty. Indeed, having fewer than three goats means that it is very difficult to grow a herd, thus, in effect, making it difficult to sustain a pastoralist way of life. In the observed 2018 distribution, extreme poverty of this type is relatively rare, with less than 6.2% households below the threshold. However, for the drought year of 2017, this proportion increases to 11.6%.

Droughts are not rare events in Turkana. In particular, rainfall data that we analyse in Appendix A.5 reveal that limited rainfall, less than or equal to that of the drought year 2017, occurred on average every 2-3 years over the past decades and sometimes persisted for more than one year (consistent with findings in e.g. McPeak (2004) and McPeak *et al.* (2011) on droughts in northern Kenya). These findings highlight the importance for Turkana pastoralists of the resource risk that droughts generate. While pastoralists are also subject to further aggregate-level shocks (e.g. floods or locust plagues), droughts are their main concern. For example, in our interview and focus group data, participants refer to droughts as the main aggregate shock to their livelihoods. The concerns generated by droughts are also reflected in formal government interventions under the auspices of the National Drought Management Authority (NDMA), whose remit includes monitoring of droughts and their impacts to allow them to prioritise interventions providing basic support where and when it becomes critical. Existing research also acknowledges the pressures that droughts generate for pastoralists (see e.g. McPeak (2004) and McPeak *et al.* (2011) for effects on livestock and McGuirk and Nunn (2022) for implications for conflict). We focus therefore on droughts — the effects of which on both livestock and resource risk we can capture in our data — as the main aggregate shock in our analysis.

2.3 Household-specific resources and risk

We analyse variation between households in terms of household-specific shocks to the growth rate of livestock holdings and the time available to use as an input in productive activities, as well as variation in income from non-livestock sources. In Section 4, we use the information from these three sources of variation to construct corresponding stochastic processes in the model.

2.3.1 Growth rate of livestock holdings

A first source of household-specific risk relates to stochasticity regarding herd growth, resulting from the number of animals that were born, stolen or died from natural causes.[4] To capture this risk, we construct a random variable l_t, the household-specific growth rate of livestock in livestock units per capita for 2017 and 2018 (i.e. separately for droughts and non-droughts). To do this, we first use the survey data to construct a variable capturing the growth rate of livestock holdings in per capita livestock units $\widetilde{l}_t^i$, for each household i, for $t = \{2017, 2018\}$, [5]

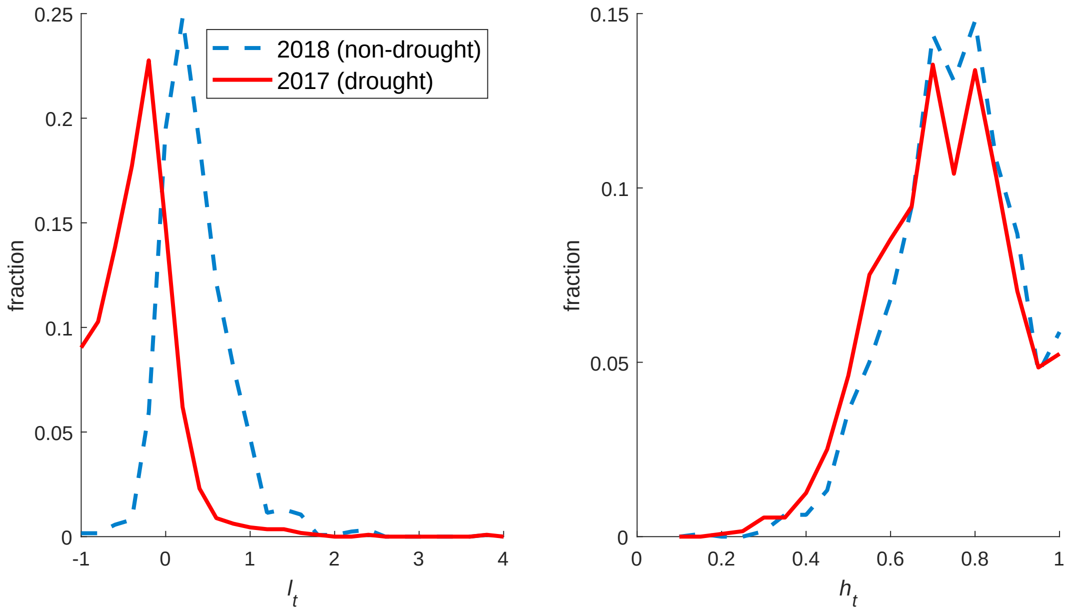
$$\widetilde{l}_t^i = \frac{\left[\frac{\text{births}_t^i - \text{stolen}_t^i - \text{deaths}_t^i}{N_{hh,t}^i}\right]}{\left[\frac{a_{t-1}^i}{N_{hh,t-1}^i}\right]}, \tag{1}$$

[4]On the importance of rainfall and of idiosyncratic shocks leading to variation in herd growth among pastoralists in East Africa, see also e.g. McPeak (2004) and McPeak *et al.* (2011).

[5]For additional details of the sample and construction of this variable, see Appendix A.

where $N^i_{hh,t}$ denotes the size of household i in period t and a^i_{t-1} is household i's livestock in period $t-1$. Note that births, deaths, thefts, and a_{t-1} are measured in LU.

Figure 2: Distributions of the household-specific component of shocks to the growth rate of livestock holdings and of time input



Note: The histograms show the stochastic household-specific components of livestock holdings growth rates and of time input. They are obtained by partialling out observable characteristics.

Table 2: Statistics of shock distributions

	l_t		h_t	
	2017	2018	2017	2018
mean	-0.314	0.357	0.719	0.750
St. Dev.	0.440	0.422	0.152	0.139
skewness	1.600	1.539	-0.266	-0.338
kurtosis	12.281	9.619	2.742	2.980

Note: Statistics of the distribution of shocks to livestock holdings growth rates and to time input (shown in Figure 2).

To capture shocks to the growth rate of livestock, we then construct the variable l^i_t for household i, for $t = \{2017, 2018\}$, by partialling out household characteristics from $\widetilde{l}^i_t$. We do this using linear regressions on a set of dummies for the age of the head of the household (a dummy per decade of age), dummies for the gender and education of the head, variables capturing the composition of the household (number of adults, spouses, and children by sex) and a dummy for the location of the boma. These characteristics are observable to the households and thus are not part of uncertainty regarding livestock growth for a given household. The regressions are run separately for each year. Before running these regressions, we standardise $\widetilde{l}^i_t$ by multiplying it by the ratio of the total standard deviation of $\widetilde{l}^i_t$ over the standard deviation of the sublocation i.e. $\widetilde{l}^i_t = l^{i,\varkappa}_t \frac{\sigma_{t,l}}{\sigma_{t,l,\varkappa}}$, where $\varkappa$ denotes the sublocation. This removes dependence of the variance of the shock distribution on sublocation-specific factors that would be common across households within a sublocation and thus not idiosyncratic.[6] The results from these regressions are shown in Appendix A.6. In general, they show that household characteristics contribute little to explaining variation in herd growth,

[6]The Breusch-Pagan and White tests reveal heteroskedasticity in the residuals from the non-standardised regressions but do not detect heteroskedasticity after standardisation.

suggesting that households are approximately *ex ante* identical in terms of herding returns and risk. We retain the residuals from the standardised regressions as a measure of the household-specific component of shocks to livestock growth. Finally, to construct the variable l_t, we re-centre these residuals on the unconditional mean of the net growth rates per period, about 36% in 2018 and -31% in 2017.

In the left panel of Figure 2 we plot the distribution of the household-specific component of livestock growth rates separately for 2017 and 2018 and, in Table 2, we report key statistics of these distributions. The spread of the distribution, demonstrating that both losing the whole herd (100% reduction, i.e. $l_t = -1$) and more than doubling the herd (more than 100% growth, i.e. $l_t \geq 1$) are outcomes with non-trivial probabilities, is revealing of the extent of household-specific (or herd-specific) uncertainty regarding livestock returns. The difference in the shape and location of the density functions between the two years confirms that droughts are periods of increased downside risk and an increase in the asymmetry of the distribution. The uncertainty implied by the distribution of the shocks to herd growth seen in Table 2 and Figure 2 is comparable to that of economies with developed financial systems. For example, the statistics capturing risk are similar to those estimated from administrative data for Norway for returns to non-financial wealth (Fagereng *et al.* (2020)). This is consistent with livestock wealth being used as non-financial equity in household-level entrepreneurial activity, namely herding. However, in contrast to the persistence of entrepreneurial risk in economies with a more complex production structure (e.g. Quadrini (2000), Cagetti and De Nardi (2006), Fagereng *et al.* (2020)), shocks to household-specific herd growth are not persistent. In particular, the first-order autocorrelation of l_t is only -0.16, suggesting that the household-specific component of stochastic returns to livestock, after partialling out aggregate-level effects associated with droughts, does not show sizeable persistence. This suggests that unobservable household-specific characteristics that may relate to herd growth (e.g. herding ability) matter little for the idiosyncratic variation in herd growth rates that we measure, because these characteristics should imply persistence in household-specific livestock shocks. The risk that we uncover is thus primarily associated with demographic stochasticity regarding the natural processes of birth and death of animals, and losses due to theft. Note, nevertheless, that there is persistence in shocks to herd growth, driven by the persistence of the aggregate state.

2.3.2 Household time

A second source of uncertainty regarding the household's ability to generate resources relates to the effective time input of its members. In particular, the effective time input may vary between households because of variation in the demographic composition of the household or availability for work of its members due to ill health, or the need to devote time to matters that do not directly generate resources (e.g. caring responsibilities).

We use our survey data to construct h_t, a measure of the stochastic component of household-level time availability. We first set a member's time input to one if an individual is between 7 and 70 years old and zero if she/he is outside this age bracket. This age range is motivated by the observation that household members in this age bracket, when they are able to do so, use time to contribute to household activities to generate resources. When an individual between 7 and 25 years old goes to school, they support the household when not in school and we thus adjust these members' time input to 0.5. The individual's time input is then multiplied by the share of the year he/she was available to work, based on information we have from the survey data (i.e. if an individual was available for 11 months, we multiply his/her productivity by 11/12). If an individual died or left the household during the year, we set their individual time input to zero. Following this logic, we construct the variable $\widetilde{h}_t^i$, the per capita time input, for each household i and for $t = \{2017, 2018\}$, defined as the sum of household members' time input divided by the number of household members

$$\widetilde{h}_t^i = \frac{\left[\sum_{n=1}^{N_{hh,t}} \widetilde{h}_{n,t}^i * (1 - \frac{mc_{n,t}}{12})\right]}{N_{hh,t}^i}, \tag{2}$$
$$\widetilde{h}_n^i = 1 \text{ if } 7 \leq age \leq 70 \text{ \& not studying},$$
$$\widetilde{h}_n^i = 0.5 \text{ if } 7 \leq age \leq 25 \text{ \& studying},$$
$$\widetilde{h}_n^i = 0 \text{ if age} \leq 6 \text{ or } 71 \leq age\text{, or if died, or left},$$

where $\widetilde{h}_n^i$ is the time input of individual n and mc_n is the number of months during which individual n's activities were curtailed.

Using $\widetilde{h}_t^i$, we then construct the variable h_t^i capturing the household-specific shocks to time input for household i, for $t = \{2017, 2018\}$, by removing the life-cycle and location-specific effects that are observable to the household from $\widetilde{h}_t^i$ via a Tobit regression and re-centring.[7] Observable effects are those also used to isolate shocks to the growth rate of livestock holdings (see Appendix A.6 for results from these regressions). We keep the prediction errors from these estimations as a measure of the household-specific shocks and re-centre them on the unconditional mean of household time input to construct the variable h_t^i. We show the household-specific component of time input shocks in Figure 2 (right panel) and report key statistics of the distributions in Table 2. With the exception of a reduction in average time input during droughts, the distributions are very similar for the two years. We also find that there is persistence in the probability of receiving a negative shock: households that reported $\widetilde{h}_t^i < 1$ in the survey for 2017 have a 98.6% probability of reporting $h_t^i < 1$ in 2018, and those reporting $\widetilde{h}_t^i = 1$ in 2017 had a 58.2% probability of reporting $\widetilde{h}_t^i = 1$ in 2018.

2.3.3 Non-livestock income

Households in our study area have some opportunities for income beyond herding. Only a very small number of households (N=13) reported waged employment, which also generated very low levels of income. A larger number had income from selling items at market and from small businesses. In our sample, 197 households had income from selling items at a local market (e.g. baskets or other artefacts). We do not have detailed information on funds generated via this income stream, but, typically, these are relatively small amounts that are highly volatile over time and used to complement herding activities. In addition, 117 households reported running a small business (shops/kiosks, livestock trading, renting rooms, boda-boda). Engagement in this kind of activity is often related to education and skills and associated with aspirations for higher standards of living, suggesting generally higher income levels than selling items at market. For example, in our interviews, a university student involved in a local community group and who runs a kiosk, told us that 'you know to go to school, you get that knowledge, be educated ... and also it opens up your mind and also have the skills to run a business'. In total, 22 households had income from both selling items at market and small business activities.

Households also have access to natural resources such as water, material to make tools and construct houses and fences to keep animals, as well as trees that provide wood for charcoal used for cooking or for roadside selling. Some households may receive remittances from relatives or others outside of the community (e.g. family members living in a town). Furthermore, households may receive short-term support from government sources, international organisations and non-governmental organisations (charitable organisations), via a range of programmes, either directly in the form of livestock or food, or via cash transfers, with the aim to support a minimum level of consumption in extreme difficulty and to allow households to restart a herd. In drought years,

[7] The estimation method is motivated by the range of values that $\widetilde{h}_t^i$ can take on, which is $[0, 1]$.

households in areas we cover are targeted for emergency response aid from programmes managed by governmental structures and sometimes supported by NGOs. In 2018, 30% of households in our survey reported receiving remittances from relatives, friends or other sources such as NGOs or the government.

2.4 Livestock net acquisitions

In our survey data, we also have information on decisions regarding acquisition and reduction of livestock. In particular, we record 'number of animals bought/ acquired' and 'number sold/ permanently given away/ slaughtered'. The difference between these two categories defines, in effect, net livestock acquisitions and we use this empirical measure to examine how these relate to beginning-of-period livestock and shocks, exploiting the panel dimension of our sample to partial out effects of droughts and household characteristics via household-specific effects.[8] We do not have information on whether any of the changes in the 'bought/acquired' and 'sold/permanently given away/slaughtered' categories refer to changes in livestock for reasons we do not study in this paper, e.g. in relation to a significant life event like marriage, separation, or relocation of household members. To minimise the potential impact of such effects on our results, we partial out changes in household demographic characteristics that could be related to such life events using our survey information to include relevant variables in the statistical analysis and we trim the top and bottom 2.5% of net savings to exclude transactions of livestock that are likely outliers with respect to normal decision making in response to annual variation in stocks and shocks. We therefore estimate

$$x_t^i = \beta_1 a_t^i + \beta_2 \tilde{l}_t^i + \beta_3 \tilde{l}_t^i * a_t^i + \beta_4 \tilde{h}_t^i + \beta_5 \tilde{h}_t^i * a_t^i + \beta \mathbf{X}, \tag{3}$$

where i is a household index, $t = \{2017, 2018\}$, x_t^i is net livestock acquisitions (measured in livestock units per capita at the household level), a_t^i is beginning of period livestock holdings and the matrix $\mathbf{X}$ contains time-varying household-specific characteristics, but also household-specific time-invariant effects, dummies for the sublocation in which the boma is located and a dummy for 2018. Detailed results from this estimation are in Appendix A.7. Here we show, in Table 3, the estimates for the key variables of interest and, in Figure 3, the predicted marginal effects for different livestock units of beginning-of-period livestock, for different levels of the shock to livestock holdings growth.[9]

Table 3: Effects of shocks on net livestock acquisitions

β_1	β_2	β_3	β_4	β_5
-0.208**	0.0148*	-0.197**	0.103*	-0.00746
(0.104)	(0.00803)	(0.0951)	(0.0545)	(0.0234)

Notes: The coefficients β_j, $j = 1, ..5$ are defined in (3). Coefficient estimates are shown below β_j and standard errors in parentheses. Further detail is in Appendix A.7.

$^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$

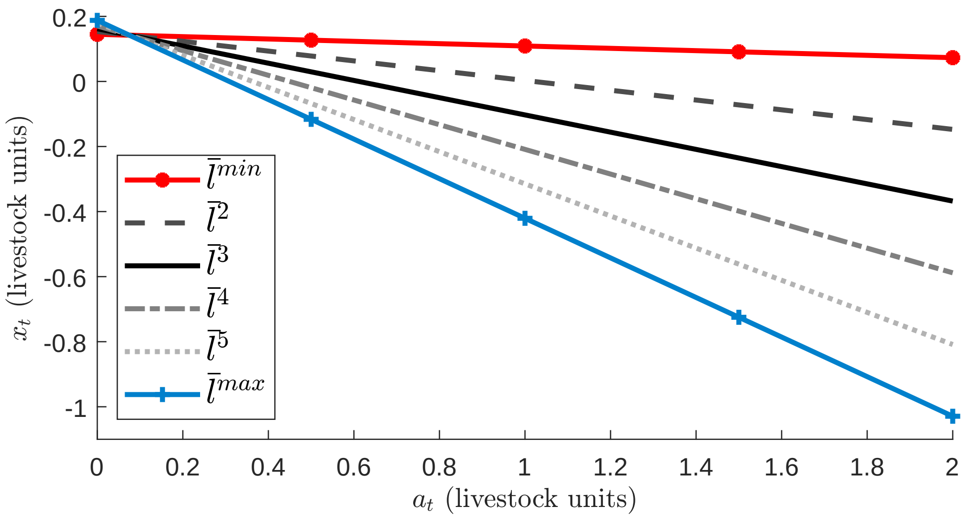
The main pattern that emerges from Table 2 and Figure 3 is that net acquisitions are a negative function of beginning-of-period livestock holdings and of more positive shocks to livestock holdings growth rates. In other words, livestock is acquired when livestock holdings are low and when the household receives large negative livestock shocks, implying that a large part (or even nearly all) of livestock has been lost; on the contrary, livestock is sold or consumed in the case of positive shocks and when numbers are higher. This type of behaviour suggests incentives to smooth the impact

[8] Our results are thus obtained by exploiting variation across households in the change in household-level livestock net acquisitions from 2017 to 2018. Because we only observe income from market and business activities in 2018, we cannot estimate their relationship with net acquisitions (they are part of the household-specific effects).

[9] The levels of livestock holdings growth shown in Figure 3 have been chosen to match the discretisation of the range of these variables used to estimate the underlying probability distributions (see Section 4).

of livestock shocks on herd size, rather than as a buffer. In contrast, there is some evidence that households use livestock to smooth the impact of time input shocks on consumption. In particular, the effect of time input on net livestock acquisitions is positive, although statistically significant only at 10%, and does not significantly depend on beginning-of-period livestock holdings. Research that has studied whether livestock acts as a buffer to income fluctuations in agrarian and pastoralist economies where livestock is used to produce income, by studying livestock sales in response to income shocks, finds mixed evidence, with most results suggesting that livestock sales do not increase in periods of bad shocks (e.g. Rosenzweig and Wolpin (1993), Udry (1995), Fafchamps *et al.* (1998), Lim and Townsend (1998), and McPeak (2004)). We return to discuss our findings in the context of the literature in more detail after we have also presented relevant model predictions.

Figure 3: Net livestock acquisitions by a_t and $\tilde{l}_t$



Note:The figure shows predicted marginal effects of a_t on x_t for different levels of $\tilde{l}_t$, estimated using (3).

2.5 Community-level support

Pastoralist communities provide some support to households to mitigate certain household-specific shocks. Firstly, given the centrality of herding for livelihoods, help with herding is offered when households face difficulties. For example, interviewees explained that 'When a person is not well, neighbours will take care of the animals or when there is an aged person the neighbours can now come and take the camels on the other side, they take care until you regain [strength] because you are ill, you can't perform tasks, you explain to them and they can see why you are asking for that kind of help'. This is consistent with our survey data, in which variation in household-specific livestock growth $\widetilde{l}_t$ is unrelated to household-specific time input $\widetilde{h}_t$, or indeed to changes in the time input of the head or of adult males.[10] Secondly, the social norms in Turkana provide some support to households that are impacted by adverse livestock shocks via transfers of a small number of livestock from a relative or friend in a position to help. Community-level support in adversity has been documented for Turkana pastoralists in Anderson and Broch-Due (1999) and in other pastoralist communities (e.g. the analysis and further references in Borgerhoff Mulder *et al.* (2010), McPeak (2006) and McPeak *et al.* (2011)).

The data we collected via interviews confirm the existence of assistance in the form of transfers when households face extreme livestock shocks but provide no evidence of support that extends

[10] As shown in Appendix A.8, these variables are not significant in regressions of $\widetilde{l}_t$ that also partial out a number of household-specific characteristics.

to more generalised sharing of resources with those who have low levels of livestock. For example, interviewees explained that 'if you have been stricken by drought or the issues of raids, community members who are close to you, they can donate goats so you can start up again', underlining that support is conditional on receiving a negative shock. The need for support is more common during droughts, because, as already analysed, large negative livestock shocks are more likely. However, these are also periods in which other community members find it hard to offer support. The assistance offered is limited, aiming to make it possible for the herder to start a new herd if they have lost their livestock. For example, one interviewee noted that 'if your animals are raided or they die, you go to your relatives, they maybe assist you and maybe give you 5, 3 or 1, just to make you at least recover from the loss of animals'. Indeed, Anderson and Broch-Due (1999) observe that support from other households is a means to help those facing adverse exogenous circumstances to escape extreme poverty, not those who remain poor because of bad choices. The co-insurance mechanisms among Turkana pastoralists are thus different in scope from those in some other small-scale societies analysed in e.g. Borgerhoff Mulder *et al.* (2009, 2010) (see also reviews of relevant research in Scheidel (2017)), where such mechanisms imply a more redistributive social model, or in rural village economies in e.g. Townsend (1994) and Samphantharak and Townsend (2018), where informal insurance arrangements between households allow them to insure away a larger part of idiosyncratic risk. The limited effectiveness of between-household transfers in mitigating the negative impact of livestock shocks in other pastoralist communities in East Africa has been noted in McPeak (2006) and McPeak *et al.* (2011). To a large extent, this is likely to be due to the importance of droughts, which create a very large non-diversifiable risk that does not allow for substantial transfers — when they are needed — because most households are negatively affected.

3 Modelling the link between resource risk and wealth inequality

We present a model in which wealth inequality is determined by household decisions to accumulate livestock under uncertainty regarding resources. In the model, the household is the unit of analysis and household-level quantities are expressed in household-average per capita terms (we do not study within-household resource allocations or household composition effects). The main resources of each household come from their livestock, which provide them with milk and which they can consume as meat. Additional resources can come from other economic activity and community-level or external support schemes. Households make decisions about how much of their resources to consume and how much to transfer to future periods via savings in a single asset, livestock. Households are *ex ante* identical: they are assumed to have the same preferences, technology, opportunities to generate resources and uncertainty regarding these. However, because they cannot fully insure against household-specific shocks, they have different resources and make different resultant choices regarding wealth accumulation.

3.1 A model of savings under resource risk for Turkana pastoralists

We model a continuum of infinitely many households, in discrete time, with a time step of a year. We present the resource allocation problem for a *typical* household in Turkana.[11] Households are herders who own and raise livestock that produces milk; in each period, subject to exogenous shocks to their resources, they decide how much of their livestock to consume (as meat or via sales), how much to keep and how much to buy. By buying more livestock, or by keeping some of the animals born into their herd, they increase the capital they hold in their business, which is assumed to be the only form of investment. In each period t, the household receives shocks from three exogenous Markovian processes that determine the net growth rate of livestock numbers (l_t) due to natural

[11] Given that households are *ex ante* identical, to simplify notation, we suppress the explicit dependence of each household's actions on a household index and present the problem of any household.

demographic turnover and theft, human time input available to support the production of milk (h_t), and the amount of income from other sources (e_t). These other sources of income include income derived from natural resources and external support that together define the lower bound of available resources, as well as income from market activity. Shocks are household-specific but also incorporate dependence on aggregate conditions, namely droughts, modelled as the binary variable $d_t \in \{0, 1\}$ that is Markovian. We also model community-level support, captured by the process (s_t), that depends on droughts and which takes the form of a transfer of a small number of animals to households that have lost their herd, with the burden shared among other households in the community. Acknowledging the dependence of the random variables l_t, h_t, e_t, s_t on d_t, we can denote their purely idiosyncratic component, conditional on a specific realisation of d_t, as l_t^d, h_t^d, e_t^d and s_t^d and we use this notation later when we want to highlight the effect of droughts on the stochastic processes.

The typical household chooses plans $\{c_t, a_{t+1}\}_{t=0}^{\infty}$, i.e. sequences of consumption c_t and next-year livestock a_{t+1}, that depend on the histories of shocks received, to maximise its expected lifetime utility

$$\max_{\{c_t, a_{t+1}\}_{t=0}^{\infty}} E_0 \left\{ \sum_{t=0}^{\infty} \beta^t u(c_t) \right\}, \tag{4}$$

where $u(\cdot)$ is a per-period utility function and $\beta \in (0, 1)$ discounts future outcomes, subject to the resource constraint

$$c_t + a_{t+1} = (1 + l_t)a_t + \eta y^d (h_t, l_t, a_t; w_t) + e_t + s_t, \tag{5}$$

taking initial conditions $\{a_0, l_0, h_0, e_0, s_0\}$ as given.

In this specification, $y(\cdot)$ denotes milk production, which is a function of livestock during the year (itself a function of beginning of year livestock a_t and of the growth of livestock during the year l_t) and time input available to tend to the herd and obtain the milk. Given the results we discussed in Section 2 showing that the livestock holdings growth rate is not related to household time input, we do not also include h_t in herd growth, which is only determined by l_t. The variable w_t captures natural resources which may include, for example, plants and trees that provides material to produce stools or other tools, mats or baskets, or to maintain fences or the boma. In recent decades, there has been support from governmental, non-governmental and international organisations (e.g. in the form of food, cash, animals to increase herd size, animal feed, provision of water and veterinary services). The resources included in w_t are limited, but they are important to support survival when livestock fails and indeed allow the model to ensure a strictly positive income which is required for an equilibrium in which a zero livestock state is transient. These resources, the quantity of which depends on droughts, can provide consumption to the households but are also an input to milk production. Therefore, we include w_t in e_t, determining its lowest state in drought and non-drought years, but also as an input to y_t.

In (5), we express all quantities except for milk in livestock units. In particular, community-level support in s_t is typically directly in the form of livestock, while e_t can be monetary and in this case, we convert the monetary valuation into livestock units using livestock prices that are taken as exogenous at the level of the communities we study. The livestock unit equivalent of a given quantity of milk is calculated as the quantity of meat from livestock that would provide the same number of calories. Specifically, we convert milk into livestock units, defining $\eta \equiv \frac{\eta^m}{\eta^l}$, where η^l denotes the calorie content of one unit of meat (from livestock) and η^m the calorie content of one tonne of milk. Livestock prices are determined outside of the pastoralist communities and are normalised to be one.[12]

We impose the following assumptions on the maximisation problem to ensure consistency with ecological constraints and well-defined solutions. First, the utility function $u : [0, +\infty) \to \mathbb{R}$ is

[12]In Appendix D.3 we show that the main results are robust to allowing for a reduction in livestock prices during droughts to reflect reduction in weight (e.g. reported in NDMA (2020)), so we abstract from this in (5).

assumed to be twice continuously differentiable, strictly increasing and strictly concave. In addition, we assume that it satisfies the conditions $\lim_{c\to 0} u_c(c) = +\infty$, $\lim_{c\to\infty} u_c(c) = 0$ and $\lim_{c\to\infty} \inf -\frac{u_{cc}(c)}{u_c(c)} = 0$.[13] Second, we define the state spaces for the exogenous processes as follows, noting that the state spaces expressed in this paragraph are those of the union of possible outcomes in drought and non-drought years. The random variable l_t takes outcomes in the state space that is determined by the $1 \times N^l$ vector $L = \left[\bar{l}^{\min}, ..., \bar{l}^{\max}\right]$, $\bar{l}^{\min} \geq -1$, where -1 corresponds to 100% herd loss. The random variable h_t takes values in the state space that is determined by the $1 \times N^h$ vector $H = \left[\bar{h}^{\min}, ..., \bar{h}^{\max}\right]$, $\bar{h}^{\min} > 0$. The random variables e_t and s_t take values, respectively, in the state spaces determined by the $1 \times N^e$ vector $E = \left[\bar{e}^{\min}, ..., \bar{e}^{\max}\right]$, $\bar{e}^{\min} > 0$ and $1 \times N^s$ vector $S = \left[\bar{s}^{\min}, ..., \bar{s}^{\max}\right]$, where $\bar{s}$ is allowed to be negative to capture households that contribute to community-level support while requiring their consumption to remain non-negative. Third, livestock at the level of the household takes values in the set $a_t \in A = [0, \bar{a}^{\max}]$. The upper bound is motivated by the idea that, at the aggregate level, there is a maximum number of livestock that can be sustained by the environment, commonly referred to as the carrying capacity, determined by the ecosystem. It is therefore reasonable to assume an upper bound for household livestock holdings; we denote this value, in per capita terms, by $\bar{a}^{\max}$, which cannot exceed the carrying capacity. Fourth, we require that the function $y\left(h_t, l_t, a_t; w_t\right) : H \times L \times A \times E \to \left[y^{\min} > 0, y^{\max}\right]$ is continuous, increasing and concave, with decreasing returns to livestock and, more specifically, with the marginal product and the average product of livestock decreasing in livestock and satisfying the condition that $\lim_{a_t\to\infty} \frac{\partial y_t}{\partial a_t} = 0$, thus bounding incentives to accumulate livestock.

3.2 Our model in the context of a general framework

We now describe how our model fits within the broader framework of studies employing models that have been used for quantitative analysis of inequality. A general representation of the problem of a typical household that encompasses several theoretical and quantitative studies of savings decisions and wealth inequality is given by maximising (4), given initial conditions of all state variables and subject to a resource constraint

$$c_t + a_{t+1} = (1 + r(v_t^a, v_t^h, a_t))a_t + e_t + s_t, \tag{6}$$

where c_t is consumption, a_t assets, v_t^a aggregate-level shocks, v_t^h household-specific shocks, $r(\cdot)$ the return to assets and e_t other stochastic income sources (e.g. through labour income); s_t captures pertinent social insurance mechanisms (e.g. via government policy or some other redistributive mechanism).

There is a long-standing and large literature that uses versions of this household problem as a key ingredient in modelling analysis to study wealth inequality, arising through asset accumulation decisions under imperfectly insured shocks to resources that generate variation in income across households. An important modelling choice in this literature refers to the quantities that enter into the function $r(\cdot)$. For example, models of the Bewley-Huggett-Aiyagari type (Bewley (1987) Huggett (1993), Aiyagari (1994)) are used to study economies without aggregate shocks, assuming that the return r is fixed over time and across households; models introduced by Imrohoroglu (1989) and Krusell and Smith (1998) allow r to be a function of aggregate shocks; and models in e.g. Benhabib *et al.* (2017), Benhabib and Bisin (2018), and Stachurski and Toda (2019) examine the importance of household-specific stochasticity in r.

In our model, $r(\cdot)$ incorporates both aggregate and household-specific shock processes, while also being a decreasing function of household-level assets via milk production. To see this, note

[13] Regarding these assumptions in incomplete markets models, see, e.g. Aiyagari (1994), Miao (2014) and Benhabib *et al.* (2015).

that (5) implies that:

$$c_t + a_{t+1} = \left[(1 + l_t) + \frac{\eta y \left(h_t, l_t, a_t; w_t \right)}{a_t} \right] a_t + e_t + s_t. \tag{7}$$

The expression in square brackets in (7), determining returns to the asset, shows that the dividend (average milk production per livestock unit) is a decreasing function of asset holdings and makes clear that returns are risky. More specifically, in our model, the stochastic processes entering into the relevant expressions show that both the dividend and the increase in capital stock (analogous to capital gain) are stochastic, involving a household-specific and an aggregate-level component.

More generally, the household problem at the core of this strand of the literature has been extensively used to analyse precautionary savings and consumption smoothing (e.g. Deaton (1991), Zeldes (1989) and Kimball (1990)). This literature includes studies that adapt this model to the characteristics of agrarian economies in which livestock is used in crop production (e.g. Rosenzweig and Wolpin (1993), Fafchamps *et al.* (1998)) as well as to those of pastoralist economies where livestock produces milk (McPeak (2004)), allowing dividends and thus returns to the asset to be a linear or decreasing function of the stock. In these studies, which characterise household savings decisions under risk and do not examine the distribution of wealth across households, the return to the asset is stochastic, reflecting idiosyncratic and aggregate shocks.

3.3 Dynamic paths and cross-sectional distributions

We define the joint distribution $z_t = (l_t, h_t, e_t, s_t)$, which is assumed to follow a Markov chain, with state space $Z = L \times H \times E \times S$ and transition matrix Q, the entries of which give the conditional probabilities $\pi \left(z_{t+1} | z_t \right)$. Note that the random variables l_t, h_t, e_t, s_t are defined in such a way to subsume the outcomes of d_t. We assume that (z_t) has a unique invariant distribution ξ, comprising the unconditional probabilities and implying partial invariant probability distributions denoted by ξ_j, for $j = l, h, e, s$. The dynamic paths for livestock and consumption are obtained by a dynamic programming solution to the household problem. Dynamic programming theory implies the existence of policy functions $a_{t+1} = g \left(a_t, z_t \right)$ and $c_t = q \left(a_t, z_t \right)$, which are unique and continuous (see Appendix B, where, to aid intuition about the workings of the model, we also analyse further wealth accumulation and net savings with respect to the state variables in a two-period version of the model). We examine these policy functions for the model calibration below to confirm that the savings behaviour predicted by the model is empirically relevant. The household-level joint distribution (a_t, z_t) generated by the policy function and the process (z_t), with transition matrix $\mathcal{Q}$, has an invariant distribution $\lambda \times \xi$ (see Appendix B). This theoretical distribution represents the proportion of time that each household spends in each state in the long run. We confirm that for the model calibration below, this theoretical distribution is unique, by verifying that all transition probabilities in $\mathcal{Q}$ are positive; this also implies that $\lambda \times \xi$ is the same for all households.

In our analysis, we focus on the computation of cross-sectional wealth distributions. These change over time and are determined by household choices and random shocks, as encapsulated in the policy function $g(\cdot)$. Note that $a_{t+1} = g \left(a_t, z_t \right)$ can be written, for each outcome of d_t, as $a_{t+1} = g^d \left(a_t, l_t^d, h_t^d, e_t^d, s_t^d; d_t \right)$, which makes clear that the function that describes livestock choices given the household-level state variables varies over time, and in particular that the function itself changes depending on the aggregate state d_t. We are interested in the *cross-sectional joint distribution* $\left(a_t, z_t^d; d_t \right)$ for each time period t in the stationary regime, where initial conditions $\{a_0, z_0\}$ for each household are drawn randomly from $\lambda \times \xi$ and households use the functions $a_{t+1} = g^d \left(a_t, l_t^d, h_t^d, e_t^d, s_t^d; d_t \right)$ to generate the time series for livestock, implying that the household-level time series is governed by the theoretical distribution $\lambda \times \xi$. Although the household-level dynamics are governed by the invariant theoretical distribution, the cross-sectional distribution changes over time because of aggregate shocks, which imply that time-invariant cross-sectional distributions do not exist.[14] In the stationary regime, a given history of the aggregate state, i.e. of droughts, generates a specific time series of cross-sectional distributions. To obtain our results below, we study the time series of cross-sectional distributions that is generated by the realised history of the aggregate state between 1920 and 2018. The path of the cross-sectional distributions is computed using non-stochastic simulation following Heer and Maussner (2009) and Young (2010), starting from a guess for the initial distribution for a date preceding 1920. As discussed in Appendix B, the start date ensures that the initial guess does not influence key properties of the time series of the cross-sectional wealth distribution after 1920.

4 Estimation of exogenous processes and calibration

To solve the model numerically, we first use the survey data to estimate the exogenous processes. A fundamental source of uncertainty is the possibility of drought, which is an aggregate-level shock that, in turn, influences the dynamic paths of the four random variables that determine the idiosyncratic, household-level shocks. We thus approximate this aggregate-level stochastic process first and then, conditional on this, we approximate the processes determining household-level shocks.

4.1 Droughts

To model droughts, we denote the aggregate shock in period t by $d_t \in \{0, 1\}$ and model it assuming that it follows a Markov process. We let d_t take the value one if there is a drought and zero otherwise, with transition probabilities given by the 2×2 transition matrix Q^a. Using local monthly precipitation data, we calculate for each month during the rainy seasons (March-May and October-December), for the period between 1920 and 2018, the deviation from the long-run mean for the corresponding month. We then define drought years as those having precipitation during the rainy seasons as those in the bottom 40% of the distribution of deviations, ensuring that the known drought year, 2017, is correctly identified (for data sources and more detail, see Appendix A)). Then, using the transitions between the two states in the data, we calculate the probabilities for the Markov chain for the aggregate shocks in Q^a (shown in Appendix C).

4.2 Growth rate of livestock holdings

The random variable l_t determines the growth rate of livestock holdings and captures the net annual change in livestock due to only stochastic natural factors. The shocks in l_t contain both an aggregate element, driven by d_t, and an idiosyncratic element, denoted as (l_t^d), the distribution of which depends on the aggregate state that arises under d_t. The survey data allow us to construct the cross-sectional distributions of shocks to the livestock growth rate for 2017 (a drought year) and 2018 (a non-drought year) separately, giving rise to two distributions of idiosyncratic shocks shown in Figure 2. Because there is little correlation between the household-specific shocks across periods, we model (l_t) such that, conditional on the aggregate state, idiosyncratic shocks do not have persistence. Therefore, any persistence in the shocks to livestock growth rates is driven by the persistence of the aggregate state and not by the idiosyncratic shocks, with the latter adding further uncertainty in the form of variability that is conditional on the aggregate state.

The random variables l_t^d, where $d = \{0, 1\}$, take values in the state space that is determined by the $1 \times N^{d,l}$ vectors $L^d = \left[\bar{l}^{d,\min}, ..., \bar{l}^{d,\max}\right]$, $\bar{l}^{d,\min} \geq -1$, with probabilities given by ξ^d. We use the cross-sectional distribution of the variable l_t^i (constructed following information in Section 2) for 2017 and 2018 to estimate L^d and ξ^d for $N^{d,l} = 6$, applying the data-based discretisation proposed

[14] For examples of this type of equilibrium dynamics of household-level distributions, see, e.g. Imrohoroglu (1989) and Heer and Maussner (2009).

by Toda (2021), which is an automatic version of the Golub and Welsch (1969) algorithm. We hence obtain the Markov chain (l_t) as given by the state space that is determined by the $1 \times N^l$ vector $L = \left[L^0 \; L^1\right]$, $N^l = 12$, and 12×12 transition matrix Q^l, which is constructed using ξ^d and Q^a. We report L^d, ξ^d, Q^a, as well as the state space L, the invariant distribution ξ_l and the transition matrix Q^l for (l_t) in Appendix C. We also plot in Appendix C the observed distributions and corresponding approximations to confirm the accuracy of the approximation.

4.3 Household time input

In the model, the random variable h_t corresponds to the household time input that is used for the production of milk. This random variable depends on d_t, and as discussed in Section 2, the idiosyncratic component also has persistence, which occurs in the $h_t^i = 1$ outcome. As shown in the right-hand panel of Figure 2, the empirical distribution of h_t^i is very similar for the two years, both having a mass of households clustered at the outcome $h_t^i = 1$, with a difference in the means.

Considering the information above, we model the stochastic process (h_t) as follows. First we calculate a Markov chain for a binary time input status, $hp_t = 1$ for $h_t = 1$, or $hp_t = 0$ for $h_t < 1$. The respective transition matrix is denoted by Q^{hp}, and its elements are obtained directly from the data by calculating the proportion of transitions between the two states across the households. Second, suppose the household is in $hp_t = 0$. In this case, it is assumed to draw a purely idiosyncratic shock, $h_t \in (0, 1)$ from distribution $h^{n,d}$ with probability density P_{h^n}, for $d = 0, 1$. Motivated by the previous results on the distributions of the residuals, the h^n distribution depends on the aggregate state because the state space differs by a constant. We then use the cross-sectional distribution of h_t^i, conditional on $h_t^i < 1$ and demeaned for each year, to approximate the demeaned empirical density of $h_t < 1$, P_{h^n} using a discrete four-state probability distribution, applying the discretisation method in Toda (2021). The discretised distribution is finally re-centred for each period so that the means between the two periods match the difference $\left(\frac{E\left[h_{2017}^i\right]}{E\left[h_{2018}^i\right]} - 1\right) = -4\%$. We plot in Appendix C the observed distribution and corresponding approximation to confirm the accuracy of the approximation.

Combining the Markov chain Q^{hp} with the density P_{h^n} (and the respective state spaces), we obtain the Markov chain for household time input, with transition matrix Q^h and state space H. We report Q^{hp}, and the probability distributions for $h^{n,d}$ in Appendix C, together with the state space H and the transition matrix Q^h and the invariant distribution ξ_h for (h_t).

4.4 Calibrating non-livestock market income

The variable e_t, which we refer to as non-livestock income, combines the minimum level of resources available to all households w_t, and household income from market activity. The value of w_t, which is the lowest state in e_t, is assumed to be equivalent to two goats per household per annum (equivalent to 0.2/6=0.0333 livestock units per capita) in drought years, reflecting e.g. income from accessing natural resources (such as wood for charcoal) or support from relatives living outside of the community or via external aid. Two goats allow the household to exit the zero livestock state; moreover, their implied monetary valuation approximately corresponds to the amount of short-term support provided to households during droughts by national government 'emergency response' programmes (key informant interviews valued this support at 3800-5000 KES per month for three months), which can be thought of as the minimum required for survival[15]. We then assume that natural resources in droughts are 70% of the respective value in non-drought years (inspired by the observation that the Forage Condition Index index falls by 31% in droughts; see Table 1 in Matere *et al.* (2020)). We then assume that income from selling items at local market

[15]We convert values in KES to livestock units, using livestock valuations provided by local experts in Turkana; see Appendix A.4.

constitutes the second state in e_t. As discussed in Section 2, this kind of activities, in which 16% of households engage, provide complementary resources to a household and are not generally understood as major income generation streams. Nevertheless, if a household is to be involved in this kind of activity, it should generate the minimum amount that they would otherwise receive from government support programmes. We thus set the income generated from this activity, at the annual level, equal to 0.2 (LU per capita per annum), which is approximately the amount that they would receive from government support programmes, were they to receive this amount for the full year (i.e. 5000 KES x 12 months = 60000 KES). The third and final state of e_t is given by small business income, which as explained in Section 2, is typically associated with more lucrative activities, and applies to 9% of the households in our sample. To assign a value to this state, we assume that it is equivalent to the wage that would be earned, on average, by 2.5 full-time equivalent household members, using the mean wage of those reporting waged income among our sample (30 individuals). The implied value of 0.7 (LU per capita per annum) is also consistent with median incomes from informal enterprises in Turkana South reported in the Turkana County integrated labour market assessment report by the International Labour Organization (2022, see Table 27). Because only 13 households report waged income, with a median of 30000KES per year, we do not include this in the model. Taking these different income streams into consideration, e_t is modelled as a random variable with a probability distribution given by the possible outcomes $E^{nd} = E + w_t|_{d=0} = \begin{bmatrix} 0.0476 & 0.2476 & 0.7476 \end{bmatrix}$, $E^d = 0.7 \times E + w_t|_{d=1} = \begin{bmatrix} 0.0333 & 0.1733 & 0.5233 \end{bmatrix}$ and associated probabilities $p_E = \begin{bmatrix} 75\% & 16\% & 9\% \end{bmatrix}$ where $E = \begin{bmatrix} 0 & 0.2 & 0.7 \end{bmatrix}$.

4.5 Co-insurance via transfers

As discussed in Section 2, there is community-level support in Turkana that provides co-insurance in the form of donations by family members or friends of a small number of animals in situations where households have received severe shocks that lead to the loss of their herd. Although we do not have detailed information on donors and recipients, our modelling is able to account — at the aggregate level — for the effect of community-level support in terms of mitigating the impact of negative livestock shocks on household-level resources. The discretisation of the livestock growth process l_t implies that the worst-case shock leads to a 91% loss in droughts and 90% in non-droughts. Therefore, we assume that community support s_t takes a positive value, reflecting a transfer of livestock, if the household receives the worst-case livestock shock. We set the value of this transfer to 0.2/6=0.0333 (2 goats per household or 0.2/6 livestock units per capita), based on information we collected during interviews (see Section 2). The value of the transfer we use is also consistent with McPeak (2006), who also estimates the average transfer to be about 0.15 livestock units per household in other pastoralist communities in northern Kenya. In our model, this implies that transfers of this type are provided to 17% households in droughts and to 0.5% in non-droughts, consistent with the information we collected from interviews that it is mainly in droughts that support from other households is required (see Section 2). These transfers are provided by other households within the community, who consequently see their own assets reduced accordingly. To implement this mechanism, we assume that households that receive positive livestock growth shocks contribute equally to these transfers. Ensuring that total contributions equal total transfers implies that each household with a positive livestock growth shock donates 0.0063 livestock units in non-droughts and 0.0618 in droughts. Our modelling reflects the assumption that households that have good luck are expected to provide some minimal support to others who, through bad luck, risk losing their livelihoods as pastoralists.

4.6 Model parameters

To obtain the numerical results, we specify functional forms for the utility function $u(c_t)$ and for milk production $y^d\left(h_t^d, l_t^d, a_t; w_t^d\right)$. We use a logarithmic utility function. The production function of milk is given by $y_t^d = M^d(h_t^d)^\gamma \left((1+l_t^d)a_t + w_t^d\right)^{(1-\gamma)}$. We then choose parameter values for η, β, M^d, γ and $\overline{a}^{\max}$. To obtain $\eta \equiv \frac{\eta^m}{\eta^l}$, we use information on the calorie content of meat and milk.[16] To calibrate γ, we take inspiration from production functions for farming. Estimates of production functions of farming in the US from earlier decades in Griliches (1963) suggest a $\gamma = 0.5$. Alternatively, thinking of it as being closer to a production function for the Kenyan economy, we note that the labour share in the Kenyan economy is around 44% (Guerriero (2019)). Given these considerations, we present results for $\gamma = 0.5$ and in Appendix D we show that our results are robust to a range of values for γ, between 0.3 and 0.7. The parameters M^d and β are chosen so that the model quantities of y_t and a_t are expressed in empirically relevant units. In particular, M^d scales y_t^d, while β affects the desire of the household to accumulate livestock and thus the average level of a_t. In our sample, the average level of per capita livestock is 0.5665 livestock units (averaged over 2017 and 2018) and we choose β so that model predictions match this value. We approximate annual household per capita production of milk in Turkana between 2006 and 2019, using information from NDMA (2020) to be about 0.146 tonnes on average, and about 45% higher in non-drought years.[17] We choose M^d so that the model simulated paths imply that milk production reproduces average milk values for wet and dry years between 2006 and 2018. Our calibration implies values of $\beta = 0.896$, $M^0 = 0.267$ and $M^1 = 0.232$. We set $\overline{a}^{\max}$ equal to 25, which is well above the maximum value of household livestock holdings in livestock units per capita we observe in the data, and higher than household livestock holdings in the model.

5 Model results

Taken together, our results show that the wealth inequality observed among Turkana pastoralists can be explained as the outcome of resource risk and the decision-making it implies. We first examine whether the model-generated distributions of livestock holdings correspond well to the empirical distributions. We then analyse choices regarding savings to augment livestock holdings and different sources of resource risk that shape the distribution of livestock.

5.1 Model generated wealth distributions match the data

The model predicted time series of cross-sectional livestock distributions generated by the household-level stochastic processes and the history of drought years between 1920 and 2018 provide an excellent match for the empirical livestock distributions. We confirm this fit using a range of evaluation methods.

We first calculate the model-generated wealth distributions for 2017 and 2018 and compare them to their empirical counterparts in the same years in the form of both probability density functions and cumulative density functions.[18] Figure 4 shows the model predictions (in red) for 2017 and 2018, with the empirical wealth distributions for 2017 and 2018 (in blue) overlaid. The

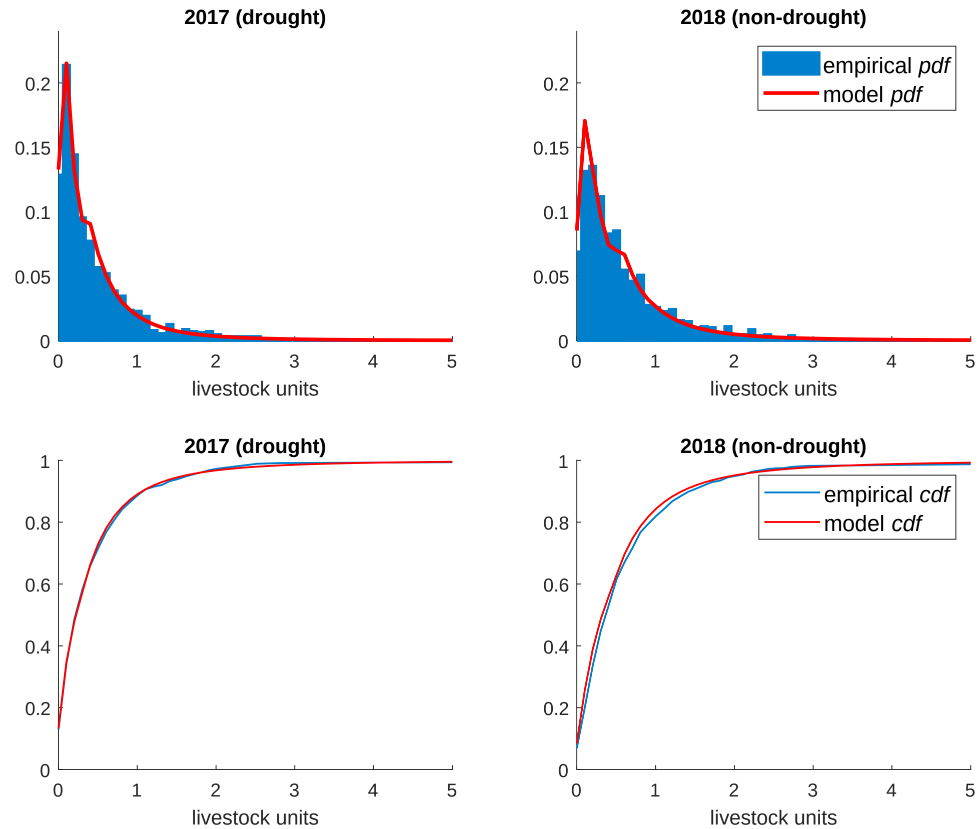
[16] In particular, 100g of meat contains approximately 143.5 calories (see Anaeto et al. (2010)), while 100ml of goat milk contains 76.5 calories (see Collard et al. (2021)). Hence η is equal to $\frac{\eta^m}{\eta^l} = \frac{74.1}{143.5} = 0.5329$

[17] In particular, NDMA (2020) estimates milk production in Turkana at about 2.4 litres per household per day on average between 2006 and 2019, being about 45% higher in wet relative to dry years. We approximate the annual per capita equivalent using a median household size of six.

[18] To make the empirical and model distributions comparable, we discretise all distributions on the same equally-spaced grid in A with 100 gridpoints (bins).

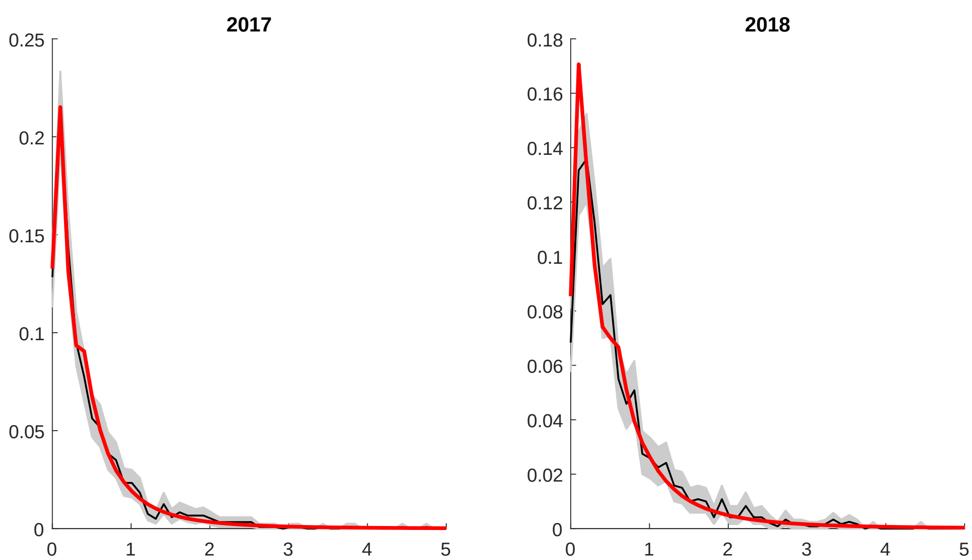
model-generated distributions are remarkably similar to their empirical counterparts.

Figure 4: Empirical and model-generated distributions, 2017 and 2018



The model-generated distributions are calculated by simulating the model economy using the historical time series for droughts since 1920. For the empirical distributions, see Section 2.

Figure 5: Model generated and re-sampled empirical distributions, 2017 and 2018



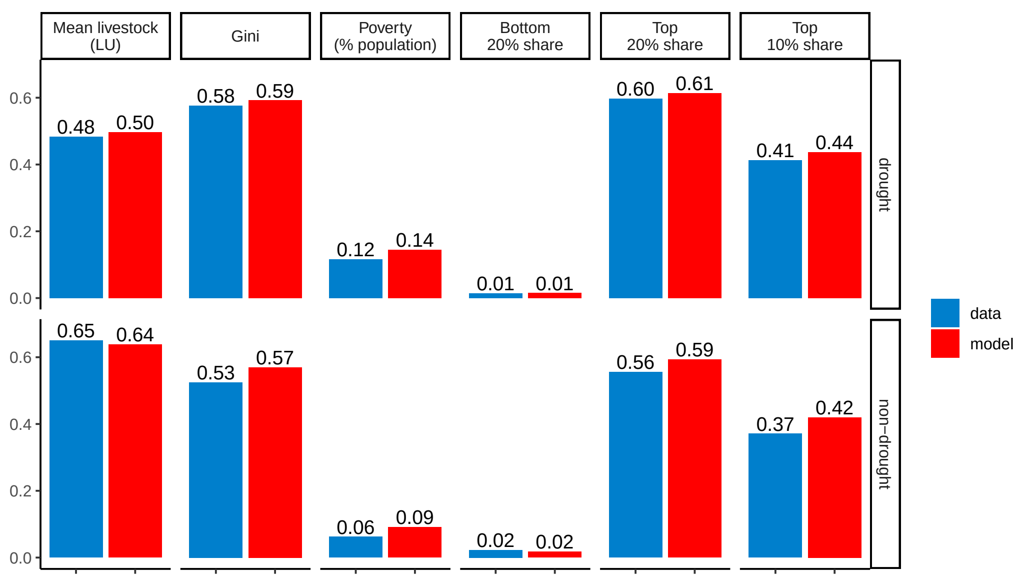
The grey areas denote the 80% confidence interval of the histogram of the empirical distribution from 1000 random samples with replacement; the black line is the median. The red lines are calculated by simulating the model economy using the historical time series for droughts since 1920.

Next, to examine sensitivity to the specific sample used to generate the empirical distributions of wealth, we plot, in Figure 5, the model-generated distributions (red lines) with the 80% confidence intervals of the empirical histograms (the grey area) obtained by re-sampling 1000 times with replacement from the data. The model predictions are within the range of plausible empirical outcomes.

We now focus on selected distributional statistics. In Figure 6, we present key statistics of the distributions for 2017 and 2018 for the empirical and model-predicted distributions. The model generated statistics are very close to those calculated from the data, also implying that the model captures the impact of droughts on wealth inequality and poverty. Note also that comparing the model-generated statistics in Figure 6 with the confidence intervals for their empirical counterparts in Table 1, we see that the model-generated statistics are always within the confidence intervals of their empirical counterparts.

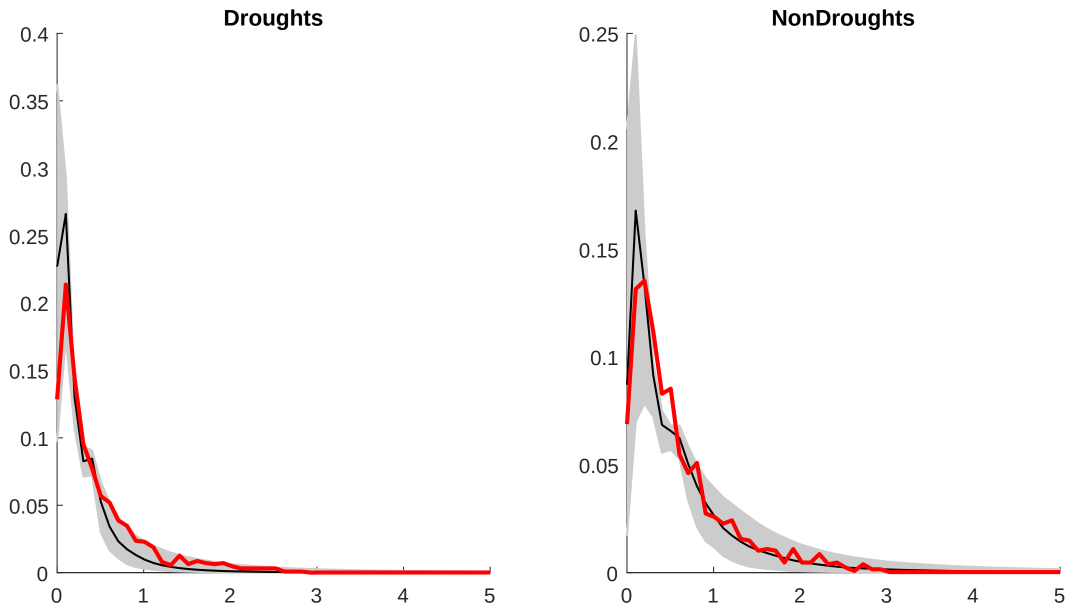
An additional form of evaluation of the empirical relevance of the model predictions treats the empirical distributions for 2017 and 2018 as draws from the time series of cross-sectional wealth distributions and thus examines whether they are consistent with the time series of cross-sectional wealth distributions generated by the model. We simulate the model using the historical time series of droughts since 1920 and calculate the prediction interval, point-wise, separately for drought and non-drought periods. We plot these intervals and the observed empirical distributions in Figure 7 and find that the empirical drought and non-drought wealth distributions are within the prediction intervals of the model-generated distributions.

Figure 6: Model-generated and empirical distributional statistics, 2017 and 2018



Note: Poverty is defined as the proportion of households that own less than 0.05 LU per capita. The model-generated distributions are calculated by simulating the model economy using the historical time series for droughts since 1920. For the empirical distributions, see Section 2.

Figure 7: Empirical distributions for 2017 and 2018 and model-generated prediction intervals for droughts and non-droughts



Note: The grey areas show the 80% prediction interval for drought and non-drought years from a model simulation using the historical time series of droughts since 1920; the black lines show the respective medians. For the empirical distributions (in red), see Section 2.

In summary, the results above show that the model-generated distributions of wealth and their properties are very similar to those in the data.[19] We next explore how household saving decisions and different sources of household-specific risk contribute to wealth inequality.

5.2 Inspecting the resource risk mechanism: the role of livestock savings

The functions $g^d\left(a_t, l_t^d, h_t^d, e_t^d, s_t^d; d_t\right)$ (see Section 3), which summarise wealth accumulation across households, encapsulate the working of the resource risk mechanism and generate the model predictions regarding the livestock distributions in Section 5.1. They also reflect incentives to accumulate or de-accumulate livestock under risk and thus conditions under which livestock acts as a buffer. Therefore, to understand the resource risk mechanism we analyse savings behaviour implied by the model and to evaluate its empirical relevance we examine whether model predictions regarding savings under risk are consistent with savings behaviour observed in the data.

We illustrate key properties of the functions $g(\cdot)$ in panels A and B of Figure 8, which plots a_{t+1} against a_t, for different levels of household-specific shocks.[20] In panel A, we plot a_{t+1} against a_t for different levels of the shocks to livestock holdings growth l_t, in non-drought periods, for households that receive the lowest non-livestock income e_t (which is the case for the majority of households in our sample), for time input $h_t = 1$ and see that it is increasing in both a_t and l_t. This illustrates the basic idea behind the resource risk mechanism for wealth inequality in the model. In particular, conditional on a given level of initial livestock, households that receive more positive l_t shocks make consumption and savings choices that lead to them having higher next-period livestock. Other things equal, this higher level of next-period livestock leads to even higher

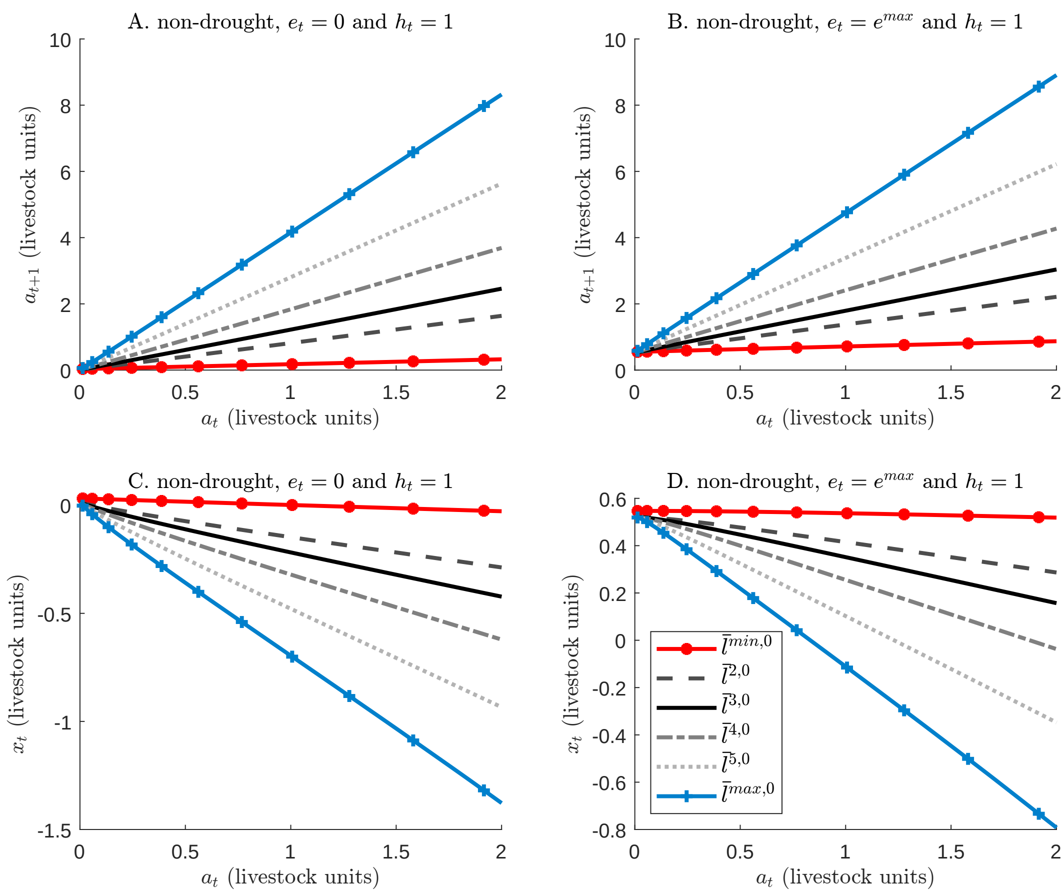
[19]Further exercises to verify the empirical relevance of model predictions regarding the properties of the wealth distributions are in Appendix D.

[20]See also Appendix B.3, for monotonicity properties of wealth accumulation and net savings with respect to the state variables in a two-period version of the model.

livestock in the following period, because a_{t+1} is a positive function of a_t. Therefore, the impacts of a more positive shock on livestock holdings accumulate over time, leading to persistently higher wealth.

In panel B of Figure 8, we repeat panel A for households that receive the highest non-livestock income shock e_t. By comparing the lines to those in panel A, we confirm that a positive e_t shock also leads to higher wealth accumulation. We do not show results for lower levels of the time input variable, h_t, because its effects are quantitatively very small (i.e. panels A and B change very little), suggesting that variation in h_t should not matter much for livestock inequality (a result we return to in Section 5.3). In Appendix D.2, we repeat panels A and B for drought periods, confirming the same patterns. By comparing drought to non-drought periods, we see that droughts (which imply an increased probability of more negative shocks; see Sections 2 and 4), lead to lower average a_{t+1}, with higher variation between households.

Figure 8: Next-period livestock and net livestock acquisitions

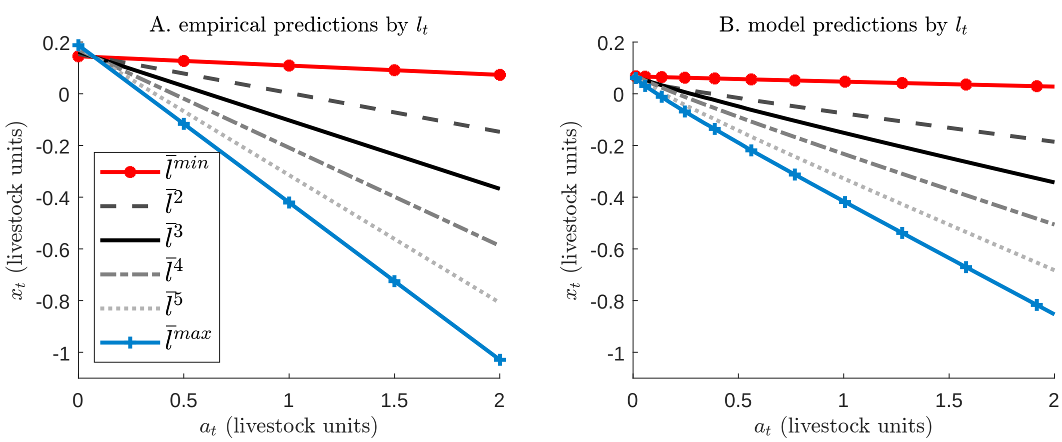


Note: Panels A and B show $a_{t+1} = g^d\left(a_t, l_t^d, h_t^d, e_t^d, s_t^d; d_t\right)$ for different values of the state variables. Panels C and D show $x_t \equiv a_{t+1} - (1 + l_t^d)a_t$ for different values of the state variables.

The household's decision rule $g(\cdot)$ that determines next-period wealth in panels A and B of Figure 8 is, in effect, the choice of the size of net livestock acquisitions, defined as $x_t \equiv a_{t+1} - (1 + l_t^d)a_t$, which is a function of the beginning of period livestock and shocks. Net acquisitions defined in this form refer to net acquisition of livestock over and above changes in livestock holdings as a result of natural shocks to livestock. The savings functions x_t, in effect an alternative representation of the $g(\cdot)$ functions in panels A and B, are plotted in panels C and D of Figure 8, which plot x_t against a_t, for different levels of household-specific shocks for non-drought periods (see Appendix D.2 for drought periods, showing similar patterns). As can be seen, net savings are a decreasing function of livestock a_t, being positive for low levels of livestock and becoming (more) negative as livestock increases (except for the worst-case livestock shock, which we analyse below). This behaviour implies that pastoralists aim to maintain a large enough herd size; this is required to sustain consumption because resources are predominantly generated by livestock. When their livestock holdings are very low, they use their available resources to increase herd size and thus consumption potential for future periods. When their livestock holdings are higher (and when they receive sufficiently positive l_t shocks) they use some of the increase in herd size due to natural sources to increase consumption via meat or other goods, financed by sales of livestock.[21]

These incentives to maintain a herd size are also seen when examining net savings as a function of shocks to the growth rate of livestock holdings. A larger positive l_t shock leads to lower net livestock acquisitions, implying that pastoralists in the model do not view livestock as a buffer stock used to smooth consumption in response to livestock shocks; instead, they aim to smooth herd size in response to negative livestock shocks, which is needed to ensure that consumption recovers quickly. On the contrary, comparing panels C and D in Figure 8, we see that net livestock acquisitions respond positively to non-livestock income shocks, consistent with consumption smoothing behaviour (i.e. suggesting their use as a buffer): when e_t is higher, so are net livestock acquisitions. In Appendix D.2, we show net livestock acquisitions as a function of time input to milk production, h_t, and see a similar pattern, suggesting that shocks that reduce time input to production require pastoralists to reduce livestock holdings to smooth consumption. On the contrary, when time input is higher, which increases the productivity of livestock, a larger herd size is preferred.

Figure 9: Empirical and model predicted net livestock acquisitions



Note: Panel A shows marginal effects of beginning-of-period livestock on net livestock acquisitions for different levels of l_t, estimated using the survey data (see Figure 3). Panels B shows the equivalent effects for model-predicted net livestock acquisitions. In both cases, effects are averaged over the remaining variables.

We can test whether the model predictions regarding household net livestock acquisitions, which give rise to the cross-sectional wealth distributions, are also consistent with empirical evidence on net livestock acquisitions from the survey data presented in Section 2.4. Empirical validation of the mechanism that links resource risk to that wealth inequality is an additional test for the resource risk mechanism to explain wealth inequality in the data, in addition to generating a good fit to the empirical wealth distribution. More generally, this analysis can contribute to understanding household choices in a risk-exposed environment under limited mitigation options, which we analyse further in the next section. We compare the empirical predictions regarding net livestock acquisitions in Figure 3 to equivalent model predictions in Figure 9. In panel A, we repeat, for

[21] However, note that, when net savings are negative, they are less in absolute value than the increase in herd size due to l_t, implying that a_{t+1} increases despite negative net savings in these cases, as is shown in panels A and B, respectively.

convenience, the empirical predictions from Figure 3 and in panel B we plot model-predicted net livestock acquisitions as a function of a_t and l_t, averaged over h_t, e_t, s_t and droughts.[22] As can be seen, the model predictions are very similar to the estimated relationship from the survey data. Although slightly smaller in absolute terms, they are of comparable magnitudes and within the 90% confidence intervals (see Appendix A.7). The model prediction for the average marginal effect of time input on net savings is positive, as in the data shown in Table 3, and although at 0.0261 it is smaller than the respective estimate from the data (0.0985), it falls within the 90% confidence interval [0.0121,0.1850].

We conclude that the household savings behaviour in the model that gives rise to wealth inequality as a function of random shocks to resources is empirically relevant. We now proceed to examine the relative importance of different forms of resource risk in generating the observed levels of inequality.

5.3 Inspecting the resource risk mechanism: the role of household-specific risk

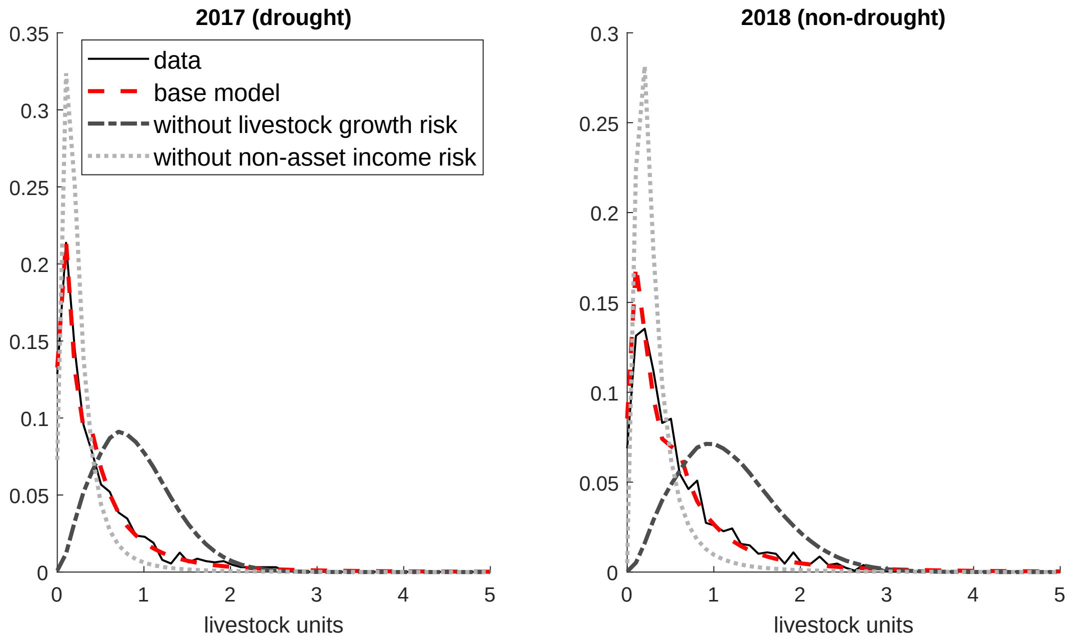
We now conduct counterfactual analysis using the model to assess the contribution of the different types of household-specific risk. For this analysis, we repeat the simulations of the model under the historical time series of droughts for different variants of the base model we have examined so far. In the first variant, we turn off shocks to the growth rate of livestock holdings (l_t); in the second, we turn off shocks to market income (e_t); and in the third, we turn off time input shocks (h_t). To ensure that there are no mean-level effects from this analysis, in all cases, we assume that all households receive the mean value of the variable we change in droughts and non-drought years. In the fourth variant, to assess the impact of community-level support in reducing critical poverty, we turn off community co-insurance via s_t. We summarise the results from these counterfactual model experiments in Figure 10 and Table 4. In Table 4, we present key distributional statistics from the base model and from the counterfactual analysis. In Figure 10, we show the model-generated distributions for 2017 and 2018 when we turn off l_t and e_t (the distribution changes very little when we turn off the h_t and s_t and thus the resulting distributions are not shown); for comparison, we also repeat the distributions generated by the base model and the empirical distributions.

The main result from Figure 10 and Table 4 is that shocks to the growth rate of livestock holdings are the primary driver of wealth inequality and poverty. As seen by comparing columns 0 and 1 in Table 4, the Gini measures and wealth ownership at higher deciles are approximately halved in the case where all households receive the mean livestock returns in droughts and non-drought periods with certainty; moreover, the proportion of households in extreme poverty falls to zero, while wealth ownership of the bottom quintile increases approximately sixfold. The contribution of variation in income from market activity is sizeable but substantially smaller than the effects of livestock holdings growth risk. Indeed, by comparing columns 2 and 0 in Table 4, we see that measures of inequality reduce by about 20% when all households receive the mean income from these sources for drought and non-drought years with certainty, whereas the reduction of the concentration of wealth at the higher quintile is lower. Extreme poverty is also eliminated, although the effect is mechanical because all households in this experiment receive the average value of e_t, which implies that they all, in effect, have resources above the poverty line. Note also that livestock holdings growth rate risk and non-asset income risk have diametrically opposite — and sizeable — implications for the extent of mean savings. In particular, while average assets are nearly halved in the absence of non-asset income risk, they are approximately doubled in the absence of livestock growth risk. The effect of household time input into milk production, shown in column 3 of Table

[22] To do so, we solve the model imposing the same state space for l_t between droughts and non-droughts.

4, is very small across the distribution.

Figure 10: The contribution of different sources of risk to wealth inequality



The model-generated distributions are calculated by simulating the model economy using the historical time series for droughts since 1920. For the empirical distributions, see Section 2.

Table 4: Wealth inequality indices by sources of risk (model predictions)

	[0] base model	[1] no livestock growth risk	[2] no market income risk	[3] no time input risk	[4] no co-insurance
Mean Livestock 2017	0.496	0.905	0.272	0.496	0.493
Mean Livestock 2018	0.637	1.171	0.355	0.637	0.633
Gini Livestock 2017	0.592	0.280	0.461	0.592	0.609
Gini Livestock 2018	0.570	0.274	0.422	0.569	0.584
Poverty 2017 (% households)	0.145	0.000	0.020	0.145	0.182
Poverty 2018 (% households)	0.091	0.000	0.000	0.092	0.127
Bottom 20% share of wealth 2017	0.015	0.078	0.048	0.016	0.009
Bottom 20% share of wealth 2018	0.018	0.078	0.064	0.019	0.014
Top 20% share of wealth 2017	0.614	0.352	0.515	0.613	0.626
Top 20% share of wealth 2018	0.593	0.349	0.493	0.592	0.603
Top 10% share of wealth 2017	0.438	0.199	0.354	0.437	0.447
Top 10% share of wealth 2018	0.420	0.196	0.338	0.419	0.429

Note: Poverty is defined as the proportion of households that own less than 0.05 LU per member. The model-generated statistics are calculated by simulating the model using the historical time series for droughts since 1920.

The effect of community-level support, as can be seen by comparing columns 0 and 4 in Table 4, is small in terms of inequality, but it is significant in terms of poverty and livestock ownership for households at the lower end of the distribution. Indeed, reducing community-level support for households that receive the worst-case livestock growth shocks increases extreme poverty by 30-50%. There is also a reduction in wealth ownership at the bottom 20% of the distribution of about 30%. The effects of community-level support for poverty and the left tail of the wealth distribution highlight the significance of co-insurance mechanisms, even though they appear to be limited in scope (see the discussion of relevant data and information from Turkana in Section 2).

6 Discussion

Overall, our results show that, for the pastoralist economy that we study, shocks to resources generate the observed variation across households in wealth via decision-making to accumulate assets, which is, itself, a function of resource risk and available resources. Here, we further discuss how our analysis and results contribute to research studying aspects of risk, savings, and inequality.

6.1 Resource risk and inequality in small-scale and in early human societies

Our work is inspired by studies of contemporary societies that preserve key characteristics of early human societies to understand the emergence of inequality in human societies (this literature is reviewed in e.g. Halstead and O'Shea (1989), Bar-Yosef (2001), Barker (2006), Halstead (2014), Scheidel (2017), and Dow and Reed (2023)). Our analysis contributes to this literature by emphasising the role of resource risk in generating wealth inequality, operating via household-level savings decisions in response to risk and shocks to resources. We now contextualise our work with respect to key studies from this literature.

In the influential study of Borgerhoff Mulder *et al.* (2009), idiosyncratic variation in resources is assumed as an essential ingredient in the generation of wealth inequality in contemporary small-scale societies, but its role is not explicitly examined because the focus in this work is instead on the role of cultural norms and technologies for wealth transmission. In particular, Borgerhoff Mulder *et al.* (2009) examine differences in wealth inequality between small-scale societies, focusing on the importance of cultural incentives to accumulate wealth over time and of the storage technology that allows for intergenerational transfers of different forms of wealth, for given stochastic variation in resources. Although stochastic variation in resources is assumed in Borgerhoff Mulder *et al.*'s (2009) model, it is critical, because without it there can be no wealth inequality. In contrast, we take as given in the society that we study both preferences and the storage technology that determines the ability to transfer resources over time, to focus on the importance of resource risk — the exogenous component of variation in resources — and household savings decisions in response to risks and shocks. Our results show that resource risk and the savings decisions it leads to can fully account for wealth inequality among the Turkana pastoralists that we study. These findings, therefore, provide empirical validation of the assumption of stochastic variation in resources in Borgerhoff Mulder *et al.* (2009). Our results further suggest that differences in resource risk across economies should also help to explain differences in wealth inequality, alongside other factors.

Our finding that risk to the returns to assets has such large effects on wealth inequality also has implications for our understanding of the differences in inequality between societies. In particular, our findings suggest that societies that are subject to either higher levels of variation in returns to assets or where the effect of such variation on the production of resources is more pronounced, should, other things equal, have higher inequality. First, higher risk leading to variation in returns to assets can occur, for example, due to increased variability in climate as a result of climate change. Second, when production is more dependent on assets relative to labour, the same variation in assets implies greater variation in output. Indeed, archaeological evidence in Bogaard *et al.* (2019) and Fochesato *et al.* (2021) suggests that inequality was higher in early human societies where production depended more critically on land (the asset) relative to labour. Bogaard *et al.* (2019) explain this finding by arguing that higher wealth inequality should be observed in societies where farming depends more heavily on land and animal traction than in those where farming depends more on labour and manure because shocks to assets (land and animals required for traction) tend to be larger than the equivalent shocks to human capacities. Our finding of a substantially greater impact on wealth inequality of the variation arising from shocks to the growth rate of livestock holdings than that arising from time input shocks is consistent with this logic.

Another strand of research on the pre-historical emergence of inequality and of its evolution during historical times has focused extensively on the role of socio-political conditions and formal and informal institutional arrangements that can lead to inequality between elites and commoners and determine property rights and co-insurance (Bar-Yosef (2001), Scheidel (2017), Ullus and Ellenblum (2021), and Dow and Reed (2013, 2023)). These factors influence inequality but also, in turn, adapt to changes in inequality. The link between co-insurance arrangements and resource risk is particularly relevant to our study. On the one hand, formal and informal insurance arrangements determine how much of (or even whether) the effect of idiosyncratic variation in income translates into resources available for consumption or asset accumulation;[23] on the other hand, widespread inequality and poverty that creates social instability generate pressure for societal or institutional change (e.g. examples in Scheidel (2017) and Ullus and Ellenblum (2021)). In our analysis, we take institutional arrangements as given because of their relative stability over the period we examine, accounting for the effect of existing co-insurance arrangements on wealth inequality. By conducting counterfactual model analysis without these arrangements, we confirm that co-insurance arrangements in the Turkana pastoralist society are important for mitigating poverty, or else the concentration on the left tail of the wealth distribution.

6.2 The dominance of asset return risk and unimportance of time input risk

Our finding that shocks to the returns to assets are a major driver of the wealth distribution complements recent research on wealth inequality that highlights the importance of stochasticity in returns to savings as a critical generator of inequality (e.g. Benhabib *et al.* (2015, 2017), Benhabib and Bisin (2018), and Stachurski and Toda (2019)). Although the above studies focus on the right tail of the wealth distribution, in the environment that we study, in which asset-generated income is the main source of income, risk in the returns to assets is also critical for the left tail. Because households in the model are entrepreneurs (in which the business is herding), our results are also consistent with research that demonstrates the importance of entrepreneurial risk for wealth inequality (e.g. Quadrini (2000), Cagetti and De Nardi (2006)). However, in the pastoralist economy that we model, entrepreneurial risk mainly takes the form of asset return risk, where the assets are invested in the household business, and thus differs from the stochasticity associated with entrepreneurial ability which has been emphasised in more complex production and market structures (see e.g. Cagetti and De Nardi (2006) for a review and Quadrini (2000) for a model incorporating both types of entrepreneurial risk). The importance for wealth inequality of shocks to the rate of return to assets is also consistent with findings from analysis of factors that determine wealth accumulation in villages in Thailand in Pawasutipaisit and Townsend (2011), which highlight the importance of variation in the rate of return across households.

In contrast, we find that shocks to time input have very little effect on wealth inequality. In small-scale societies, this may reflect arguments in Bogaard *et al.* (2019) that variation in labour input should be lower than that in assets such as land and livestock because human capacities are less variable are less risky than returns to these assets. In Turkana, the fact that shocks to human input have so little effect on wealth accumulation may also reflect household-level smoothing of individual-specific shocks to time input through the reallocation of tasks to other household members. Indeed, a variation decomposition exercise reveals that most variation in time input across

[23] This is exemplified in egalitarian hunter-gatherer societies (see e.g. Borgerhoff Mulder *et al.* (2009) and Scheidel (2017) for examples of such societies and relevant research) and in analysis of resource risk in small-scale rural communities where informal community co-insurance mechanisms work to, in effect, insure away a large part of the impact of idiosyncratic negative shocks to resources (see e.g. Townsend (1994) and Samphantharak and Townsend (2018)).

individuals in our sample is within households as opposed to between households.[24] Moreover, as discussed in Section 2, there is evidence of co-insurance of human shocks between households, including arrangements in which friends and neighbours help with herding or similar activities in the case of illness. This is probably reflected in the insignificant relationship between variation in time input and herd growth rates (discussed in Section 2.5) and could further explain the relatively small effect of variation in time input across households, both on savings decisions (Section 5.2) and on wealth inequality (Section 5.3). In turn, this suggests another potentially important form of community-level co-insurance, that of providing time input to support others, that goes beyond the transfers of resources that have been analysed in the literature (e.g. Townsend (1994), Lim and Townsend (1998), McPeak (2006), Kinnan and Townsend (2012)).

6.3 Savings decisions under risk in agro-pastoralist and pastoralist economies

Theoretical analysis of incomplete insurance markets has established that assets can serve as a buffer to help households smooth consumption in response to income shocks (i.e. non-asset shocks) (e.g. Sandmo (1970), Deaton (1991), Zeldes (1989) and Kimball (1990)). The logic behind this self-insurance mechanism is that households accumulate assets during periods of higher income in order to have more resources to liquidate to reduce the impact of temporary negative income shocks on consumption. By the same logic, an increase in income risk leads to increased precautionary savings in assets. Quantitative macroeconomic studies building on the basic incomplete markets model of Bewley-Huggett-Aiyagari, are consistent with these results. In our pastoralist model economy, the asset is livestock and income shocks are those that lead to variation in non-livestock income (i.e. market income). Consistent with this research, we find that households accumulate livestock in response to positive market income shocks and de-accumulate in response to negative income shocks (Section 5.2). Moreover, we find that households accumulate livestock in response to an increase in the uncertainty of market income (Section 5.3).

In contrast to income (i.e. non-asset) risk, theory shows that the impact of an increase in risk to returns to assets on asset accumulation cannot be signed because it is subject to income and substitution effects (Sandmo (1970)). Specifically, it depends on the relative magnitudes of forces acting in opposite directions: incentives to accumulate assets to ensure income does not drop too low following a negative shock; and the increased loss of investment in the case of a negative shock. In a quantitative work, these trade-offs can be evaluated, and indeed, a negative relationship between risk and asset accumulation can emerge in developed economies (see e.g. Angeletos (2007)). We find similar results in our model pastoralist economy, specifically that increases in uncertainty about the growth rate of livestock holdings lead to reduced asset accumulation (Section 5.3). This implies that households do not use livestock as a buffer against shocks to assets. This behaviour is indeed confirmed when we examine savings in response to shocks. Specifically, households accumulate livestock in response to negative livestock growth shocks and de-accumulate it in response to positive ones (Section 5.2).

The question of savings under risk has also been studied in pastoralist and agro-pastoralist economies, which have special characteristics thought to matter for savings behaviour. First, the assets that can be used for self-insurance are effectively limited, in the case of pastoralists, to livestock, and in agro-pastoralists, to livestock, land and grain. Second, these assets are production assets, and thus determine household resources. Third, while the returns to these production assets are risky, a significant source of risk is to the asset itself, in the form of death of livestock. This is obviously of critical importance in pastoralist societies. Although inconclusive, the weight of the evidence from small-scale agrarian and pastoralist economies seems to suggest that livestock are not used as a buffer against shocks to household resources. Regarding agro-pastoralist economies,

[24] A decomposition of the Generalised Entropy Index with coefficient 2 calculated using our data shows that 81% of inequality in time input is within household variation, while only 19% is due to between household variation.

results in Rosenzweig and Wolpin (1993) suggest that livestock is used as a buffer against income shocks in agrarian economies in India, but Lim and Townsend (1998) comment that the data for these economies actually suggest that livestock is bought in bad periods and sold in good periods. Udry (1995) and Fafchamps *et al.* (1998) study agro-pastoralist economies in West Africa in which livestock is used in the production of crops and find that net livestock sales do not respond to income shocks, suggesting that livestock, in this context, is not used as a buffer. Less is known about savings under risk in pastoralist economies. McPeak (2004) studies pastoralist economies in East Africa in which livestock is used to produce milk and finds that livestock sales increase in response to herd growth, the opposite of what would be expected if used as a buffer.

By distinguishing between the sources of risk, our study reveals a negative relationship between net livestock acquisitions and shocks to the growth rates of livestock holdings, but a positive relationship between net livestock acquisitions and shocks to income from other sources. There are two factors that are important in explaining the negative relationship between net livestock acquisitions and shocks to herd growth. Firstly, the relatively high probability of large negative shocks to the asset itself, in the form of death (or theft) of livestock, makes it less attractive to further accumulate it when natural processes already lead to positive herd growth and/or large herd size. Second, because livestock is the primary means to generate resources, households have a strong incentive to maintain a sufficient herd to generate the resources they require. Indeed, we find that households tend to acquire livestock when herd size is low and/or in the case of very large negative livestock shocks (which imply about a 90% drop in livestock), meaning that they convert resources they may have during these periods into livestock. Households in these difficult periods must, therefore, have access to additional resources to start a new herd. This highlights the importance of community-level co-insurance, alongside external support schemes, for households with limited livestock to escape the poverty trap. The positive relationship between net livestock acquisitions and shocks to time input and market income suggests the use of livestock as a buffer against these shocks. That the magnitude of the response to time input shocks is small possibly reflects the importance of other forms of community co-insurance against shocks that affect humans directly, such as co-herding arrangements in the case of human illness. Overall, our findings highlight the importance of distinguishing sources of risk and the mechanisms by which shocks affect assets and production.

7 Conclusions

The theory that underpins our analysis is the incomplete insurance markets approach to wealth inequality, key ideas of which have also been incorporated in analysis of wealth inequality in pastoralist and early human societies. According to the resource risk mechanism at the core of this approach, when there is stochastic variation in resources, and where technology, institutional arrangements and social norms allow for resources to be transferred over time, wealth inequality should emerge. Our analysis provides evidence that the resource risk mechanism can, indeed, explain observed wealth inequality in the Turkana pastoralist society. To provide this evidence, we developed a stochastic model in which pastoralist households choose livestock subject to uncertainty about the growth rate of livestock holdings, time input into production, market income, and drought occurrence, and given the available technology for resource production and storage and existing community-level co-insurance. We collected bespoke data via a large household survey to measure shocks and wealth inequality. We used the shocks as inputs to the model to generate the distribution of wealth across the population and over time. We found that the model-generated cross-sectional distributions for both drought and non-drought years match the empirical distributions. Model-predicted savings behaviour is also consistent with empirical evidence regarding net livestock acquisitions, in particular showing that livestock is not used as a buffer against shocks to herd size. Model-based counterfactual analysis further revealed that the main component of idiosyncratic resource risk that drives inequality is livestock holdings growth risk.

Our results contribute to research on the origins of inequality that has studied early human and small-scale contemporary societies (e.g. Bar-Yosef (2001), Barker (2006), Borgerhoff Mulder *et al.* (2009), Bogaard *et al.* (2019) and Dow and Reed (2023)). Specifically, our results provide evidence for the importance of idiosyncratic variation in resources for wealth inequality in these economies, thus supporting explanations in studies such as Borgerhoff Mulder *et al.* (2009) and Bogaard *et al.* (2019). Moreover, our results contribute to the literature using quantitative analysis of wealth inequality under incomplete insurance markets, following the contributions of Bewley (1986), Aiyagari (1994) and Huggett (1993). Specifically, our main result that the model generates observed wealth inequality in an economy that partials out most of the complexity of modern economies provides support for the premise of the incomplete insurance markets approach to modelling wealth inequality. In particular, our results confirm the importance of risk to asset returns in the generation of observed wealth inequality in this modelling framework, in line with recent research (Benhabib *et al.* (2015, 2017), Benhabib and Bisin (2018), and Stachurski and Toda (2019)). Finally, our analysis contributes to the literature on savings and risk in agro-pastoralist and pastoralist economies (e.g. Rosenzweig and Wolpin (1993), Udry (1995), Fafchamps *et al.* (1998) and McPeak (2004)), by studying the effects of different sources of risk in a pastoralist economy in which livestock, the only asset, is critical to production but subject to catastrophic loss. We find that incentives work to increase livestock acquisitions in response to losses and against accumulating livestock to buffer potential livestock losses.

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A Survey and quantitative data collected

A.1 Description of survey

The quantitative data that we use for our analysis are drawn from a survey of 1,347 households (recording data on 9,179 individuals), conducted during November-December 2018. The survey instrument was developed to address the questions of interest and was tailored to the specific local context (e.g. in relation to question wording and the specific forms of shocks to use as prompts for enumerators). Wherever relevant, standard questions from the Kenyan decadal census were used (e.g. for additional belongings). Ethical approval for the survey was obtained from the College of Social Sciences Ethics Committee at the University of Glasgow prior to data collection. Permission to undertake research was also obtained from the Country Government of Turkana, Office of the Governor.

Data were collected from three neighbouring sublocations - Loperot, Kalapata and Napusimoru - within Kalapata and Lokichar wards, in a rural part of Turkana County. These sublocations were selected because traditional pastoralist lifestyles are maintained in this area. For instance, we avoided areas closer to towns, or adjacent to Lake Turkana where fishing is also common. The dates for data collection were chosen to avoid periods during which pastoralists tend to take livestock further afield for grazing. The year 2018 was a non-drought year, whereas 2017 was a drought year, meaning that information collected regarding the previous year covers the effects of a drought. Data collection was carried out by a team of enumerators (data collectors) led by Dorice Agol. The field team, comprising enumerators and data entry clarks, was recruited through information provided by Friends of Lake Turkana and subsequent referrals, and all individuals were interviewed by Dorice Agol prior to recruitment. We recruited ten enumerators and four data entry clerks, with equal gender balance. The field team was provided with two days of training covering the survey questions to be asked (in the form of role plays), ethics, code of contact, and how to manage difficult situations (e.g. ambiguous responses or issues related to personal safety). All enumerators were fluent in English as well as the local language, Kiturkana, and training covered the most appropriate way to translate the questions into the local language. Training was followed by a day spent piloting the survey instrument in Lokichar (the nearest town to the study area), and a further half-day of debriefing, including discussions on additional issues arising from piloting experience and how to manage them. Final adjustments to the survey instrument were implemented to facilitate accurate data collection.

Data collection at each sublocation started with a meeting with representatives of the local administration (e.g. chief or village elders) to identify all the villages in each sublocation and the number of households in each village. Two enumerators then visited each village, aiming to cover all the households within each village, except in the case of householder absence. The enumerators introduced the research project and survey, gaining informed consent before conducting a structured interview with a representative (or occasionally two representatives) of each household. The enumerator noted down responses on a pre-prepared form for later electronic data entry. Enumerators made an assessment of the quality of data provided based on the progress of the discussion (e.g. consistency of responses and their alignment with enumerator assessments of the information provided on livestock, etc.) and recorded their resultant confidence in the answers provided by householders, using three categories (high, medium, low). This allowed us to exclude data judged by enumerators to be of 'low' quality. Dorice Agol accompanied enumerators to the sublocations and was involved in the meetings with the local administration and was responsible for assigning enumerators to villages. She also helped to ensure quality control by making spot checks during data collection and answering questions and providing rapid feedback and general support to enumerators. Data were entered by clerks based in Kenya into specially prepared spreadsheets which were encrypted for secure storage and transfer. Data were checked for internal consistency and to ensure that all information was entered in the correct formats during data entry and inconsistencies/information in incorrect formats were checked against paper copies and followed up with enumerators if required.

A.2 Description of survey variables used in the analysis

We collected data on both individual-level and household-level characteristics. The household was chosen as the unit at which to examine livestock inequality because key economic decisions concerning livestock are taken at the household level; household members share consumption and basic accommodation within the household *boma* (see also, e.g. Sutter (1987)).

Variables relating to individual members of each household included the age, gender and education of the household member, as well as their relationship with the head, and whether they had recently joined the household or died during the period. We recorded the number of weeks or months that the normal activities (school, work, herding, caring) of each household member had been interrupted due to shocks such as ill-health, flooding, drought, injury or death. For household members who had engaged in waged or paid employment, we recorded the number of months (or partial months) that they worked, as well as the wage for the kind of job they were involved in. The individual or individuals in charge of making decisions about the purchase and sale of livestock were also recorded.

Livestock numbers (wealth) and shocks to livestock were recorded at the household level, differentiating between goats, sheep, cattle, camels and donkeys. For each livestock species, we recorded the current number and the number one year previously at the end of 2017. We also collected data relating to livestock population dynamics over the years 2017 and 2018. Specifically, we recorded the number of animals born, the number of stillbirths, the number that died, the number that were ill but survived, and the number stolen. We also recorded the number of livestock acquired, and the number that households had parted with because they were sold, slaughtered for consumption, or permanently given away. We also recorded the number currently being looked after by friends or relatives. The questionnaire contained questions about crop cultivation, but no respondents engaged in these activities; similarly, poultry was rare.

We recorded information on other belongings and sources of income. In addition to a general question about any additional belongings of value, we used standard questions on household belongings (corresponding to those in e.g. the census) to enquire about the number of bicycles, motorcycles (including boda-boda/tuk-tuk), carts, cars, and vans/trucks owned by the household. Respondents reported a small number of bicycles and motorcycles, but no large motorised vehicles, cars or vans. To understand whether any individuals were self-employed in activities other than herding, we asked about engagement in selling at market, and whether any household member had a business. To understand market penetration of financial services, we asked whether anyone in the household had a bank account (or mobile telephone account M-Pesa), whether anyone in the household had savings, the existence of household debt to financial institutions (banks, microcredit, loans), whether they had informal debt or owed anything to anyone else (e.g. to friends/relatives, table banking, women's groups, pastoralist groups), and similarly whether they currently had informal loans to others. The majority of the questions in this category were binary in nature, given sensitivities relating to questions about details of income. We also asked households whether they receive support from relatives, friends, or via external programmes.

A.3 Sample for empirical analysis

The sample consists of 1,347 households, including in total 9,179 individuals (after we exclude individuals recorded who died or left the household outside the period 2016-2018, 214 individuals in total).[25] We drop households with low data quality. The final sample consists of 1,278 households,

[25] We impute the age for 4 individuals, 3 'sons/daughters' and one 'in-law'. The age of the 'sons/daughters' imputed is the age of the head minus 25 years, and the age of the person 'in-law' is set to be the same as that of the head.

corresponding to 8,740 individuals. Numbers of households by sublocation were Kalapata (N=454), Loperot (N=353), Napusmoru (N=471). We compute the age for 2017 and 2016 as the age in 2018 minus 1 and 2, respectively.

We calculate the total number of household members for each year and construct the household size variable, $N^i_{h,t}$, for household i, $t = \{2016, 2017, 2018\}$. Note that $N^i_{h,t}$ includes people if they were recorded as having died/left during the year. The median household size is 6 members (mean household size is 6.71 members). Heads of household were primarily male (male N=1067, mean age 45.3, female N=211, mean age 53), and 95% of these individuals had had no formal education.

A.4 Wealth/livestock inequality

In 2018, the majority of households held a single species of livestock (n=458, mostly goats) or two species (n=477). Fifty-eight households had no livestock, and 285 had 3 species or more.

Table A1: Livestock numbers per type, 2018

	mean	P10	P50	P90	Gini
	Livestock numbers				
goats	22.06	4	16	46	0.46
sheep	4.68	0	0	13	0.79
cattle	0.13	0	0	0	0.99
camels	1.95	0	0	6	0.83
donkeys	0.25	0	0	0	0.95
total	29.08	5	20	60	0.48

Our headline measure of wealth inequality is based on a measure of wealth in livestock units. This is constructed using conversion information in FAO (2011), which expresses livestock units relative to 1 unit of US breed cow (455kg). Specifically, we calculate this measure, denoted as a^i_{2018} for each household i, as:

$$\begin{aligned} a^i_{2018} = {} & 0.1 * N^i_{goats,2018} + 0.1 * N^i_{sheep,2018} + 0.5 * N^i_{cattle,2018} + \\ & + 0.7 * N^i_{camel,2018} + 0.5 * N^i_{donkeys,2018}, \end{aligned} \tag{8}$$

where $N^i_{v,2018}$ denotes the size of the herd for animal type $v = \{goats,\ sheep,\ cattle,\ camel,\ donkeys\}$ in period 2018. We then construct measures of livestock for the previous 2 years retrospectively. In particular, for 2017 (and similarly for 2016), for each animal type, we impute the number of animals as: $N^i_{v,2017} = N^i_{v,2018} - Born^i_{v,2018} - Bought^i_{v,2018} + Died^i_{v,2018} + Stolen^i_{v,2018} + Sold^i_{v,2018}$. Then, we use (8) to calculate wealth in 2017, which is also expressed in livestock units. We discard households for which wealth calculated as above is negative for either 2017 (8 households) or 2016 (47 households).

To construct an alternative measure of livestock wealth, we used information on prices for cattle (10,000 KES), goats (4,000 KES), sheep (4,500 KES), donkeys (10,000 KES) and camels (20,000 KES) gathered from local representatives in Turkana. The results regarding per capita livestock wealth inequality using this approach are similar to those in Table 1. In Table A2 we report a range of statistics regarding wealth inequality for different measures of wealth in 2018. In particular, we repeat information provided for this year in Table 1 where wealth is measured in livestock units, supplementing this with measures based on livestock counts (see Table A1) and livestock value in KES.

For robustness, we considered the importance of the valuables for which we have information, on the monetary measure of wealth. In particular, we have information on bicycles (14 households), valued by local experts at 5,000 KES, and motorcycles (28 households) at 9,000 KES (assuming these are bought second-hand). Moreover, nearly 14% of households (N=174) reported additional valuables, and among the 130 households providing a value for these, the median was 2,000 KES. Wealth inequality, in terms of Gini and concentration in tails, was the same to the third significant digit, when including this information in the calculation of wealth (see Table A2).

Table A2: Wealth Inequality in 2018

	Gini	Q1	Q2	Q3	Q4	Q5
Goats	0.476	2.82%	8.24%	14.59%	23.83%	50.52%
Sheep	0.792	0.00%	0.00%	1.40%	16.60%	82.01%
Cattle	0.987	0.00%	0.00%	0.00%	0.00%	100.00%
Camels	0.829	0.00%	0.00%	0.00%	11.43%	88.57%
Donkeys	0.950	0.00%	0.00%	0.00%	0.00%	100.00%
Total livestock (numbers)	0.480	2.99%	8.31%	14.13%	23.24%	51.33%
Livestock Units (LU)	0.525	2.32%	7.01%	12.81%	22.27%	55.59%
Livestock Value (KES)	0.507	2.54%	7.54%	13.41%	22.65%	53.86%
Livestock Value + Valuables (KES)	0.506	2.56%	7.59%	13.44%	22.65%	53.76%

Note: All variables per capita at the household level. See Table 1 for definitions of statistics.

We did not include savings or debt to financial institutions in our monetary measure of wealth, as only 27 households reported having savings and only 7 had some debt to banks or other financial institutions, despite 392 having a bank account or M-Pesa. One hundred and forty-five households reported having other forms of debt (e.g. from friends/relatives, table banking, women's groups, pastoralist groups). In Turkana pastoralist communities, these debts are typically for small amounts and only loaned over short periods. Because we did not have precise information, we did not include them in the calculation of wealth. For similar reasons, we did not include information on the 209 households that reported being owed something by others.

A.5 Droughts

We obtain a time series of drought versus non-drought years as follows. Using monthly precipitation data for Lodwar, we calculate for each month between 1920 and 2018 the deviation of precipitation from the long-run mean, averaged over the years, for the corresponding month. In particular, we use monthly precipitation data for Lodwar provided by the International Research Institute - World Bank (IRI (2019)) from 1920 to 1960 and monthly precipitation data from www.worldclim.org, from 1961 to 2018, for the geographical area around Lodwar (latitude: from 2.9375 to 3.1458 and longitude: from 35.3958 to 35.6042). We calculate the average precipitation for each month of the year for each dataset separately. Following McPeak (2004) and McPeak *et al.* (2014), we focus on deviations in rainfall during the rainy seasons. There are two rainy seasons: the long rains, March to May, and the short rains, October to December. Therefore, we calculate the difference between the observation for each month and the corresponding average for that month and then we calculate the sum of these deviations over the rainy seasons of each year. We calculate the 40th percentile of these annual summed deviations of rainfall and define drought as the years when total precipitation is less than the 40th percentile, to ensure that 2017, an acknowledged drought year, is correctly identified as a drought year. This implies that we use a definition of a drought period that is similar to that of the Kenya Meteorological Service (2010) which defines a normal meteorological drought as a situation in which rainfall over an area is less than 75% of the climatological normal, which we approximate by the median. Note that the IRI provides data until 1995, but we prefer to use the more accurate data from www.worldclim.org. Nevertheless, our definition of droughts gives similar results across datasets for the overlapping period.[26]

[26] There are some missing values in the IRI dataset, which we fill by interpolating between the two neighbouring observations. We discard 1996 and 1997 because they contain too many missing values.

A.6 The random component of livestock growth rate and time input

A.6.1 Growth rate of livestock holdings

To approximate the household-specifc risk, we construct a random variable l_t, the household-specific growth rate of livestock in livestock units per capita for 2017 and 2018 (i.e. separately for droughts and non-droughts). We first use the survey data to construct a variable capturing the growth rate of livestock holdings in per capita livestock units $\widetilde{l_t^i}$, for each household i, for $t = \{2017, 2018\}$,

$$\widetilde{l_t^i} = \frac{\left[\frac{\text{births}_t^i - \text{stolen}_t^i - \text{deaths}_t^i}{N_{hh,t}^i}\right]}{\left[\frac{a_{t-1}^i}{N_{hh,t-1}^i}\right]},$$

where $N_{hh,t}^i$ denotes the size of household i in period t and a_{t-1}^i is household i's livestock in period $t-1$. Note that births, deaths, thefts, and a_{t-1} are measured in LU.

From data inspection, we found that there is location-specific heteroskedasticity. To deal with this form of heteroskedasticity, we standardise $\widetilde{l_t^i}$ by multiplying it by the ratio of the total standard deviation of $\widetilde{l_t^i}$ over the standard deviation of the sublocation i.e. $\widetilde{l_t^i} = l_t^{i,\varkappa} \frac{\sigma_{t,l}}{\sigma_{t,l,\varkappa}}$, where $\varkappa$ denotes the sublocation. After this standardisation, do not detect heteroskedasticity.

We then construct the variable l_t^i for household i, for $t = \{2017, 2018\}$, by partialling out household characteristics from $\widetilde{l_t^i}$. We regresss $\widetilde{l_t^i}$ on a set of dummies for the age of the head of the household (a dummy per decade of age), dummies for the gender and education of the head, variables capturing the composition of the household (number of adults, spouses, and children by sex) and a dummy for the location of the boma. These characteristics are observable to the households and thus are not part of uncertainty regarding livestock growth for a given household. We run these regressions separately for each year (see Table A3). The l_t^i are the residuals from these regressions and re-centred on the unconditional mean of the net growth rates per period, about 36% in 2018 and -31% in 2017. We set any observations of l_t^i less than -1 equal to -1 (2 observations in 2018 and 35 in 2017). The first four moments of l_t^i distributions are shown in Table 2 in the main text.

Table A3: First step linear regression of $\tilde{l}_t$

	(1)	(2)
	2017	2018
age of head: '30s	0.018	0.000
	(0.050)	(0.046)
age of head: '40s	0.002	0.042
	(0.052)	(0.048)
age of head: '50s	-0.034	0.033
	(0.056)	(0.052)
age of head: '60s	-0.088	0.103*
	(0.064)	(0.058)
age of head: '70+	-0.023	0.044
	(0.073)	(0.066)
male	0.153**	0.023
	(0.067)	(0.061)
Loperot	-0.176***	0.066**
	(0.034)	(0.031)
Napusimoru	-0.319***	0.277***
	(0.032)	(0.029)
$\frac{N_{adults}}{N_{hh}}$	-0.067	0.085
	(0.113)	(0.099)
$\frac{N_{boys}}{N_{hh}}$	-0.133	0.103
	(0.112)	(0.102)
$\frac{N_{girls}}{N_{hh}}$	-0.165	0.166
	(0.115)	(0.105)
$N_{spouses}$	-0.078	-0.052
	(0.051)	(0.048)
Head some educ.	0.053	-0.082
	(0.061)	(0.056)
Constant	-0.144**	0.196***
	(0.071)	(0.066)
N	1,129	1,230
R^2	0.093	0.091
Adj. R^2	0.083	0.082

Notes: Standard errors in parentheses. Similar to Section 2, before running these regressions, we standardise $\tilde{l}_t^i$ by multiplying it by the ratio of the total standard deviation of $\tilde{l}_t^i$ over the standard deviation of the sublocation i.e. $\tilde{l}$

${}^*p < 0.10$, ${}^* * p < 0.05$, ${}^* * *p < 0.01$

A.6.2 Household time

We use our survey data to construct h_t, a measure of the stochastic component of household-level time availability. We first set a member's time input to one if an individual is between 7 and 70 years old and zero if she/he is outside this age bracket. This age range is motivated by the observation that household members in this age bracket, when they are able to do so, use time to contribute to household activities to generate resources. When an individual between 7 and 25 years old goes to school, they support the household when not in school and we thus adjust these members' time input to 0.5. The individual's time input is then multiplied by the share of the year he/she was available to work, based on information we have from the survey data (i.e. if an individual was available for 11 months, we multiply his/her productivity by 11/12). If an individual died or left the household during the year, we set their individual time input to zero. Following this logic, we construct the variable $\widetilde{h}_t^i$, the per capita time input, for each household i and for $t = \{2017, 2018\}$, defined as the sum of household members' time input divided by the number of household members

$$\begin{aligned}
\widetilde{h}_t^i &= \frac{\left[\sum_{n=1}^{N_{hh,t}} \widetilde{h}_{n,t}^i * (1 - \frac{mc_{n,t}}{12})\right]}{N_{hh,t}^i}, \\
\widetilde{h}_n^i &= 1 \text{ if } 7 \leq age \leq 70 \text{ \& not studying}, \\
\widetilde{h}_n^i &= 0.5 \text{ if } 7 \leq age \leq 25 \text{ \& studying}, \\
\widetilde{h}_n^i &= 0 \text{ if age} \leq 6 \text{ or } 71 \leq age\text{, or if died, or left},
\end{aligned}$$

where $\widetilde{h}_n^i$ is the time input of individual n and mc_n is the number of months during which individual n's activities were curtailed.

To apporximate the household-specific component of the time input variable, h_t^i for t=2017, 2018, we remove the variation due to observable characteristics. In particular, we run Tobit regressions (see Table A4) of $\widetilde{h}_t^i$ on a set of dummies for the age of the head of the household (a dummy per decade of age), dummies for the gender and education of the head, variables capturing the composition of the household (number of adults, spouses, and children by sex) and a dummy for the location of the boma. The estimation method is motivated by the range of values that $\widetilde{h}_t^i$ can take on, which is $[0, 1]$. We then keep the residuals and re-centre them on their unconditional means before these regressions. If after re-centering any observation is above 1, we set it equal to 1 (56 observations in 2018 and 67 in 2017). The distributions of these recentered distributions are shown in Figure 2. Except for a reduction in average time input during droughts, the distributions are very similar for the two years. Thus, our calibration assumes that time input risk is time-invariant apart from the mean.

Table A4: First step censored regressions (Tobit) of $\widetilde{h}_t$

	(1)	(2)
	2017	2018
age of head: '30s	0.097***	0.107***
	(0.019)	(0.018)
age of head: '40s	0.233***	0.258***
	(0.020)	(0.019)
age of head: '50s	0.296***	0.298***
	(0.022)	(0.021)
age of head: '60s	0.283***	0.278***
	(0.024)	(0.024)
age of head: '70+	0.074**	0.065**
	(0.029)	(0.027)
male	0.102***	0.039
	(0.028)	(0.027)
Loperot	0.024*	0.029**
	(0.013)	(0.013)
Napusimoru	0.055***	0.044***
	(0.012)	(0.012)
$\frac{N_{adults}}{N_{hh}}$	0.040***	0.033***
	(0.004)	(0.004)
$\frac{N_{boys}}{N_{hh}}$	-0.020***	-0.023***
	(0.005)	(0.005)
$\frac{N_{girls}}{N_{hh}}$	-0.020***	-0.023***
	(0.005)	(0.005)
$N_{spouses}$	-0.058**	-0.050**
	(0.023)	(0.022)
Head some educ.	-0.002	-0.001
	(0.023)	(0.023)
Constant	0.533***	0.630***
	(0.022)	(0.022)
N	1,278	1,278
Pseudo R^2	1.3857	1.2033

Standard errors in parentheses

$^{*}p < 0.10$, $^{*} * p < 0.05$, $^{*} * *p < 0.01$

A.7 Determinants of net livestock acquisitions

To estimate the marginal effects in Figure 3, we estimate equation (3), where $\mathbf{X}_t$ contains household-specific dummies, location-specific dummies, a dummy for 2018 and time-varying demographic characteristics of the household: i) an indicator for the sex of the head of the household; ii) dummies for different age groups, {20s,30s,40s,50s,60s,70+}; iii) the share of working-age adults to the total number of members of the household (above 16 years old and less than 70); iv) the share of boys to the total number of members of the household (less than 16 years old); v) the share of girls to the total number of members of the household (less than 16 years old); and vi) the number of female spouses (if they exist) who are members of the household (above 16 years old). Results from the estimation of (3) with different sets of control variables are reported in Table A5.

Table A5: Linear regression with dependent variable net livestock acquisitions

	(1)	(2)	(3)	(4)	(5)	(6)
2018	-0.0116	-0.0112	-0.0336	-0.0105	-0.0108	-0.0113
	(0.0232)	(0.0226)	(0.0215)	(0.0232)	(0.0232)	(0.0232)
age of head: '30s	0.00224	0.00138	0.00179	0.000388	0.0000947	0.00142
	(0.0238)	(0.0233)	(0.0271)	(0.0237)	(0.0236)	(0.0238)
age of head: '40s	0.0193	0.0188	0.0283	0.0191	0.0183	0.0191
	(0.0198)	(0.0197)	(0.0225)	(0.0198)	(0.0197)	(0.0198)
age of head: '50s	0.0192	0.0189	0.0198	0.0222	0.0189	0.0189
	(0.0206)	(0.0205)	(0.0237)	(0.0205)	(0.0205)	(0.0206)
age of head: '60s	0.0168	0.0166	0.0161	0.0216	0.0170	0.0166
	(0.0201)	(0.0201)	(0.0230)	(0.0201)	(0.0200)	(0.0201)
age of head: '70s	0.00757	0.00754	0.0101	0.0120	0.00958	0.00823
	(0.0234)	(0.0234)	(0.0262)	(0.0234)	(0.0233)	(0.0233)
male	-0.00920	-0.00838	0.0704	-0.112**	-0.0660	-0.0454
	(0.0897)	(0.0905)	(0.0919)	(0.0534)	(0.0713)	(0.0841)
Loperot	0.254**	0.252**	0.113	0.250***	0.229***	0.234**
	(0.117)	(0.118)	(0.116)	(0.0779)	(0.0826)	(0.113)
Napusimoru	0.109	0.109	0.0914	0.000409	0.00230	0.0876
	(0.0896)	(0.0897)	(0.117)	(0.0474)	(0.0491)	(0.0852)
$\tilde{h}_t$	0.103*	0.0981*	0.0857	0.0969*	0.0951*	0.107*
	(0.0545)	(0.0525)	(0.0564)	(0.0555)	(0.0559)	(0.0546)
a_{t-1}	-0.208**	-0.214**	-0.0225***	-0.208**	-0.208**	-0.208**
	(0.104)	(0.0924)	(0.00861)	(0.104)	(0.103)	(0.104)
$\tilde{h}_t * a_{t-1}$	-0.00746			-0.00769	-0.00641	-0.00744
	(0.0234)			(0.0238)	(0.0234)	(0.0234)
$\tilde{l}_t$	0.0148*	0.0150*	0.0000727	0.0142*	0.0145*	0.0149*
	(0.00803)	(0.00779)	(0.00858)	(0.00810)	(0.00804)	(0.00802)
$\tilde{l}_t * a_{t-1}$	-0.197**	-0.198**		-0.198**	-0.196**	-0.197**
	(0.0951)	(0.0942)		(0.0945)	(0.0944)	(0.0950)
$\frac{N_{adults}}{N_{hh}}$	-0.0405	-0.0385	0.0821		0.107	-0.00429
	(0.149)	(0.151)	(0.150)		(0.0811)	(0.143)
$\frac{N_{boys}}{N_{hh}}$	-0.0870	-0.0866	-0.0587			-0.0437
	(0.151)	(0.151)	(0.164)			(0.146)
$\frac{N_{girls}}{N_{hh}}$	-0.324*	-0.323*	-0.243			-0.282*
	(0.177)	(0.178)	(0.201)			(0.170)
$N_{spouses}$	-0.0445	-0.0445	-0.0392			
	(0.0433)	(0.0433)	(0.0432)			
Constant	0.0862	0.0889	-0.0356	0.110	0.0652	0.0696
	(0.114)	(0.111)	(0.111)	(0.0854)	(0.101)	(0.111)
N	2259	2259	2259	2259	2259	2259
R^2	0.774	0.774	0.733	0.773	0.773	0.774
adj. R^2	0.488	0.488	0.395	0.487	0.487	0.488
hh FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. In all estimations, we include individual-specific dummies.

$^{*}p < 0.10$, $^{*} * p < 0.05$, $^{*} * *p < 0.01$

Table A6: Margins at specific values of a and $\tilde{l}$

Margin	a	$\tilde{l}$	CI_{lb}^{90}	CI_{ub}^{90}
0.1449	0	-0.9	0.0746	0.2153
0.1535	0	-0.32	0.0812	0.2258
0.1621	0	0.26	0.0872	0.2370
0.1707	0	0.84	0.0924	0.2489
0.1792	0	1.42	0.0971	0.2614
0.1878	0	2	0.1013	0.2743
0.1270	0.5	-0.9	0.0623	0.1917
0.0783	0.5	-0.32	0.0564	0.1001
0.0296	0.5	0.26	0.0078	0.0515
-0.0191	0.5	0.84	-0.0837	0.0456
-0.0677	0.5	1.42	-0.1754	0.0399
-0.1164	0.5	2	-0.2671	0.0343
0.1090	1	-0.9	0.0496	0.1684
0.0031	1	-0.32	-0.0271	0.0333
-0.1028	1	0.26	-0.2204	0.0148
-0.2088	1	0.84	-0.4144	-0.0031
-0.3147	1	1.42	-0.6084	-0.0210
-0.4206	1	2	-0.8025	-0.0388
0.0911	1.5	-0.9	0.0364	0.1457
-0.0721	1.5	-0.32	-0.1529	0.0086
-0.2353	1.5	0.26	-0.4490	-0.0216
-0.3985	1.5	0.84	-0.7455	-0.0515
-0.5617	1.5	1.42	-1.0421	-0.0813
-0.7249	1.5	2	-1.3387	-0.1110
0.0731	2	-0.9	0.0226	0.1237
-0.1473	2	-0.32	-0.2789	-0.0158
-0.3678	2	0.26	-0.6776	-0.0579
-0.5882	2	0.84	-1.0767	-0.0997
-0.8086	2	1.42	-1.4758	-0.1415
-1.0291	2	2	-1.8750	-0.1832

A.8 The unimportance of time input $\tilde{h}_t$ for livestock growth $\tilde{l}_t$

In Tables A7 and A8 we report results from linear regressions of $\tilde{l}_t$ on household characteristics, location and $\tilde{h}_t$, separately for 2017 and 2018, to confirm that the latter is insignificant. The observable characteristics are the same as in A.6, with the only addition of the time input of the household or the time input of the head of the household. Note the very low R^2 values, suggestive of the importance of the random component (shocks); see Section 2 for further analysis of this.

Table A7: Linear regressions with dependent variable $\tilde{l}_t$, 2017

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age of head: '30s	-0.005	-0.004	-0.001	0.022	0.023	0.024	0.017
	(0.048)	(0.048)	(0.048)	(0.050)	(0.050)	(0.050)	(0.050)
age of head: '40s	-0.023	-0.023	-0.017	0.011	0.012	0.016	0.001
	(0.050)	(0.050)	(0.051)	(0.054)	(0.054)	(0.054)	(0.052)
age of head: '50s	-0.048	-0.057	-0.052	-0.026	-0.022	-0.017	-0.036
	(0.055)	(0.056)	(0.057)	(0.059)	(0.059)	(0.059)	(0.056)
age of head: '60s	-0.086	-0.103	-0.099	-0.084	-0.076	-0.072	-0.089
	(0.060)	(0.065)	(0.065)	(0.066)	(0.066)	(0.066)	(0.064)
age of head: '70+	-0.016	-0.038	-0.038	-0.038	-0.025	-0.018	-0.052
	(0.064)	(0.072)	(0.072)	(0.072)	(0.072)	(0.073)	(0.084)
male	0.060	0.069^{*}	0.070^{*}	0.076^{*}	0.162^{**}	0.162^{**}	0.156^{**}
	(0.037)	(0.040)	(0.040)	(0.040)	(0.068)	(0.068)	(0.067)
Loperot	-0.177^{***}	-0.175^{***}	-0.174^{***}	-0.173^{***}	-0.173^{***}	-0.173^{***}	-0.174^{***}
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Napusimoru	-0.317^{***}	-0.316^{***}	-0.315^{***}	-0.314^{***}	-0.318^{***}	-0.315^{***}	-0.318^{***}
	(0.032)	(0.032)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
$\tilde{h}_t$	-0.040	-0.063	-0.062	-0.072	-0.081	-0.081	
	(0.080)	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	
$\frac{N_{adults}}{N_{hh}}$		0.064	0.043	-0.055	-0.041	-0.036	-0.064
		(0.095)	(0.102)	(0.117)	(0.117)	(0.117)	(0.113)
$\frac{N_{boys}}{N_{hh}}$			-0.054	-0.157	-0.141	-0.135	-0.134
			(0.093)	(0.111)	(0.112)	(0.112)	(0.112)
$\frac{N_{girls}}{N_{hh}}$				-0.194^{*}	-0.179	-0.172	-0.164
				(0.114)	(0.115)	(0.115)	(0.115)
$N_{spouses}$					-0.081	-0.081	-0.079
					(0.051)	(0.051)	(0.051)
Head some educ.						0.053	0.054
						(0.061)	(0.061)
Head's $\tilde{h}_t$							-0.050
							(0.074)
Constant	-0.168^{**}	-0.165^{**}	-0.154^{**}	-0.088	-0.094	-0.104	-0.098
	(0.069)	(0.070)	(0.072)	(0.082)	(0.082)	(0.083)	(0.098)
R^2	0.088	0.089	0.089	0.091	0.093	0.094	0.094
Adj. R^2	0.081	0.081	0.080	0.082	0.083	0.083	0.082

Notes: Standard errors in parentheses. Similar to Section 2, before running these regressions, we standardise $\widetilde{l}_t$ by multiplying it by the ratio of the total standard deviation of $\widetilde{l}_t^i$ over the standard deviation of the sublocation i.e. $\widetilde{l}$
$^{*}p < 0.10$, $^{*}*p < 0.05$, $^{*}**p < 0.01$

Table A8: Linear regressions with dependent variable $\tilde{l}_t$, 2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age of head: '30s	0.027	0.027	0.026	0.008	0.009	0.008	0.002
	(0.045)	(0.045)	(0.046)	(0.047)	(0.047)	(0.047)	(0.046)
age of head: '40s	0.090*	0.090*	0.089*	0.065	0.066	0.060	0.044
	(0.048)	(0.048)	(0.048)	(0.051)	(0.051)	(0.051)	(0.048)
age of head: '50s	0.081	0.078	0.076	0.055	0.059	0.052	0.037
	(0.051)	(0.053)	(0.053)	(0.055)	(0.055)	(0.055)	(0.052)
age of head: '60s	0.140**	0.134**	0.134**	0.122**	0.127**	0.121**	0.107*
	(0.056)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.058)
age of head: 70+	0.058	0.050	0.050	0.052	0.060	0.049	0.105
	(0.059)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.084)
male	-0.034	-0.030	-0.030	-0.032	0.028	0.029	0.021
	(0.034)	(0.036)	(0.036)	(0.036)	(0.062)	(0.062)	(0.061)
Loperot	0.069**	0.070**	0.069**	0.069**	0.069**	0.068**	0.062**
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Napusimoru	0.285***	0.285***	0.284***	0.284***	0.282***	0.280***	0.275***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
$\tilde{h}_t$	-0.083	-0.094	-0.094	-0.086	-0.095	-0.095	
	(0.080)	(0.087)	(0.088)	(0.088)	(0.088)	(0.088)	
$\frac{N_{adults}}{N_{hh}}$		0.024	0.030	0.115	0.124	0.118	0.077
		(0.082)	(0.088)	(0.104)	(0.104)	(0.104)	(0.100)
$\frac{N_{boys}}{N_{hh}}$			0.016	0.102	0.110	0.101	0.101
			(0.086)	(0.102)	(0.102)	(0.102)	(0.102)
$\frac{N_{girls}}{N_{hh}}$				0.164	0.172	0.161	0.160
				(0.105)	(0.105)	(0.105)	(0.105)
$N_{spouses}$					-0.057	-0.056	-0.053
					(0.048)	(0.048)	(0.048)
Head some educ.						-0.082	-0.081
						(0.056)	(0.056)
Head's $\tilde{h}_t$							0.090
							(0.075)
Constant	0.297***	0.300***	0.297***	0.237***	0.236***	0.251***	0.114
	(0.070)	(0.071)	(0.073)	(0.083)	(0.083)	(0.083)	(0.095)
R^2	0.088	0.088	0.088	0.090	0.091	0.092	0.093
Adjusted R^2	0.081	0.080	0.080	0.081	0.081	0.082	0.082

Notes: Standard errors in parentheses. Similar to Section 2, before running these regressions, we standardise $\widetilde{l}_t$ by multiplying it by the ratio of the total standard deviation of $\widetilde{l}_t^i$ over the standard deviation of the sublocation i.e. $\widetilde{l}$
$^*p < 0.10$, $^* * p < 0.05$, $^* * *p < 0.01$

B Model properties

B.1 Existence of optimal paths and policy functions

The optimisation problem of the household is given by:

$$\max_{\{a_{t+1}\}_{t=0}^{\infty}} E_0 \left\{ \sum_{t=0}^{\infty} \beta^t u(c_t) \right\}, \tag{9}$$

given $\{a_0, l_0, h_0, e_0, s_0\}$, subject to

$$c_t \geq 0, \tag{10}$$

$$a_t \in [0, \overline{a}^{max}], \tag{11}$$

$$z_t = (l_t, h_t, e_t, s_t) \in Z = L \times H \times E \times S, \tag{12}$$

$$a_{t+1} \in \Gamma^a (a_t, l_t, h_t, e_t, s_t) = \left[0, a_{t+1}^{\max}\right], \tag{13}$$

where

$$c_t = (1 + l_t)a_t + \eta y (h_t, l_t, a_t; w_t) + e_t + s_t - a_{t+1}, \tag{14}$$

$$a_{t+1}^{\max} = (1 + l_t)a_t + \eta y (h_t, l_t, a_t; w_t) + e_t + s_t. \tag{15}$$

To obtain the dynamic programming formulation of the household's problem, use the joint distribution z_t (with the appropriate Markov chain associated with transition matrix $\pi (z_{t+1}|z_t)$), and let $v(a_t, z_t)$ denote the optimal value of the objective function starting from state (a_t, z_t). The Bellman equation is:

$$\begin{aligned} &v(a_t, z_t) = \\ &= \max_{a_{t+1} \in \Gamma^a} \left\{ u(\cdot) + \beta \sum_{z_{t+1} \in Z} \pi (z_{t+1}|z_t)\, v(a_{t+1}, z_{t+1}) \right\}. \end{aligned} \tag{16}$$

The assumptions on $u(c_t)$, the continuity of c_t in $(a_t, a_{t+1}, l_t, h_t, e_t, s_t)$ and the concavity of c_t in (a_t, a_{t+1}) for given l_t, h_t, e_t, s_t, imply that the function $u(a_t, a_{t+1}, l_t, h_t, e_t, s_t) : A^2 \times Z \to \mathbb{R}$ is continuous, twice differentiable, increasing in (a_t) and concave in (a_t, a_{t+1}) for given l_t, h_t, e_t, s_t. In addition, note that the state space $A \times Z$ is compact (closed and bounded) and convex, as the Cartesian product of sets with these properties.

Further, note that $a_{t+1}^{\max}$ is continuous and increasing in (a_t, l_t, e_t, s_t) and the set $\left[0, a_{t+1}^{\max}\right]$ is compact, convex and non-empty. To see the latter, recall that $(1+l_t)a_t \geq 0$,and $\eta y^{\min} + \overline{e}^{\min} + \overline{s}^{\min} > 0$, so that $a_{t+1}^{\max} > 0$. Hence, the correspondence $\Gamma^a (a_t, l_t, h_t, e_t, s_t)$ is compact-valued, convex-valued and nonempty-valued. Moreover, the correspondence $\Gamma^a (a_t, l_t, h_t, e_t, s_t) : A \times Z \to \left[0, a_{t+1}^{\max}\right]$ is continuous (see e.g. Exercise 3.13 in Stokey *et al.* (1989)).

The graph of $\Gamma^a (a_t, l_t, h_t, e_t, s_t)$ is given by

$$A_{\Gamma^a} = \left\{(a_t, l_t, h_t, e_t, s_t, a_{t+1}) \in A \times Z \times \left[0, a_{t+1}^{\max}\right] : a_{t+1} \in \Gamma^a (a_t, l_t, h_t, e_t, s_t)\right\},$$

which is closed, given continuity of the correspondences and boundedness and closedness of target sets (Closed Graph Theorem). For given $z_t = (l_t, h_t, e_t, s_t) \in Z$, take $a_t, a_t' \in A$, $a_{t+1} \in \Gamma^a (a_t, l_t, h_t, e_t, s_t)$ and $a_{t+1}' \in \Gamma^a (a_t', l_t, h_t, e_t, s_t)$. Then, for any $\theta \in [0, 1]$, we have that $\theta a_{t+1} + (1 - \theta) a_{t+1}' \in \Gamma^a (a_{\theta t}, l_t, h_t, e_t, s_t)$, where $a_{\theta t} = \theta a_t + (1 - \theta) a_t'$. To see this, note that since $a_{t+1} \in \Gamma^a (a_t, l_t, h_t, e_t, s_t)$, it must be that

$$a_{t+1} \leq a_{t+1}^{\max} (a_t, l_t, h_t, e_t, s_t) = (1 + l_t)a_t + \eta y (h_t, l_t, a_t; w_t) + e_t + s_t,$$

and, similarly, $a_{t+1}' \in \Gamma^a (a_t', l_t, h_t, e_t, s_t)$ implies that

$$a_{t+1}' \leq a_{t+1}^{\max} \left(a_t', l_t, h_t, e_t, s_t\right) = (1 + l_t)a_t' + \eta y \left(h_t, l_t, a_t'; w_t\right) + e_t + s_t,$$

so that

$$\begin{aligned} \theta a_{t+1} + (1 - \theta) a_{t+1}' &\leq \theta a_{t+1}^{\max} (a_t, l_t, h_t, e_t, s_t) + (1 - \theta) a_{t+1}^{\max} \left(a_t', l_t, h_t, e_t, s_t\right) \\ &= \theta \left[(1 + l_t)a_t + \eta y (h_t, l_t, a_t; w_t) e_t + s_t\right] + (1 - \theta) \left[((1 + l_t)a_t' + \eta y \left(h_t, l_t, a_t'; w_t\right) + e_t + s_t\right] \\ &\leq (1 + l_t) \left(\theta a_t + (1 - \theta) a_t'\right) + \eta y \left(h_t, l_t, ((\theta a_t + (1 - \theta) a_t')); w_t\right) e_t + s_t \\ &= a_{t+1}^{\max} (a_{\theta t}, l_t, h_t, e_t, s_t), \end{aligned}$$

where the second inequality follows from the concavity of $y(a_t;\cdot)$. Therefore, $\theta a_{t+1} + (1-\theta)\, a'_{t+1} \in \Gamma^a\left(a_{\theta t}, l_t, h_t, e_t, s_t\right)$ and the constraint defined by $\Gamma^a\left(a_t, l_t, h_t, e_t, s_t\right)$ is convex.

The above analysis implies that Theorems 9.6 and 9.8 in Stokey *et al.* (1989) (or, Theorem 16.4 in Acemoglu (2009)) apply, delivering existence, uniqueness and continuity of the policy function $a_{t+1} = g\left(a_t, l_t, h_t, e_t, s_t\right)$ that solves (16) and generates the stochastic process that solves the optimisation problem in (9)-(15). Furthermore, Theorem 9.13 in Stokey *et al.* (1989) implies that the joint distribution on $(a_t, l_t, h_t, e_t, s_t)$ is Markovian, and Theorem 9.14 that it has the Feller property. Therefore, and since $A \times Z$ is compact, Theorem 12.10 in Stokey *et al.* (1989) implies that an invariant unconditional distribution on $(a_t, l_t, h_t, e_t, s_t)$ exists. To solve the problem numerically, we follow Maliar and Maliar (2013) and employ the Envelope Condition Method (ECM), adjusted to handle the occasional hitting of the lower bound of assets.

B.2 Computation and the unimportance of the initial distribution

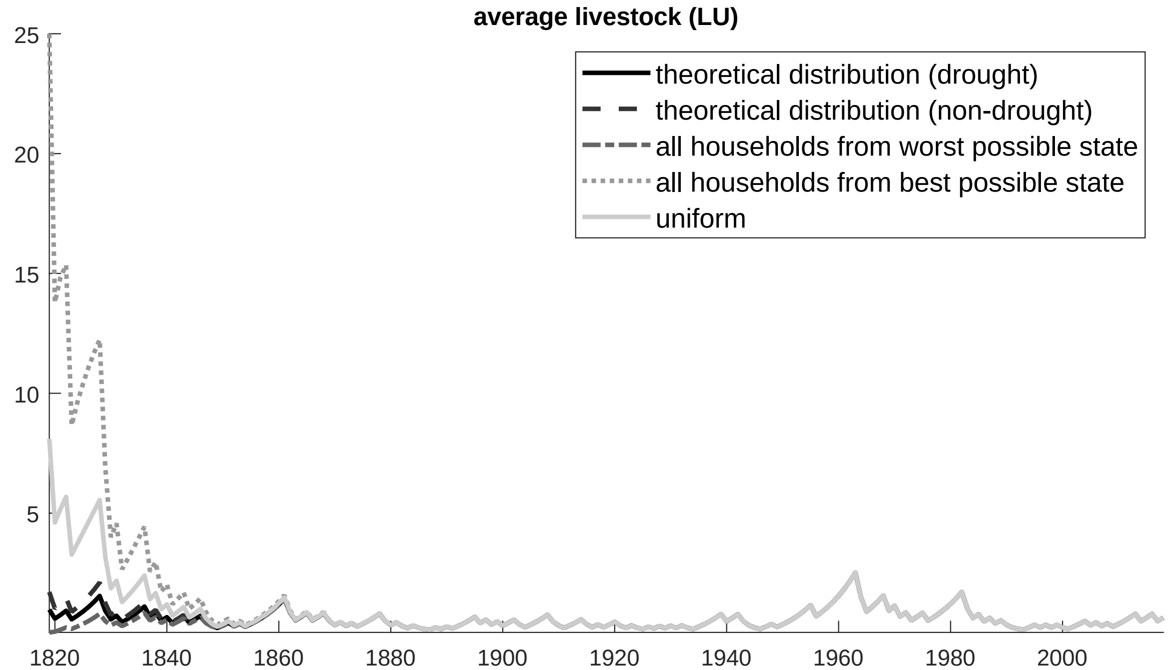
To obtain the time series of cross-sectional distributions that is generated by the realised history of the aggregate state between 1920 and 2018, we work as follows. To simulate the time series of cross-sectional distributions, we follow Young (2010) and Heer and Maussner (2009, Chapter 5.2). The key idea is the following. Define the distribution $(a_t, l_t^d, h_t^d, e_t^d, s_t^d; d_t)$ at time period t as a histogram with mass on each point (histogram bins). To compute the distribution in $t+1$ we use the transition probabilities of the exogenous Markov chains and the policy function for next period assets. In particular, the transition of the mass on each point is determined by

$$\begin{aligned} &P\left[(a_t, l_t^d, h_t^d, e_t^d, s_t^d; d_t), (a_{t+1}, l_{t+1}^d, h_{t+1}^d, e_{t+1}^d, s_{t+1}^d); d_{t+1})\right] = \\ &= \pi\left(l_{t+1}^d, h_{t+1}^d, e_{t+1}^d, s_{t+1}^d); d_{t+1} | l_t^d, h_t^d, e_t^d, s_t^d; d_t\right) \mathbf{1}[g^d\left(a_t, l_t^d, h_t^d, e_t^d, s_t^d; d_t\right) = a_{t+1}], \end{aligned} \tag{17}$$

where $\mathbf{1}[g^d(\cdot)]$ is a binary operator taking the value one if the statement is true and zero otherwise, and the notation in (17) implies that the transition probabilities $\pi(\cdot)$ and the policy function $g^d(\cdot)$ depend on the aggregate state d.

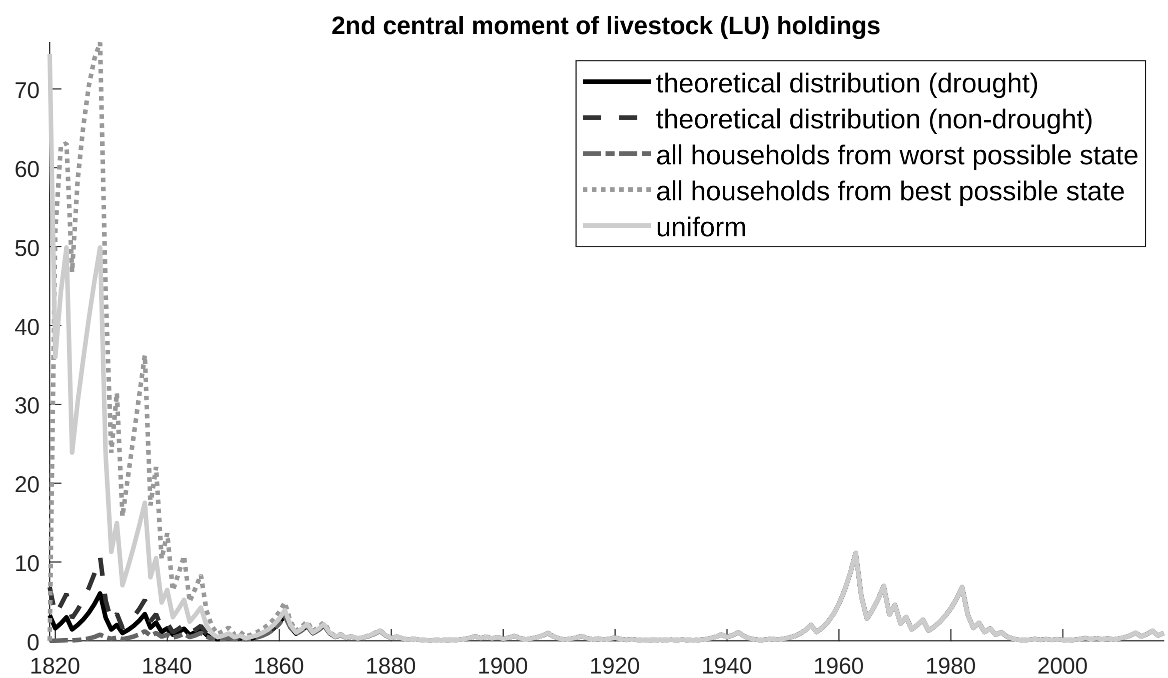
We simulate the cross-sectional distribution forward using (17) for 90 exogenous states and 250 grid points of assets, starting from a guess regarding the initial distribution $(a_0, l_0^{d_0}, h_0^{d_0}, e_0^{d_0}, s_0^{d_0}; d_0)$ for the year 1820, using a random path for d_t obtained from the estimated Markov chain until 1920 and the historical time series of droughts after 1920. Effects from the initial distribution assumed are negligible after about 30 years. As shown in Figure B1, starting from very different guesses, including from extreme distributional assumptions, leads to near-identical paths for average livestock after 1850, confirming ergodicity of the stationary regime. Using more plausible guesses for the initial distribution, such as the theoretical invariant distribution, leads to near-identical paths after the first 15 years. Indeed, given the stationarity of the time series of distributions (see Section 3), starting from the theoretical distribution for either drought or non-drought years leads to time paths that have similar statistical properties to the remaining series from the very beginning. We conclude, therefore, that any impact of the time series of the distributions prior to 1920 has negligible effects on the time series we compute after 1920.

Figure B1: The unimportance of the initial distribution



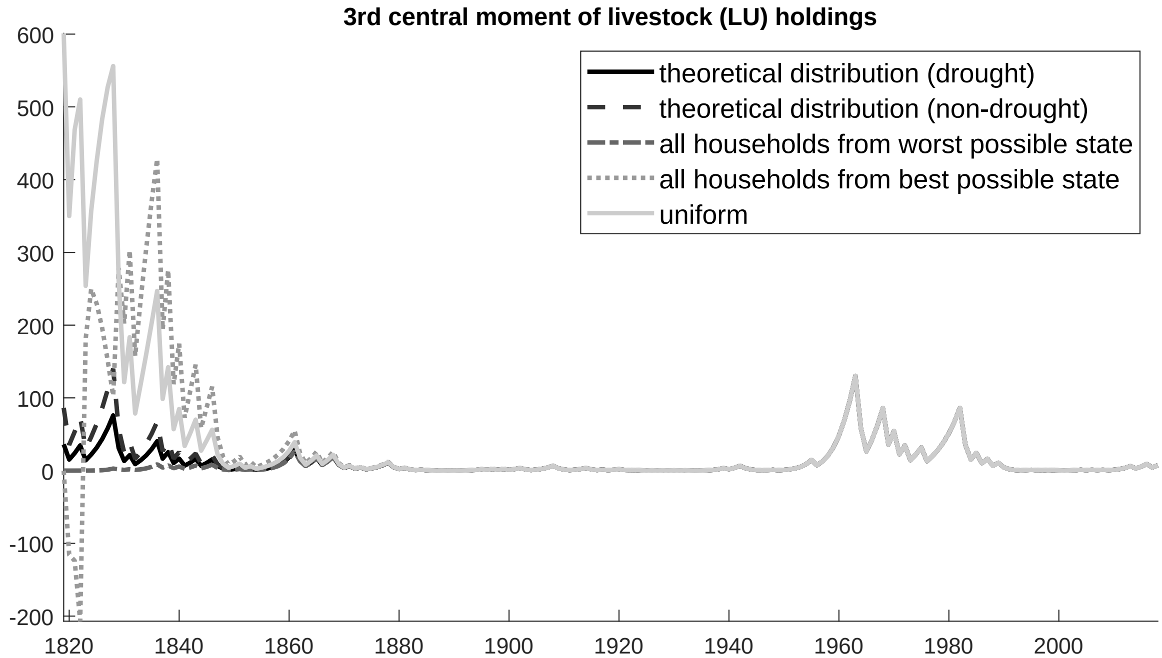
Note: Model generated outcomes from different initial distributions and using the historical time series of droughts and non-droughts since 1920.

Figure B2: The unimportance of the initial distribution



Note: Model generated outcomes from different initial distributions and using the historical time series of droughts and non-droughts since 1920.

Figure B3: The unimportance of the initial distribution



Note: Model generated outcomes from different initial distributions and using the historical time series of droughts and non-droughts since 1920.

B.3 Monotonicity of choices

We examine the monotonicity of choices regarding next period assets and net savings with respect to current assets and exogenous states in a two-period version of the model, where the first-order condition necessary for optimality is given by:

$$u'(c_t) \geq \beta E_t \left[\left((1 + l_{t+1}) + \frac{\partial y_{t+1}}{\partial a_{t+1}} \right) u'(c_{t+1}) \right], \tag{18}$$

which holds with equality if $a_{t+1} > 0$, where c_t is determined by (14)) and a_{t+2} is given.

Proposition 1

Consider the policy function $a_{t+1} = g(a_t, l_t, h_t, e_t, s_t)$: (a) $g(a_t; \cdot)$ is non-decreasing and when $a_{t+1} > 0$, it is increasing; (b) If (l_t) is *i.i.d.*, then $g(l_t; \cdot)$ is non-decreasing and when $a_{t+1} > 0$, it is increasing; (c) If (h_t) is *i.i.d.*, then $g(h_t; \cdot)$ is non-decreasing and when $a_{t+1} > 0$, it is increasing; (d) If (e_t) is *i.i.d.*, then $g(e_t; \cdot)$ is non-decreasing and when $a_{t+1} > 0$, it is increasing.

Proof

(a) For given (l_t, h_t, e_t, s_t), consider first any $a_t \in A$ for which $a_{t+1} = 0$, satisfying (18) with strict inequality. For any $a'_t < a_t$, it must be that $a'_{t+1} = 0$. To see this, suppose $a'_{t+1} > 0$; then (18) must be satisfied with equity. However, because $a'_t < a_t$, there is a decrease in c_t (see (14)) and thus an increase in $u'(c_t)$. Hence, the left-hand side (*lhs*) of (18) must decrease and the right-hand side (*rhs*) of (18) must increase. If $a'_{t+1} > a_{t+1} = 0$, then this will increase the left-hand side (*lhs*) of (18) by decreasing c_t and will decrease the right-hand side (*rhs*) of (18) by increasing c_{t+1} and decreasing $\frac{\partial y_{t+1}}{\partial a_{t+1}}$. Therefore, it must be that $a'_{t+1} = a_{t+1} = 0$, so that (18) holds with strict inequality. For any $a'_t > a_t$, $a'_{t+1} \geq a_{t+1}$, because of the lower bound on livestock.

Then consider any $a_t \in A$ such that $a_{t+1} > 0$ satisfies (18) with equality. Take any $a'_t > a_t$. This implies an increase in c_t (see (14)) and thus a reduction in $u'(c_t)$. For (18) to hold for a'_t, it must be that $a'_{t+1} > a_{t+1}$. This will increase the left-hand side (*lhs*) of (18) by decreasing c_t and will decrease the right-hand side (*rhs*) of (18) by increasing c_{t+1} and decreasing $\frac{\partial y_{t+1}}{\partial a_{t+1}}$. Take any $a'_t < a_t$. This implies a decrease in c_t (see (14)) and thus an increase in $u'(c_t)$. If $a'_{t+1} > 0$, for (18) to hold for a'_t, it must be that $a'_{t+1} < a_{t+1}$. This will decrease the left-hand side (*lhs*) of (18) by increasing c_t and will increase the right-hand side (*rhs*) of (18) by decreasing c_{t+1} and increasing $\frac{\partial y_{t+1}}{\partial a_{t+1}}$.

(b) For given (a_t, h_t, e_t, s_t), consider first any $l_t \in L$ for which $a_{t+1} = 0$, satisfying (18) with strict inequality. For any $l'_t < l_t$, it must be that $a'_{t+1} = 0$. To see this, suppose $a'_{t+1} > 0$; then (18) must be satisfied with equity. However, because $l'_t < l_t$, there is a decrease in c_t (see (14)) and thus an increase in $u'(c_t)$. Hence, the left-hand side (*lhs*) of (18) must decrease and the right-hand side (*rhs*) of (18) must increase. If $a'_{t+1} > a_{t+1} = 0$, then this will increase the left-hand side (*lhs*) of (18) by decreasing c_t and will decrease the right-hand side (*rhs*) of (18) by increasing c_{t+1} and decreasing $\frac{\partial y_{t+1}}{\partial a_{t+1}}$. Therefore, it must be that $a'_{t+1} = a_{t+1} = 0$, so that (18) holds with strict inequality. For any $l'_t > l_t$, $a'_{t+1} \geq a_{t+1}$, because of the lower bound on livestock.

Then consider any $l_t \in L$ such that $a_{t+1} > 0$ satisfies (18) with equality. Take any $l'_t > l_t$. This implies an increase in c_t (see (14)) and thus a reduction in $u'(c_t)$. For (18) to hold for a'_t, it must be that $a'_{t+1} > a_{t+1}$. This will increase the left-hand side (*lhs*) of (18) by decreasing c_t and will decrease the right-hand side (*rhs*) of (18) by increasing c_{t+1} and decreasing $\frac{\partial y_{t+1}}{\partial a_{t+1}}$. Note that because (l_t) is *i.i.d.*, it does not influence the *rhs* of (18). Take any $l'_t < l_t$. This implies a decrease in c_t (see (14)) and thus an increase in $u'(c_t)$. If $a'_{t+1} > 0$, for (18) to hold for l'_t, it must be that $a'_{t+1} < a_{t+1}$. This will decrease the left-hand side (*lhs*) of (18) by increasing c_t and will increase the right-hand side (*rhs*) of (18) by decreasing c_{t+1} and increasing $\frac{\partial y_{t+1}}{\partial a_{t+1}}$.

(c)-(d) Similar arguments to those in (b) apply. ■

Note that for the calibration of the model to the survey data for the Turkana pastoralists, conditional on the aggregate state, the idiosyncratic components of (l_t), (h_t) and (e_t) are independent of one another and of (s_t) (which is determined by (l_t)) and those of (l_t) and (e_t) also do not have persistence over time. Therefore, the results in *Proposition 1* are reflected in the patterns of the policy function shown, for example, in Section 5.2 and in Appendix D for non-droughts and droughts separately.

Proposition 2

Consider net savings out of livestock income, defined as $x^s_t \equiv a_{t+1} - (1 + l_t)a_t - \eta y_t = g^s(a_t, l_t, h_t, e_t, s_t)$: (a) $g^s(a_t; \cdot)$ is decreasing; (b) If (l_t) is *i.i.d.*, then $g^s(l_t; \cdot)$ is decreasing.

Proof

(a) Consider any $a_t \in A$ for given (l_t, h_t, e_t, s_t) such that $a_{t+1} > 0$. Then, by Proposition 1, an increase (a reduction) in a_t to a'_{t+} should be met by an increase (a reduction) in a_{t+1}. Therefore, both a_{t+1} and $(1+l_t)a_t+\eta y_t$ in x^s_t change in the same direction. However, the change in a_{t+1} should be less than the change in $(1 + l_t)a_t + \eta y_t$, implying that $x^s_t \equiv a_{t+1} - (1 + l_t)a_t - \eta y_t$ will decrease when a_t increases and *vice versa*. Consider an increase in a_t and in a_{t+1} (similar arguments apply when a_t and a_{t+1} decrease). If a_{t+1} increased by more than $(1 + l_t)a_t + \eta y_t$, then the left-hand side (*lhs*) of (18) will increase, while the right-hand side (*rhs*) of (18) decreases, meaning that (18) cannot hold.

For any a_t for which $a_{t+1} = 0$, by Proposition 1 a reduction a_t will leave a_{t+1} unchanged, implying that x^s_t increases. An increase in a_t to a'_t implies that $a'_{t+1} \geq a_{t+1} = 0$. If $a'_{t+1} = a_{t+1} = 0$, then x^s_t decreases. If $a'_{t+1} > 0$, then (18) must hold with equity. If a_{t+1} increased by more than $(1 + l_t)a_t + \eta y_t$, then the left-hand side (*lhs*) of (18) will increase, while the right-hand side (*rhs*) of (18) decreases, meaning that (18) cannot hold. Therefore, a_{t+1} must increased by less than $(1 + l_t)a_t + \eta y_t$.

In summary, net savings x^s_t are a decreasing function of a_t for all $a_t \in A$.

(b) Similar arguments to those in (a) apply. ■

Proposition 3

Consider net livestock acquisition, defined as $x_t \equiv a_{t+1} - (1+l_t)a_t = g^a(a_t, l_t, h_t, e_t, s_t)$: (a) If (e_t) is *i.i.d.*, then $g^a(e_t; \cdot)$ is non-decreasing and when $a_{t+1} > 0$, it is increasing.

Proof

(a) Consider any $e_t \in E$ for given (a_t, l_t, h_t, s_t) such that $a_{t+1} > 0$. Then, by Proposition 1, an increase (a reduction) in e_t to e_t' should be met by an increase (a reduction) in a_{t+1}, which implies that $x_t \equiv a_{t+1} - (1+l_t)a_t$ will also increase (reduce).

For any e_t for which $a_{t+1} = 0$, by Proposition 1 a reduction e_t will leave a_{t+1} unchanged, implying also that x_t remains unchanged. An increase in e_t to e_t' implies that $a_{t+1}' \geq a_{t+1} = 0$, implying that x_t does not decrease.

(b) Similar arguments to those in (a) apply. ■

C Stochastic process approximation

We summarise the estimated matrices for the stochastic processes.

$$Q_z = \underbrace{\underbrace{\begin{bmatrix} \pi^a(0|0) \otimes \left(\xi^{0\prime} \otimes J_{1\times 6}\right)' & \pi^a(1|0) \otimes \left(\xi^{1\prime} \otimes J_{1\times 6}\right)' \\ \pi^a(0|1) \otimes \left(\xi^{0\prime} \otimes J_{1\times 6}\right)' & \pi^a(1|1) \otimes \left(\xi^{1\prime} \otimes J_{1\times 6}\right)' \end{bmatrix}}_{12\times 12} \otimes \left[\underset{5\times 5}{Q^h} \otimes \underset{3\times 3}{\left(p_E' \otimes J_{1\times 3}\right)'}\right]}_{180\times 180}$$

$$Q^a = \begin{array}{c} \\ 0 \\ 1 \end{array} \begin{array}{cc} 0 & 1 \\ \left[\begin{array}{cc} 0.54 & 0.46 \\ 0.69 & 0.31 \end{array}\right] \end{array}$$

L^1	-0.9288	-0.4713	0.0208	1.0135	2.0357	3.8220
s^1	0.0333	0.0000	-0.0138	-0.0138	-0.0138	-0.0138
ξ^1	0.1668	0.4304	0.3724	0.0266	0.0029	0.0009
L^0	-0.8234	-0.0373	0.4406	1.1552	2.2836	3.8501
s^0	0.0333	0.0000	-0.0004	-0.0004	-0.0004	-0.0004
ξ^0	0.0075	0.3533	0.5236	0.1066	0.0083	0.0008

$$Q^h = \begin{bmatrix} 0.0175 & 0.2689 & 0.5182 & 0.1814 & 0.0140 \\ 0.0175 & 0.2689 & 0.5182 & 0.1814 & 0.0140 \\ 0.0175 & 0.2689 & 0.5182 & 0.1814 & 0.0140 \\ 0.0175 & 0.2689 & 0.5182 & 0.1814 & 0.0140 \\ 0.0074 & 0.1140 & 0.2196 & 0.0769 & 0.5821 \end{bmatrix}$$

$$\xi_h = \begin{bmatrix} 0.0171 & 0.2639 & 0.5086 & 0.1780 & 0.0324 \end{bmatrix}$$

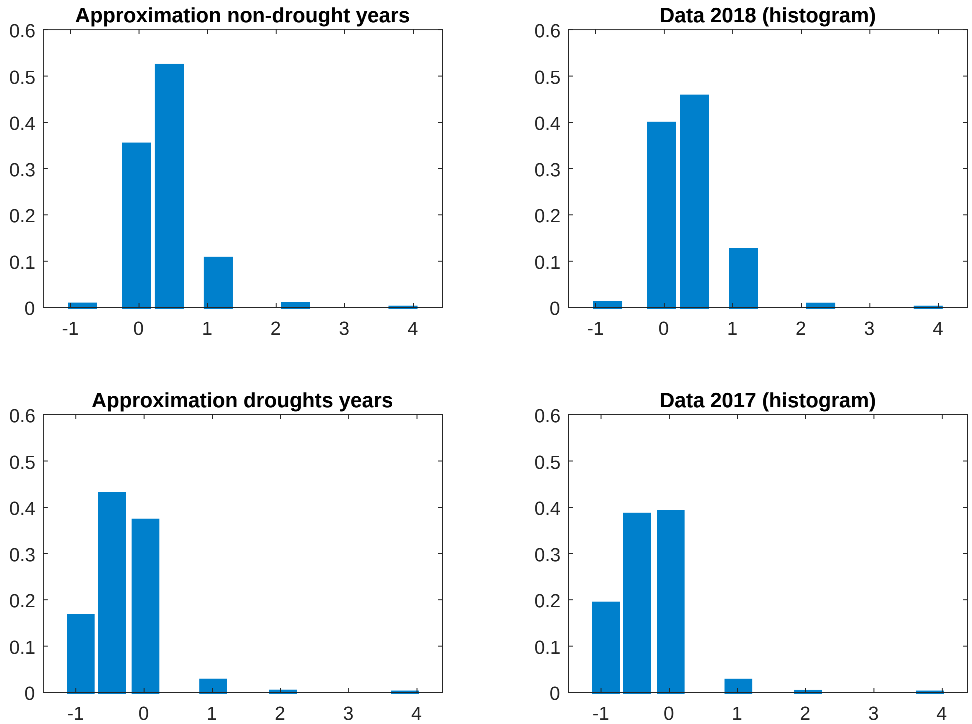
$$H^0 = \begin{bmatrix} 0.3275 & 0.5710 & 0.7727 & 0.9370 & 1.0000 \end{bmatrix}$$

$$H^1 = \begin{bmatrix} 0.2979 & 0.5414 & 0.7431 & 0.9074 & 1.0000 \end{bmatrix}$$

$$p_E = \begin{bmatrix} 0.75 & 0.16 & 0.09 \end{bmatrix}$$

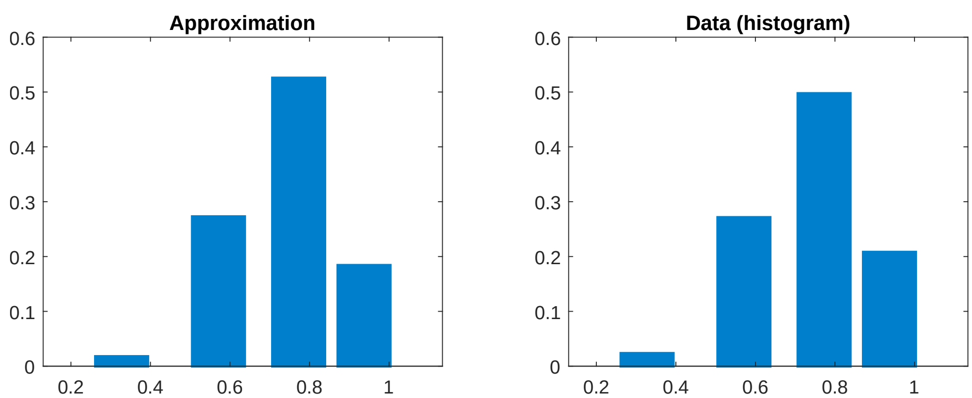
To confirm the accuracy of the approximation of the random variables for livestock holdings growth and household time input, we show in Figures C1 and C2 the empirical distributions and associated approximations.

Figure C1: Accuracy of the approximation of livestock holdings growth l_t



Note: Approximation of the empirical distribution applies the data-based discretisation proposed by Toda (2021).

Figure C2: Accuracy of the approximation of household time input, for $h_t < 1$



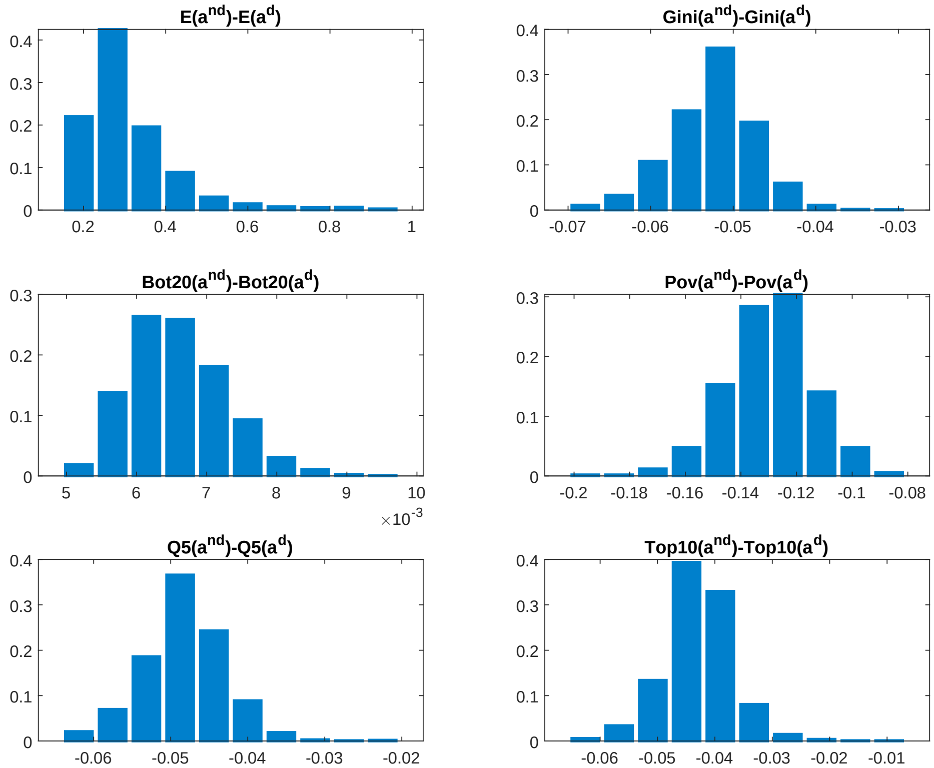
Note: Approximation of the empirical distribution applies the data-based discretisation proposed by Toda (2021).

D Additional results and robustness

D.1 Additional results on model fit

We also test whether the differences between droughts and non-droughts in key distributional statistics are statistically significant in the model-generated distributions as they are in the empirical distributions. Working as in the Monte Carlo exercise that delivers the results in Table D1, we calculate for each simulated time series the average of the statistic of interest for droughts and non-droughts separately (for the last 99 years) and then the difference between these averages for droughts and non-droughts. In Figure D2, we show the histograms of these differences, which make clear that the differences between droughts and non-droughts are statistically significant.

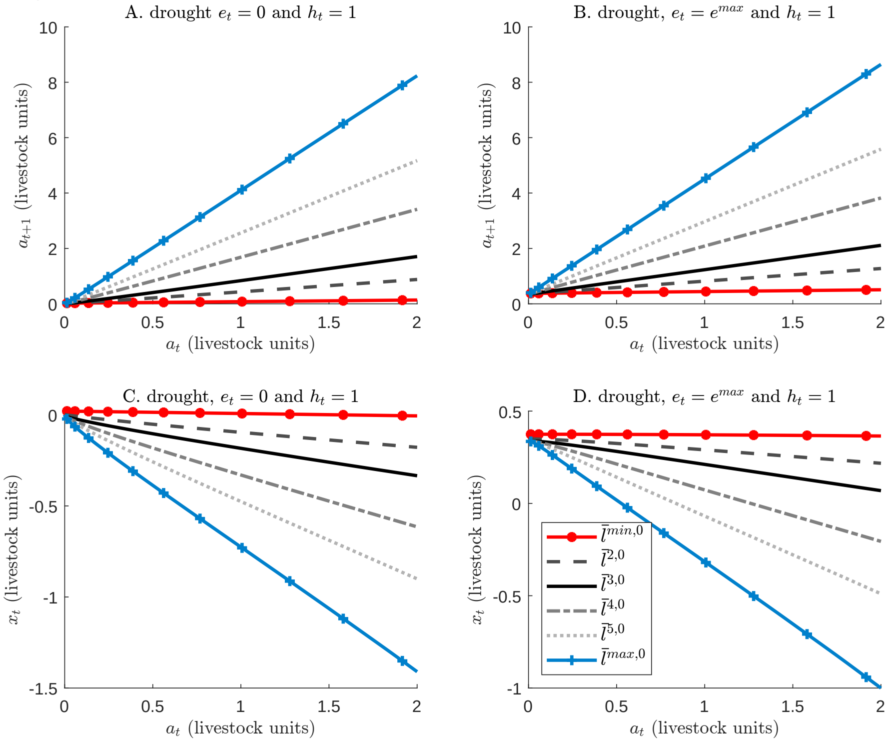
Figure D1: Monte Carlo exercise
Histograms of differences between droughts and non-droughts



Note: 1000 simulations

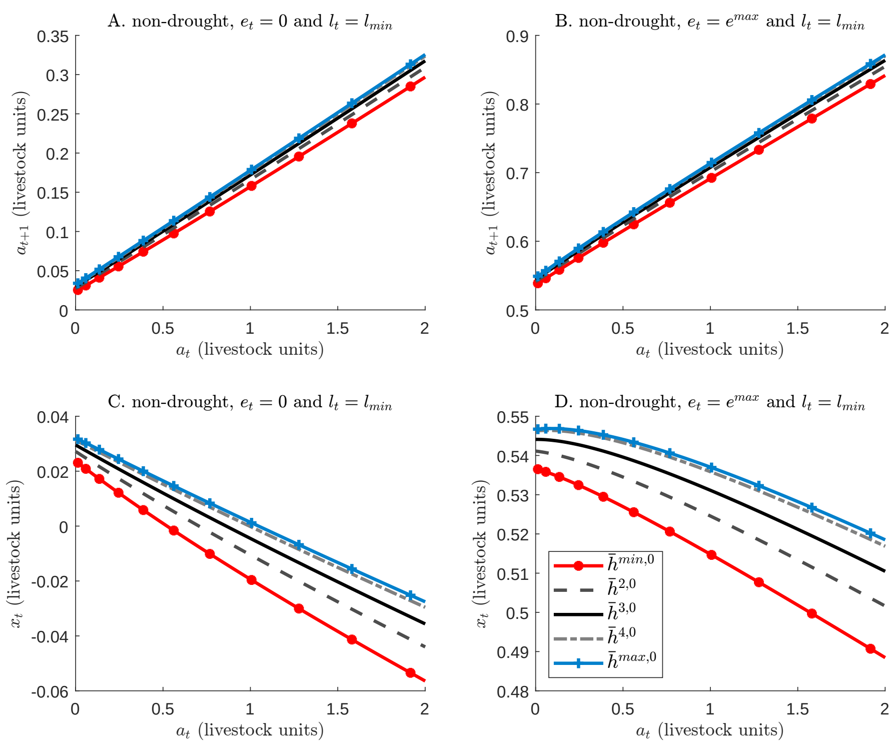
D.2 Additional results for policy functions

Figure D2: Next-period livestock and net livestock acquisitions, by l_t



Note: Panels A and B show $a_{t+1} = g^d\left(a_t, l_t^d, h_t^d, e_t^d, s_t^d; d_t\right)$ for different values of the state variables. Panels C and D show $x_t \equiv a_{t+1} - (1 + l_t^d)a_t$ for different values of the state variables.

Figure D3: Next-period livestock and net livestock acquisitions, by h_t



Note: Panels A and B show $a_{t+1} = g^d\left(a_t, l_t^d, h_t^d, e_t^d, s_t^d; d_t\right)$ for different values of the state variables. Panels C and D show $x_t \equiv a_{t+1} - (1 + l_t^d)a_t$ for different values of the state variables.

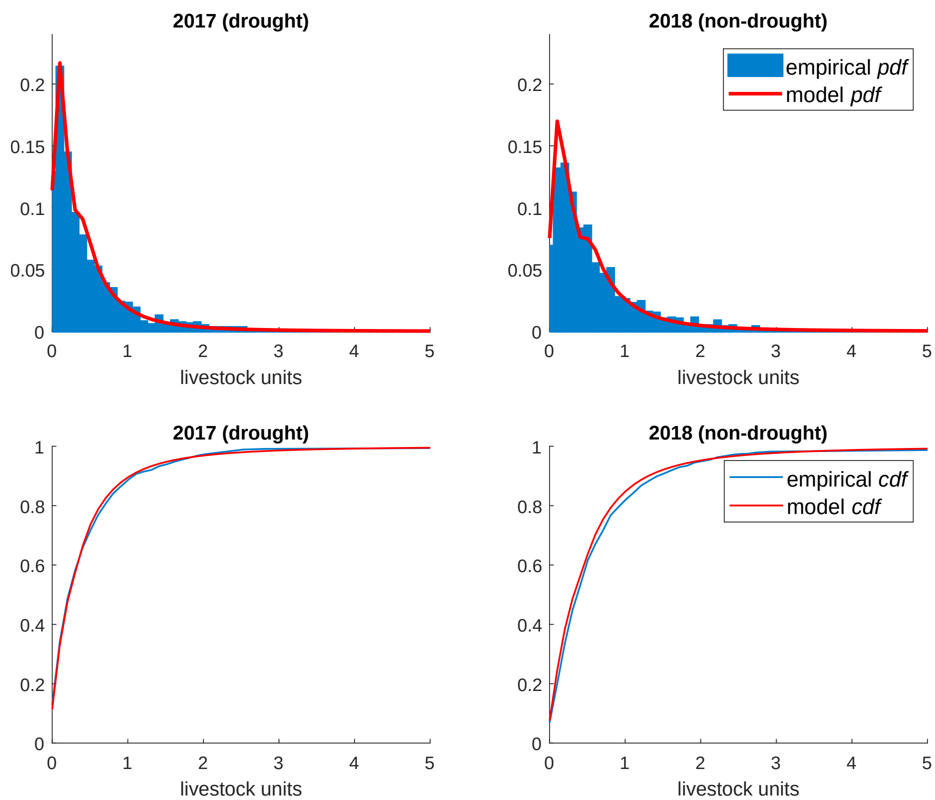
D.3 Results for drought-dependent livestock price

We solve a version of the model where the price of the livestock depends on droughts. In particular, the budget constraint of the household (5) becomes:

$$c_t + p_t^d a_{t+1} = (1 + l_t) p_t^d a_t + \eta y\left(h_t, l_t, a_t; w_t\right) + e_t + p_t^d s_t, \tag{19}$$

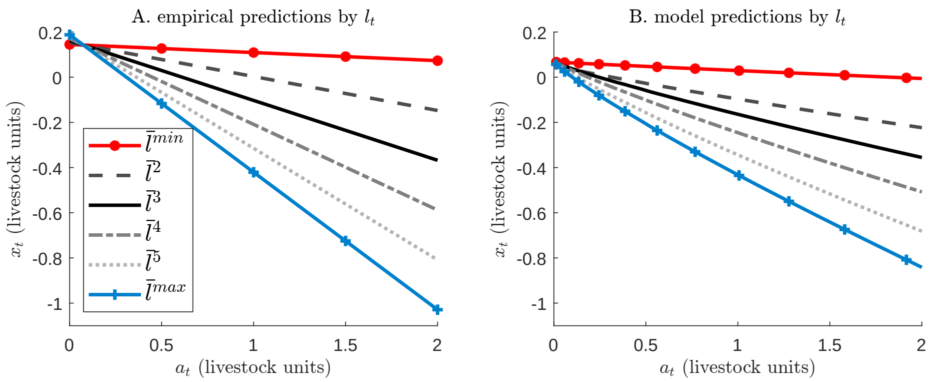
where p_t^d is 13% higher during non-droughts compared to droughts (as e.g. reported in NDMA (2020)) and normalised to be one across droughts and non-droughts. The model predictions are summarised below.

Figure D4: Empirical and model-generated distributions, 2017 and 2018



The model-generated distributions are calculated by simulating the model economy using the historical time series for droughts since 1920. For the empirical distributions, see Section 2. $\beta = 0.880$, $M^0 = 0.267$, $M^1 = 0.228$

Figure D5: Empirical and model-predicted net livestock savings



Note: Panels A and C show predicted marginal effects of beginning-of-period livestock on net savings for different levels of l_t and h_t, estimated using the survey data. Panels B and D show the equivalent effects for model-predicted net savings. In both cases, effects are averaged over the remaining variables.

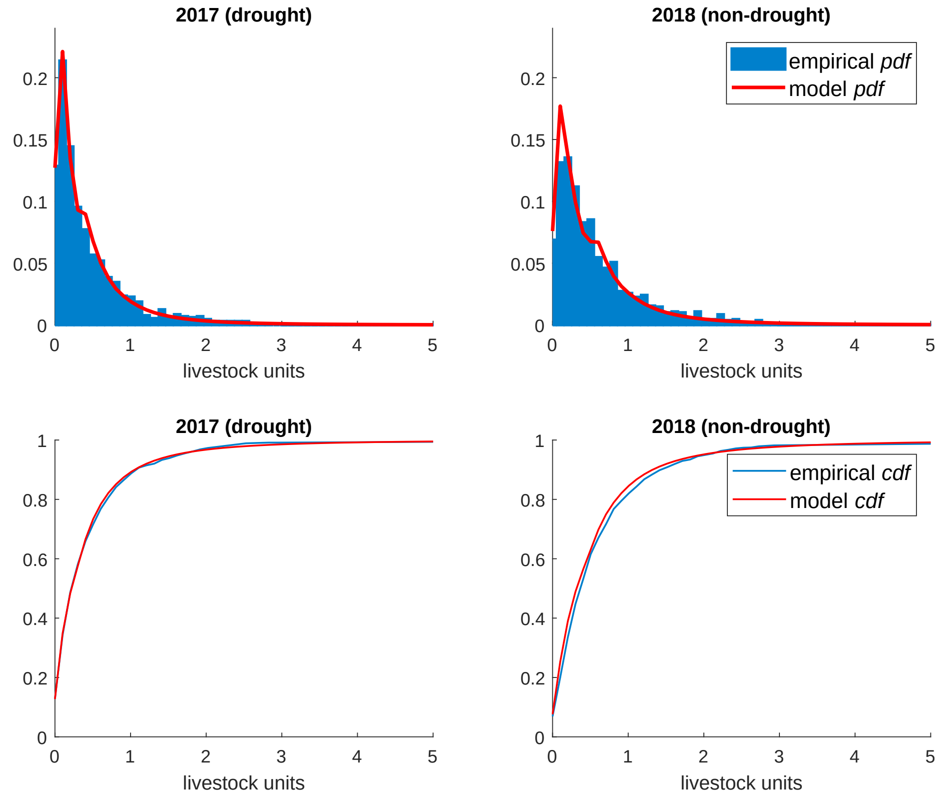
Table D1: Wealth inequality indices by sources of risk (model predictions)

	[0] base model	[1] no livestock growth risk	[2] no market income risk	[3] no time input risk	[4] no co-insurance
Mean Livestock 2017	0.495	0.771	0.244	0.495	0.494
Mean Livestock 2018	0.638	0.998	0.319	0.638	0.637
Gini Livestock 2017	0.583	0.313	0.426	0.583	0.598
Gini Livestock 2018	0.568	0.308	0.397	0.567	0.580
Poverty 2017 (% households)	0.120	0.003	0.002	0.119	0.148
Poverty 2018 (% households)	0.076	0.001	0.000	0.076	0.106
Bottom 20% share of wealth 2017	0.018	0.067	0.060	0.018	0.013
Bottom 20% share of wealth 2018	0.020	0.067	0.072	0.020	0.016
Top 20% share of wealth 2017	0.609	0.375	0.493	0.605	0.618
Top 20% share of wealth 2018	0.594	0.368	0.475	0.594	0.603
Top 10% share of wealth 2017	0.436	0.215	0.337	0.436	0.444
Top 10% share of wealth 2018	0.425	0.214	0.325	0.423	0.432

Note: Poverty is defined as the proportion of households that own less than 0.05 LU per member. The model-generated statistics are calculated by simulating the model using the historical time series for droughts since 1920.

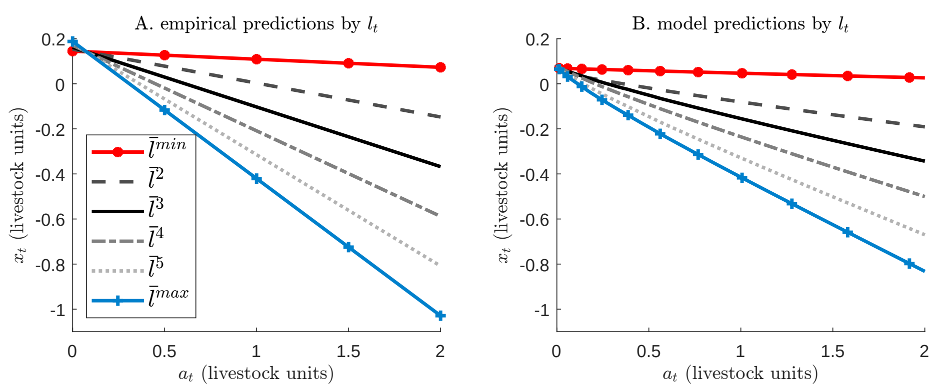
D.4 Results for $\gamma = 0.7$

Figure D6: Empirical and model-generated distributions, 2017 and 2018, $\gamma = 0.7$



Note: The upper row shows the empirical and the model implied pdf's, while the lower row shows the empirical and the model implied cdf's. $\beta = 0.920$, $M^0 = 0.253$, $M^1 = 0.205$

Figure D7: Empirical and model predicted net livestock savings, $\gamma = 0.7$



Note: Panels A and C show predicted marginal effects of beginning-of-period livestock on net savings for different levels of l_t and h_t, estimated using the survey data. Panels B and D show the equivalent effects for model-predicted net savings. In both cases, effects are averaged over the remaining variables.

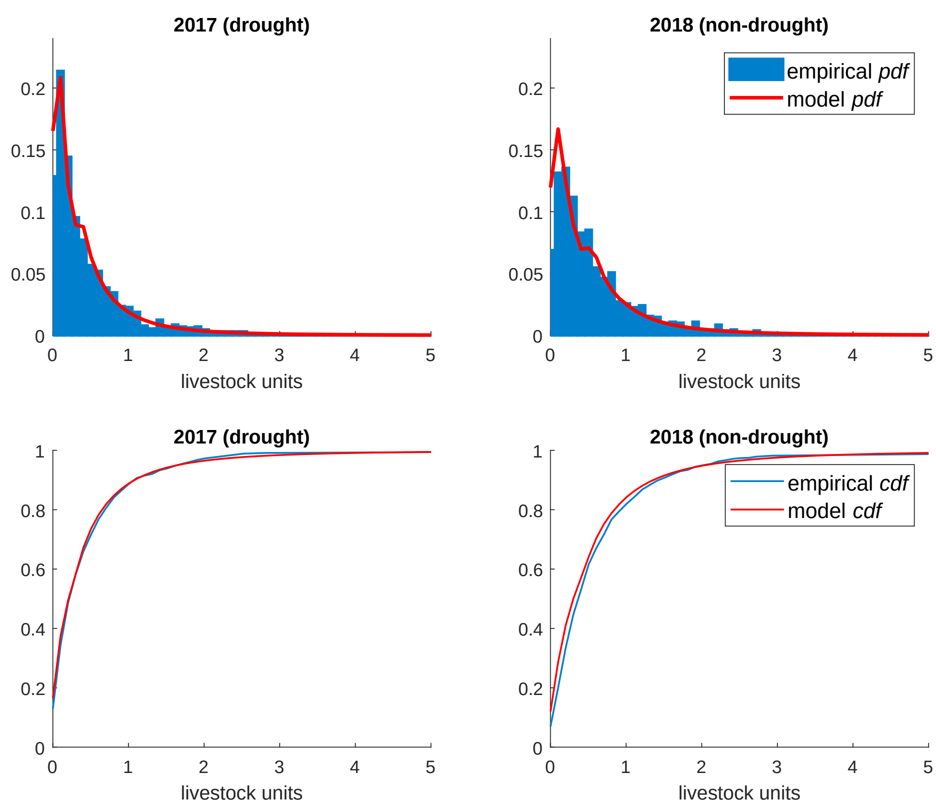
Table D2: Wealth inequality indices by sources of risk (model predictions), $\gamma = 0.7$

	[0] base model	[1] no livestock growth risk	[2] no market income risk	[3] no time input risk	[4] no co-insurance
Mean Livestock 2017	0.495	0.938	0.277	0.494	0.492
Mean Livestock 2018	0.638	1.217	0.363	0.636	0.634
Gini Livestock 2017	0.593	0.286	0.457	0.593	0.609
Gini Livestock 2018	0.569	0.281	0.417	0.569	0.582
Poverty 2017 (% households)	0.139	0.000	0.012	0.140	0.176
Poverty 2018 (% households)	0.074	0.000	0.000	0.072	0.115
Bottom 20% share of wealth 2017	0.017	0.075	0.049	0.017	0.011
Bottom 20% share of wealth 2018	0.020	0.078	0.066	0.021	0.015
Top 20% share of wealth 2017	0.616	0.355	0.512	0.614	0.626
Top 20% share of wealth 2018	0.594	0.353	0.489	0.591	0.604
Top 10% share of wealth 2017	0.441	0.201	0.352	0.438	0.449
Top 10% share of wealth 2018	0.422	0.199	0.336	0.422	0.430

Note: Poverty is defined as the proportion of households that own less than 0.05 LU per member. The model-generated statistics are calculated by simulating the model using the historical time series for droughts since 1920.

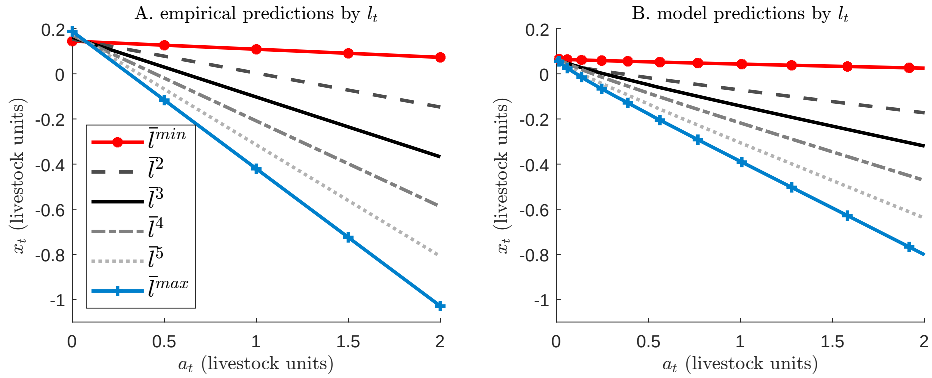
D.5 Results for $\gamma = 0.3$

Figure D8: Model fit, distributions, $\gamma = 0.3$



Note: The upper row shows the empirical and the model implied pdf's, while the lower row shows the empirical and the model implied cdf's. $\beta = 0.872$, $M^0 = 0.275$, $M^1 = 0.253$

Figure D9: Empirical and model predicted net livestock savings, $\gamma = 0.3$



Note: Panels A and C show predicted marginal effects of beginning-of-period livestock on net savings for different levels of l_t and h_t, estimated using the survey data. Panels B and D show the equivalent effects for model-predicted net savings. In both cases, effects are averaged over the remaining variables.

Table D3: Wealth inequality indices by sources of risk (model predictions), $\gamma = 0.3$

	[0] base model	[1] no livestock growth risk	[2] no market income risk	[3] no time input risk	[4] no co-insurance
Mean Livestock 2017	0.496	0.936	0.233	0.497	0.493
Mean Livestock 2018	0.637	1.216	0.305	0.638	0.634
Gini Livestock 2017	0.617	0.293	0.471	0.616	0.634
Gini Livestock 2018	0.595	0.287	0.434	0.595	0.611
Poverty 2017 (% households)	0.177	0.004	0.077	0.177	0.211
Poverty 2018 (% households)	0.131	0.002	0.000	0.130	0.160
Bottom 20% share of wealth 2017	0.011	0.070	0.048	0.011	0.005
Bottom 20% share of wealth 2018	0.013	0.071	0.063	0.013	0.008
Top 20% share of wealth 2017	0.635	0.354	0.526	0.634	0.647
Top 20% share of wealth 2018	0.615	0.354	0.504	0.615	0.626
Top 10% share of wealth 2017	0.458	0.203	0.365	0.457	0.467
Top 10% share of wealth 2018	0.441	0.199	0.348	0.441	0.450

Note: Poverty is defined as the proportion of households that own less than 0.05 LU per member. The model-generated statistics are calculated by simulating the model using the historical time series for droughts since 1920.