Drought and Herd Composition in Tanzania

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1 Introduction

There is a widespread belief and some empirical evidence that livestock herd composition has been changing in East Africa, potentially in response to drought and climate change. Ogutu et al. (2016) shows that since 1977, cattle numbers have been decreasing, while sheep and goat ("shoats") numbers have been increasing. Ahmed et al. (2019) find that shoats are more susceptible to disease compared to cattle, and that cattle are more susceptible to drought compared to shoats. A common narrative is that drought-induced attrition is worse for cattle than shoats, and that cattle losses are often replaced with shoats due to their drought tolerance. To the extent that this is true, both of these processes would lead to change in herd composition toward shoats and away from cattle. The purpose of this paper it to examine the question, "in the presence of drought, do farmers have less cattle and more shoats?" This paper adds to the body of literature as it is the first paper (to my knowledge) that shows that drought affects share of shoats.

1.1 Drought and Livestock

Although there is no universal quantitative definition of drought, drought is often defined qualitatively as a deficit of water relative to normal conditions (Kuwayama et al., 2019). A common drought index used historically is the Palmer Drought Severity Index (PDSI). It uses temperature and precipitation data to estimate relative dryness. The PDSI has proven effective in determining long-term drought; however, it is not great when there is short-term drought. Standardized Precipitation Index (SPI) is another widely used index that is closely related to soil moisture. The SPI can be interpreted as the number of standard deviations by which an observation of precipitation deviated from the long-term mean. Princeton University and the University of Washington use Variable Infiltration Capacity (VIC) in order to calculate a drought index that takes into account a number of factors, including precipitation and soil moisture. I will be using a number of variables that measure drought. I will be using the drought index derived from Princeton Climate Analytics (Princeton University, 2018), precipitation, and soil moisture.

There have been several studies done on drought and its impacts. Many concentrate on its effects on crops (Deschênes and Greenstone, 2011; Dell et al., 2012; Wheaton et al., 2008) and show that droughts negatively impact crop yields. Kuwayama et al. (2019) find that precipitation and temperature explain most of the variability in crop yields. Drought can also decrease surface water and groundwater supplies, which can also negatively impact livestock watering. These impacts can lead to decreases in revenue from both crop and livestock sales (Kuwayama et al., 2019). Drought has been shown to have negative impacts on education and human capital (Maccini and Yang, 2009; Shah and Steinberg, 2017) as well as health (Dinkelman, 2013). These effects could be brought about by the reduction in income by loss in livestock and crops, as well as the reduction in consumption.

As livestock plays a major role in the Tanzanian economy and income of its residents, its important to see what impacts drought has on livestock. According to the TNPS, 60% of rural households in Tanzania engage in livestock keeping. 20% of their income comes from livestock. Not only does livestock affect the majority of rural households' incomes, but it also affects the consumption of these households and the consumption of households that buy livestock products as livestock products contribute 13 percent to total household expenditures (Covarrubias et al., 2012).

2 Data

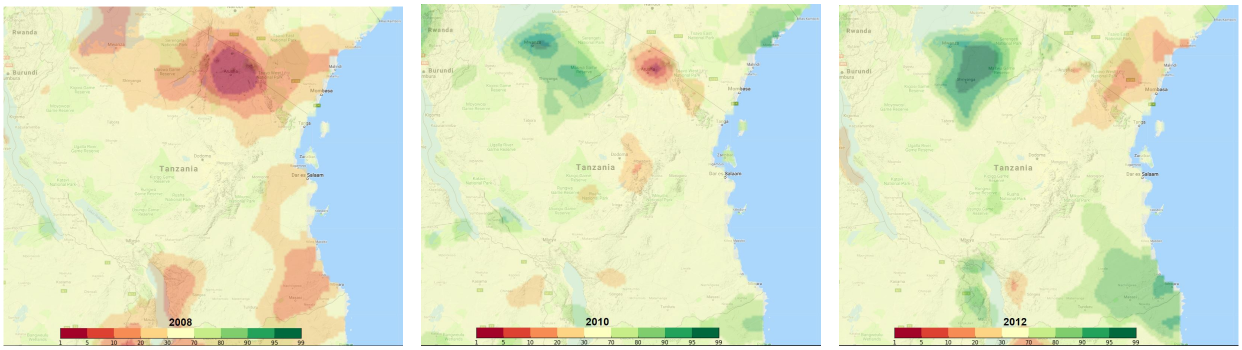
2.1 Livestock Data

The Tanzania National Panel Survey (TNPS) is a nationally-representative household survey which covers topics such as education, health, and livestock. Each wave consists of at least 3,000 households from all regions[1] and all districts of Tanzania. This analysis is restricted to the first three waves of the TNPS starting in the year 2008.

Households were interviewed and asked about the number each livestock they owned 12 months before the date they are interviewed (I will denote 12 months before the date a household is interviewed as time t). Because changes to herd composition through attrition or purchase in response to drought may take some time to transpire, we need to examine the effects of lagged drought on livestock herd composition. The variable $p_{r,t-j}$ is the (3-month rolling average of) precipitation level that corresponds to j months before time t in region r, the variable $d_{r,t-j}$ is Drought index as defined by (Princeton University, 2018) corresponding to j months before time t in region r, and $m_{r,t-j}$ is the relative soil moisture 10-100 cm under the surface.

The TNPS dataset contains many households that "split" from one period to another. It is not known why these households have split, but one could surmise a number of different reasons (for example, a child could have married and moved from the household). These splits could affect our analysis as they could potentially affect the shoat and cattle herd sizes. To account for this, observations before a split has occurred have been dropped. In section **??**, I evaluate if this . As the goal of this study is to see how drought has affected household herd composition, the dataset is subset further by only including observations with a positive number of cattle and a positive number of sheep or goats. Only households with more than two time periods of data are then kept in the dataset. Although this is

[1] The following regions are represented in the dataset: Arusha, Dar es Salaam, Dodoma, Iringa, Kagera, Kaskazini Pemba, Kaskazini Unguja, Kigoma, Kilimanjaro, Kusini Pemba, Kusini Unguja, Lindi, Manyara, Mara, Mbeya, Mjini/Magharibi Unguja, Morogoro, Mtwara, Mwanza, Pwani, Rukwa, Ruvuma, Shinyanga, Singida, Tabora, Tanga.



(a) 2008 (b) 2010 (c) 2012

Figure 1: Drought index variation across Tanzania, 2008, 2010, and 2012. Red is relatively dry, green is relatively wet (Princeton University, 2018).

subset is not a national representation of the Tanzania population, the results will give us an idea about how drought affects the choices made by individuals who have both shoats and cattle.

Table 2 provides summary descriptions of herd composition over time for households that hold both shoats and cattle. The mean household shoat share of the herd (s) is shown to increase through 2010, and then decline slightly.

2.2 Drought Data

Monthly drought data from 2007-2015 is taken from Princeton Climate Analytics (Princeton University, 2018). Drought data is merged with the TNPS dataset by year and region (specifically for the largest city in the region where the household resides).[2] Figure 1 shows how the drought index $d_{i,t}$ varies across Tanzania over space and time (Princeton University, 2018) (using the unmodified drought index) for 2008, 2010, and 2012. (Unmodified) drought index takes on values between 0 and 100, where values closer to 0 means that there is severe drought. I have reversed and rescaled the drought index. If *Drought* is the original index, I redefined $Drought = (100 - Drought)/100$ so that the drought index used takes values in $[0, 1]$, with 1 indicating severe drought.

Monthly precipitation data from 2007-2015 is taken from Princeton Climate Analytics

[2]There are 26 region/city pairs.

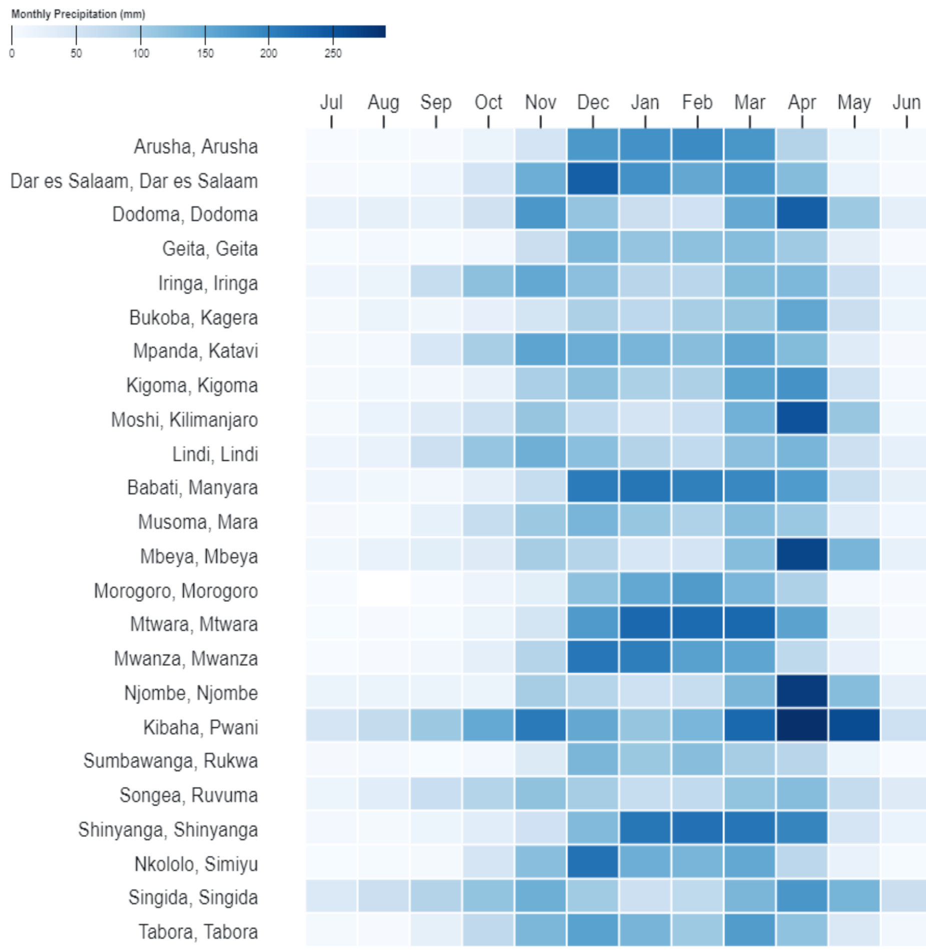


Figure 2: The above plot shows the average monthly precipitation in millimeters from 2007-2015 for capital cities in Tanzania. Although most regions have different climates and different rainy seasons, most typically have a short rainy season in November and December, and a longer rainy season in March and April.

(Princeton University, 2018). Precipitation data is then merged with the TNPS dataset by date and region (specifically for the largest city in the region where the household resides). Figure 2 shows the monthly precipitation averages in millimeters from 2007-2015 for capitals in each region. For the model specified in the methods section, precipitation is the 3 month-rolling average measured in millimeters. Thus, precipitation is the average of the current and the two previous months. Although precipitation alone is not the best indicator of drought, it will be used as it is easily interpretable. Table 1 summarizes the variables used in this analysis, and table 2 shows descriptive statistics for our sample.

Variable	Description
$Shoats_{i,t}$	Number of sheep and goats held by household i at time t.
$Cattle_{i,t}$	Number of cattle held by household i at time t.
$s^n_{i,t}$	*Shoats* as a fraction of total herd size measured in animal numbers: $s^n_{i,t} = Shoats/\left(Shoats{+}Cattle\right)$
$s^u_{i,t}$	*Shoats* as a fraction of total herd size based on Tropical Livestock Units (TLU): $s^u_{i,t} = Shoats_{i,t} \times 0.1/\left(Shoats_{i,t} \times 0.1 + Cattle_{i,t} \times 0.7\right)$
$s^v_{i,t}$	*Shoats value* as a fraction of total herd value: $s^v_{i,t} = Shoats_{i,t} \times \$^s_{r,t}/\left(Shoats_{i,t} \times \$^s_{r,t} + Cattle_{i,t} \times \$^c_{r,t}\right)$, where $\$^s_{r,t}$ are annual sheep and goat average market prices and $\$^c_{r,t}$ are annual average market prices for cattle respectively based on market price data from the TNPS.
$d_{r,t-j}$	Regional monthly drought index average. Range=(0,100); higher index numbers corresponding to more severe drought; lagged j months (occurring j months before t).
$p_{r,t-j}$	Regional monthly precipitation (mm), lagged j months.
$m_{r,t-j}$	Regional relative soil moisture, second layer (10-100 cm), lagged j months.

Table 1: Variable descriptions for both drought and livestock data. Livestock data is taken from the Tanzania National Panel Survey (TNPS), and drought data is taken from the Princeton Climate Analytics (Princeton University, 2018).

Variable	2008	2010	2012
Shoats as a fraction of total herd size (s^n)	0.53	0.59	0.58
Shoats as a fraction of total herd value (s^v)	0.16	0.22	0.17
Current Drought (d)	0.82	0.57	0.57
Current Precipitation (p)	26.25	94.77	65.27
Soil Moisture (m)	48.28	49.56	51.18
Sheep	8.41	12.10	13.40
Goats	8.14	12.53	16.91
Cattle	10.28	12.42	15.99
Sheep Average Selling Price (shillings)	25038.73	33354.75	35984.29
Goat Average Selling Price (shillings)	26121.42	37857.56	38383.46
Cattle Average Selling Price (shillings)	249900.20	276545.38	341341.06

Table 2: Descriptive statistics for households that have a positive amount of shoats and cattle for no less than 2 waves.

3 Methods

To examine the relationship between drought and herd composition, I use a multilevel fixed-effects model similar to that proposed by Dell et al. (2014). Equation 1 estimates the effects of past drought and related measures on the share of a herd held as shoats.

$$s_{it}^{x} = \sum_{j} \beta_j w_{r,t-j} + \rho_i + \eta_r + \phi_t + \varepsilon_{it}, \tag{1}$$

where index i represents households, $t \in (2008, 2010, 2012)$ are the years in which herd measurements were taken, $j \in (0, 3, 6, 9, 12)$ is weather metric lag in months, and r is a region index. The dependent variable $s_{i,t}^{x}$ is one of three measures of the share of a herd held as sheep and goats (shoats) as described below. The variable $w_{r,t-j}$ is a drought-related metric for the region (r) in which household i resides, lagged j months (in three month intervals). Regression element ρ_i is a household fixed effect, η_r is a regional fixed effect, and ϕ_t is a time fixed effect.

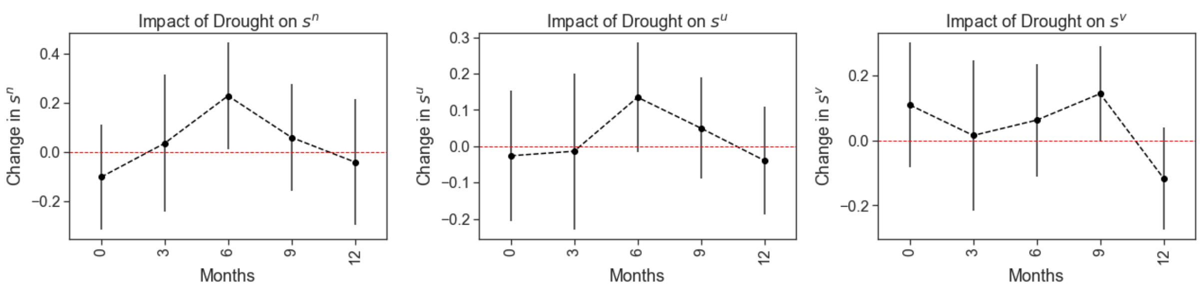
The share of a herd held as sheep and goats can be measured in several ways. We use three definitions: herd share in terms of number of animals ($s_{i,t}^{n}$), herd share in terms of tropical disease units (TLUs) ($s_{i,t}^{u}$), and herd share in terms of value ($s_{i,t}^{v}$). We also examine three different drought metrics: a Drought index ($d_{r,t-j}$), Precipitation ($p_{r,t-j}$), and Soil moisture ($m_{r,t-j}$). Table 1 describes the variables used in the analysis, and table 2 gives summary statistics for these variables.

4 Results

Table 3 shows the results of using lagged drought defined by Princeton Climate Analytics (Princeton University, 2018) index as the drought variable. Figure 3 plots the coefficients of lagged Drought index along with 95% confidence intervals. A .5 unit change in the drought index $d_{r,t-j}$ six months previous is associated with a 0.1, or 10 percentage point, increase in shoat share of herd numbers $s_{i,t}^n$. Near and far term effects (a higher drought concurrently and 3, 9, and 12 months past) have no statistically discernible effect after controlling for the 6-month lag effect. These results give evidence to the claim that drought affects future shoat share; however, the units of the drought index do not help with interpretability. I will also look at lagged soil moisture to see if I get similar results, and also look at lagged precipitation for clearer interpretation.

	s^n	s^u	s^v
$d_{t,0}$	-0.1003	-0.0261	0.1093
$d_{t,3}$	0.0370	-0.0137	0.0155
$d_{t,6}$	0.2300**	0.1348*	0.0628
$d_{t,9}$	0.0608	0.0498	0.1441*
$d_{t,12}$	-0.0395	-0.0391	-0.1165

Table 3: Results for the regressions of s^n, s^u, and s^v on drought $d_{r,t-j}$ for $j \in (0, 3, 6, 9, 12)$. $^*p < 0.10$;$^{**} p < 0.05$;$^{***} p < 0.01$



(a) Impact of $d_{r,t-j}$ on s^n (b) Impact of $d_{r,t-j}$ on s^u (c) Impact of $d_{r,t-j}$ on s^v

Figure 3: Effects of weather metrics on shoats as a share of herd numbers, TLUs, and value. Coefficients and 95% confidence intervals from regressions of s^n, s^u, and s^v on drought index ($d_{r,t-j}$) where $j \in (0, 3, 6, 9, 12)$ months.

Tables 4 and 5 show how lagged precipitation and lagged soil moisture affect shoat share, respectively. Figures 4 and 5 plot the coefficients of lagged precipitation and lagged soil moisture respectively along with 95% confidence intervals. Precipitation and soil moisture measures have a statistically significant nine-month lag effect on the shoat share of herd numbers $s_{i,t}^n$, with higher precipitation and soil moisture associated with a lower shoat herd share, all else constant. A 100 mm (monthly) decrease in lagged precipitation leads to an increase of around .10, or 10 percentage points in share of shoats, s^n, and also an increase of around .05, or 5 percentage points in share of shoats in TLU units, s^u in 9 months. The patterns are similar, with drought (measured by drought index) affecting herd composition 6 months later, and precipitation and soil moisture affecting herd composition 9 months later. One might imagine that precipitation and soil moisture have a lagged effect on drought-related forage availability, and drought has a lagged effect on herd mortality, morbidity, and replacement.

	s^n	s^u	s^v
$p_{t,0}$	-0.000	-0.000	-0.0001
$p_{t,3}$	0.0002	0.0001	-0.0003
$p_{t,6}$	0.0002	-0.0001	-0.0008***
$p_{t,9}$	-0.001***	-0.0004**	-0.0007***
$p_{t,12}$	-0.0002	-0.0001	-0.0007**

Table 4: Results for the regressions of s^n, s^u, and s^v on precipitation $p_{r,t-j}$ for $j \in (0, 3, 6, 9, 12)$. $^{*}p < 0.10;^{**} p < 0.05;^{***} p < 0.01$

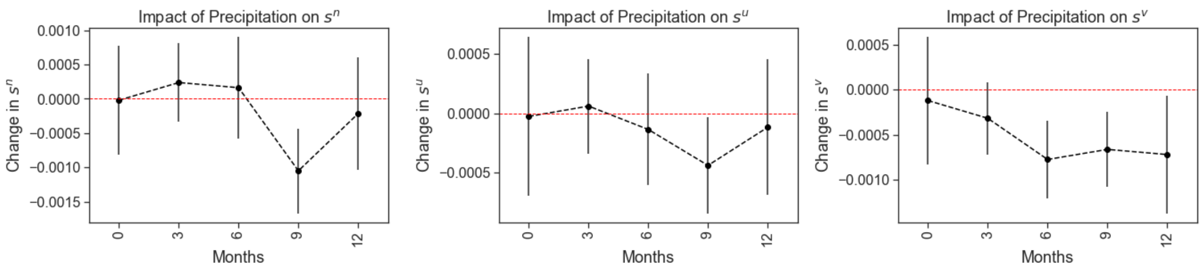
	s^n	s^u	s^v
$m_{t,0}$	0.2797	0.0977	-1.1658
$m_{t,3}$	0.5089	0.0290	-0.5082
$m_{t,6}$	-0.491	-0.307	-0.7706**
$m_{t,9}$	-1.5732**	-0.8857**	-1.3372***
$m_{t,12}$	-0.7504	-0.1754	0.8018

Table 5: Results for the regressions of s^n, s^u, and s^v on soil moisture $m_{r,t-j}$ for $j \in (0, 3, 6, 9, 12)$. $^{*}p < 0.10;^{**} p < 0.05;^{***} p < 0.01$

As we are working with an autoregressive model, multicollinearity could an issue that we should be concerned about. The following figures shows variance inflation factors for the independent variables in our model.

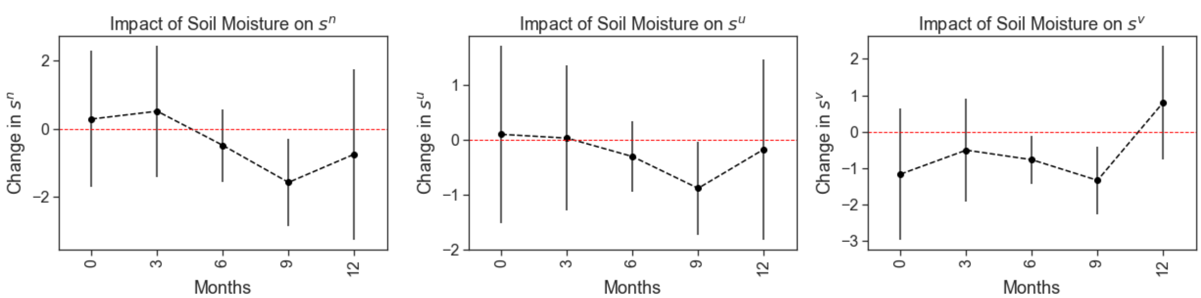
4.1 Robustness Checks

Adding herd size and feed yields as controls, shown by Figure 6, do not change our results much.



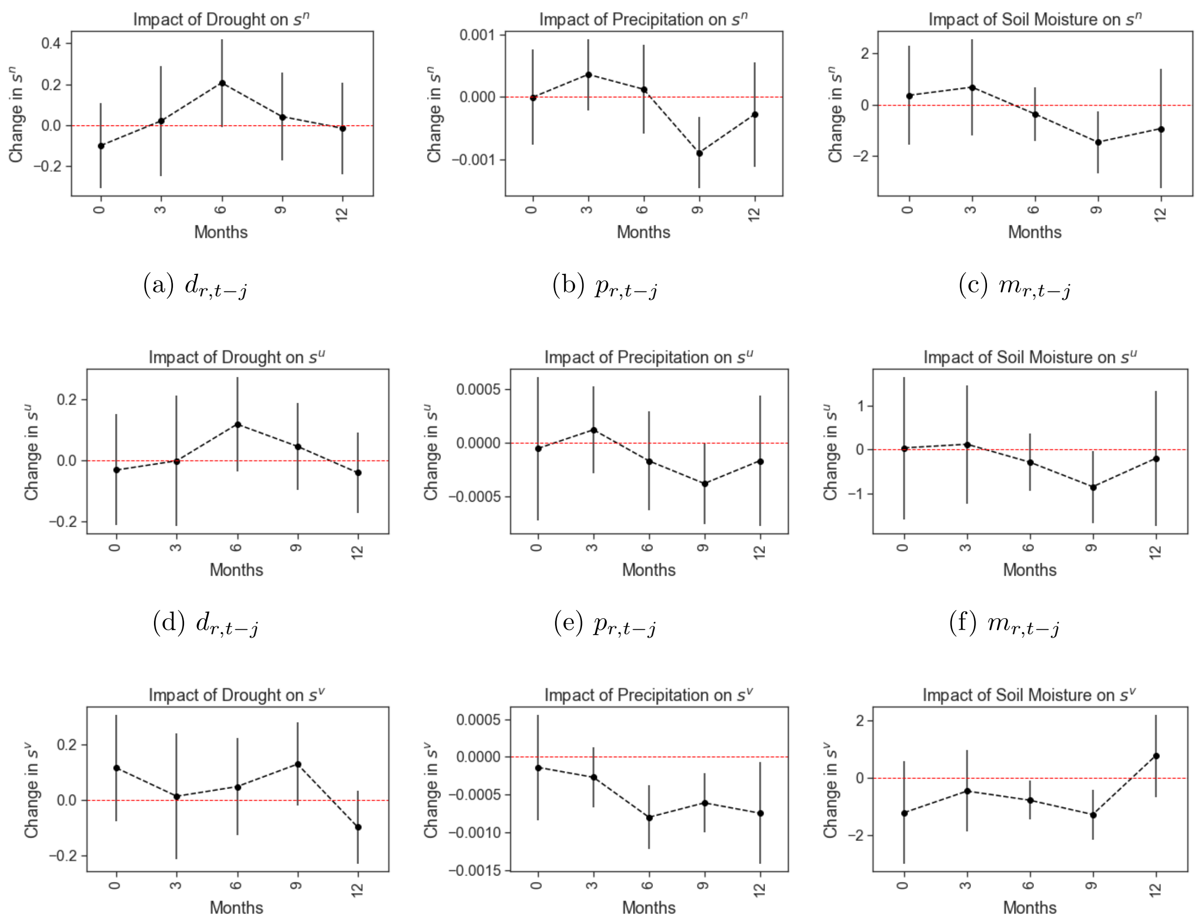
(a) $p_{r,t-j}$ (b) $p_{r,t-j}$ (c) $p_{r,t-j}$

Figure 4: Effects of weather metrics on shoats as a share of herd numbers, TLUs, and value. Coefficients and 95% confidence intervals from regressions of s^v on drought, precipitation, and soil moisture, lagged months $j \in (0, 3, 6, 9, 12)$.



(a) $m_{r,t-j}$ (b) $m_{r,t-j}$ (c) $m_{r,t-j}$

Figure 5: Effects of weather metrics on shoats as a share of herd numbers, TLUs, and value. Coefficients and 95% confidence intervals from regressions of s^v on drought, precipitation, and soil moisture, lagged months $j \in (0, 3, 6, 9, 12)$.



(a) $d_{r,t-j}$ (b) $p_{r,t-j}$ (c) $m_{r,t-j}$

(d) $d_{r,t-j}$ (e) $p_{r,t-j}$ (f) $m_{r,t-j}$

(g) $d_{r,t-j}$ (h) $p_{r,t-j}$ (i) $m_{r,t-j}$

Figure 6: Effects of weather metrics on shoats as a share of herd numbers, TLUs, and value, adding in controls for herd size and feed practices. Coefficients and 95% confidence intervals from regressions of s^v on drought index, precipitation, and soil moisture, lagged months $j \in (0, 4, 8, 12)$.

Variable	VIF
$d_{t,0}$	3.107788
$d_{t,3}$	3.689266
$d_{t,6}$	1.363035
$d_{t,9}$	1.465983
$d_{t,12}$	1.519931

Variable	VIF
$p_{t,0}$	2.432227
$p_{t,3}$	1.264292
$p_{t,6}$	2.058696
$p_{t,9}$	1.173442
$p_{t,12}$	1.576854

Variable	VIF
$m_{t,0}$	2.584923
$m_{t,3}$	2.292465
$m_{t,6}$	1.247703
$m_{t,9}$	1.405880
$m_{t,12}$	1.796055

Table 8: Variance Inflation Factors (VIFs) for drought (d), precipitation (p), and soil moisture (m).

When working with panel data, a concern is that leading variables have statistically significant coefficients. In other words, there should be no relationship between drought today and share of shoats from months ago. The coefficients for regressing share of shoats, s^n on lead and lagged precipitation along with their 95% confidence intervals are plotted in figure 7. The coefficients for all 4 lead variables are near zero, and statistically insignificant at the .05 level.

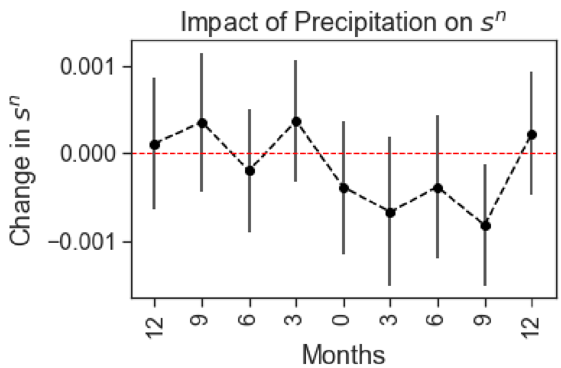


Figure 7: Coefficients and 95% confidence intervals from regressions of s^n on lead and lagged precipitation.

4.2 Mobility

The model only looks at a subset of the data, namely it excludes households that split in a previous wave. One concern is that households that split move to a new region. Figure 10 shows the proportion of split households that move from one region to another. Typically, most households that split stay in the same region after they split. Another concern is that this decision to split is affected by drought. To address this concern, I consider the following model represented in equation 2.

$$Pr(\text{Split}_i) = f(Drought_{r(i)}, X_i) \tag{2}$$

In other words, I model the probability of household i splitting as a function of drought in the region ($r(i)$) where household i originally resides as well as household controls (X_i). Table 9 shows the results when applying a logit model.

	Split
Drought	-1.5791***
	(0.4990)
Year	-0.0002
	(0.0002)
Cattle	0.0120**
	(0.0060)
Shoats	0.0075*
	(0.0043)

Table 9: Results for the logistic regression of *Split* (dummy denoting if a household splits) on average drought over the next year after a household is interviewed, year, cattle, and shoats. $^{*}p < 0.10;^{**}p < 0.05;^{***}p < 0.01$

The results from this regression are a bit concerning. We see that drought has a negative relationship with the probability of a household splitting. In other words, in a region that experiences drought, we would except fewer households in that region to split. (HOW DOES THIS AFFECT RESULTS?) Note that the amount of livestock a household has is associated with a greater probability of splitting. Thus, the data used in our model contains households with smaller amounts of livestock.

5 Additional Results and Discussion

5.1 Uganda

Using the same model as discussed in the methods, I use data from Uganda National Panel Survey (UNPS) from the 2010, 2011, 2013, and 2015 waves. Figure 8 plots the coefficients for lagged precipitation using monthly precipitation data provided by the University of Delaware Air Temperature and Precipitation dataset (as the data from Princeton Climate Analytics for Uganda is unavailable).

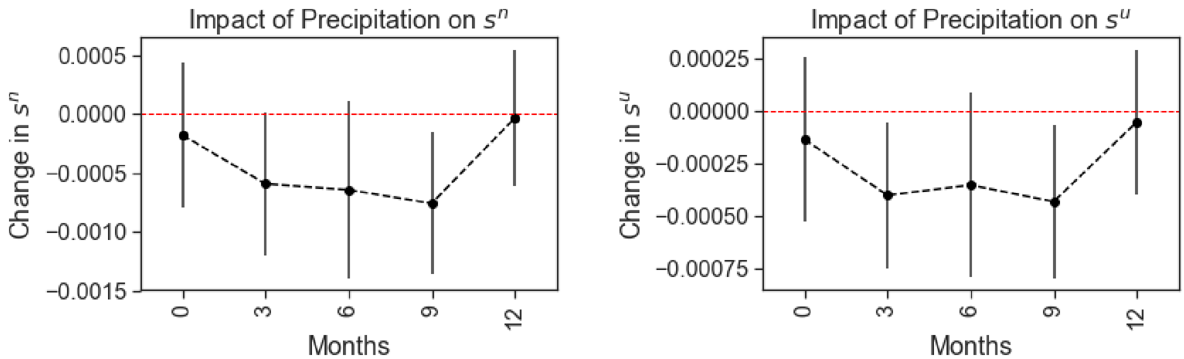


Figure 8: Coefficients and 95% confidence intervals from regressions of s_t^n and s_t^u on precipitation $p_{t,j}$ where j is lagged month.

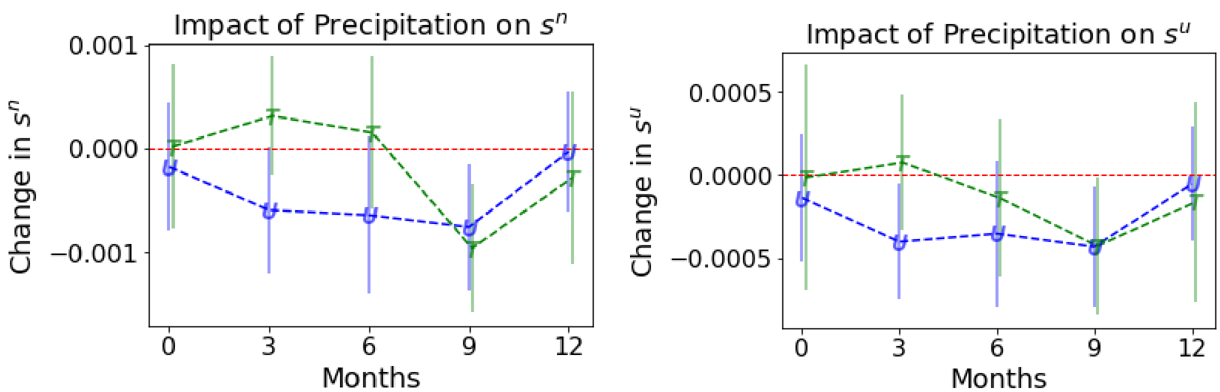


Figure 9: Coefficients and 95% confidence intervals from regressions of s_t^n and s_t^u on precipitation $p_{t,j}$ where j is lagged month. Coefficients for Uganda are in blue, while coefficients for Tanzania are in green.

Figure 9 compares the results from Uganda with the Tanzania results. This gives further evidence that reduced lagged precipitation leads to an increase in share of shoats. The coefficient for $p_{t,9}$ (both when s^n and s^u are the dependent variable) is similar for both countries.

5.2 Discussion

A few papers and some popular press articles have suggested a relationship between drought and herd composition Ogutu et al. (2016). This is the first attempt (to my knowledge) to evaluate and estimate the effects of drought on herd composition. By exploiting the variation of local drought experienced by Tanzanian households, we are able to show that (lagged) drought tends to lead to an increase in the shoat share of herd numbers, TLU's and value, and this effect manifests with a 6-month lag for the drought index, and with a 9-month lag for precipitation and soil moisture.

There are two evident mechanisms whereby we could be seeing an increase in share of shoats in the presence of drought. As has been suggested elsewhere (Ahmed et al., 2019), cattle may be more susceptible to drought, and thus should have higher mortality rates than sheep and goats during drought. This in itself may lead to an increase in share of shoats. Further, households may also be replacing lost cattle with shoats as well, magnifying the effect of drought on herd composition.

This study has focused only on a subset of the data. Namely it focused on households that held positive amounts of shoats and cattle in at least two waves. Therefore, it does not account for households that added shoats when owning no shoats before or households that added cattle when owning no cattle before. Also it does not account for households that had a reduction in shoats to 0 or households that had a reduction in cattle to 0.

6 Conclusion

In Tanzania and Uganda, I give evidence that share of shoats is affected 6-9 months after the presence of drought. In terms of precipitation levels, I find that in general, a decrease of 100 mm of monthly precipitation leads to an increase of share of shoats by 10 percentage points (or an increase of share of shoats in TLU units by 5 percentage points) 9 months later.

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7 Appendix

7.1 Mobility

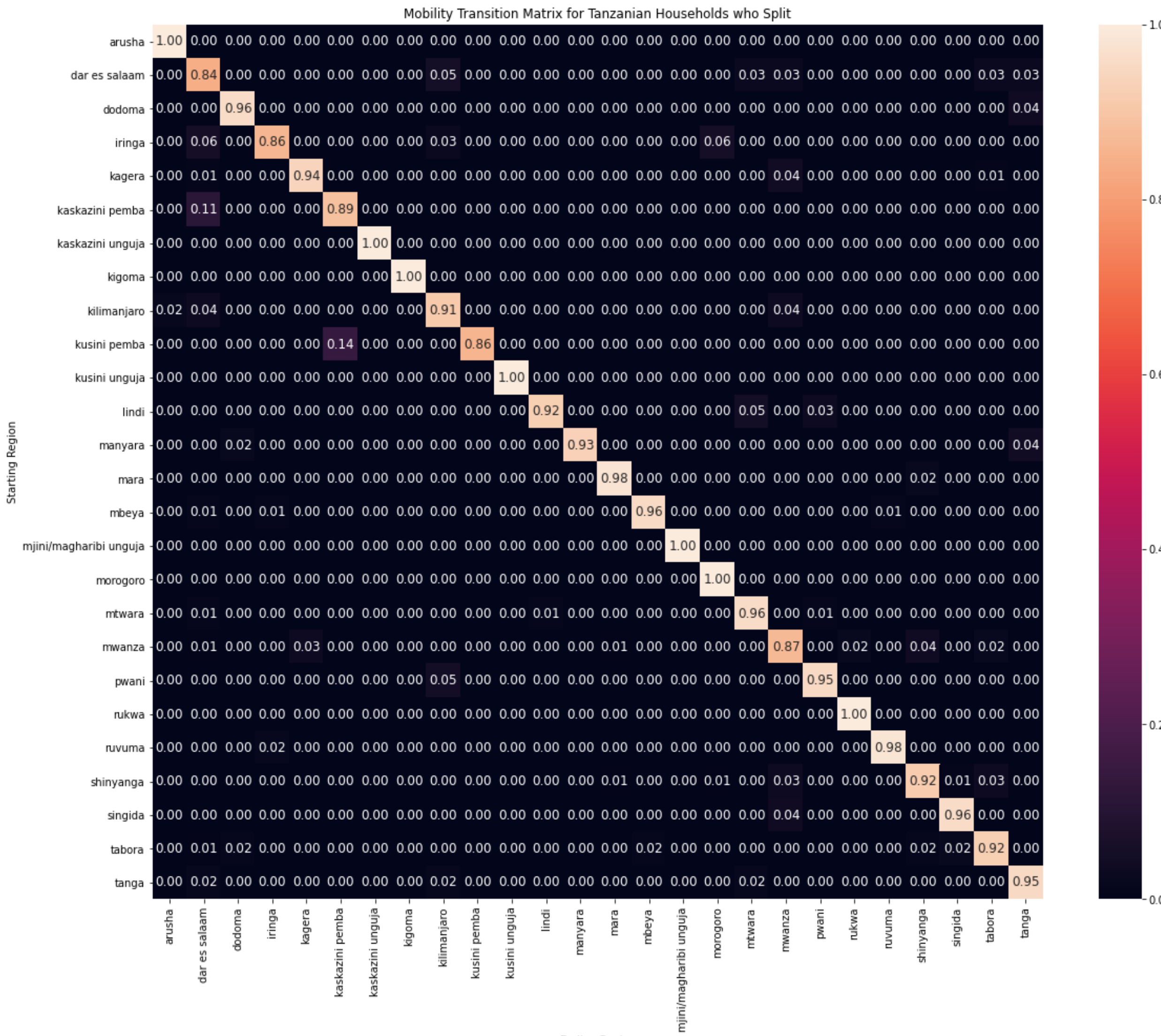

Figure 10: The above matrix shows the proportion of split households that moved to a certain region in a subsequent period.