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# Ex-post Livestock Diseases, and Pastoralists' Averting Decisions in Tanzania

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# Ex-post Livestock Diseases, and Pastoralists' Averting Decisions in Tanzania\*

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## Abstract

Little is known about the factors affecting pastoralists' livestock vaccination decisions. In this paper, we use a novel survey-based dataset on pastoralists living in the Ruaha landscape in Tanzania, and employ several econometric approaches to identify the factors affecting pastoralists' decision-making process about vaccination when disease occurrence and severity, vaccination and healthcare access costs and other related variables are known. Results from binary choice models that account for excess zeros indicate that socially and economically active households are more likely to vaccinate their livestock. The results also identify positive marginal effects of having wage earners and illness incidence on vaccination decisions. The results from mixture models also find that these same variables significantly lower the pastoralist's probability to vaccinate no livestock. Most notably, vaccination cost significantly lowers the probability that pastoralists vaccinate any livestock, as well as the number of vaccinated livestock. These findings have important policy implications considering livestock health education, veterinary service infrastructure, and supply-side management.

**JEL codes:** D13, D83, Q12, Q13, R28.

**Keywords:** Africa, averting action, averting expenditure, hurdle model, zero inflated model, vaccination decision.

## 1 Introduction

Livestock production plays a crucial role in meeting global nutritional needs, accounts for approximately 40 percent of agricultural GDP, and provides pathways out of poverty for more than one billion people whose livelihoods depend directly or indirectly on it (McPeak et al., 2011; World Bank, 2011). Livestock disease is a persistent problem in many developing countries, and Tanzania is not an exception (Perry and Sones, 2009), with approximately 60 percent of family-owned livestock suffering from some type of preventable disease like bovine and caprine pleuropneumonia, brucellosis, and foot and mouth disease (Kivaria, 2003; Covarrubias et al., 2012; Clifford et al., 2008). These

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disease affects pastoralist households through multiple pathways: it contributes to food and nutritional insecurity, loss of wealth and income, and can lead to an increased disease burden for humans. Pastoralist households, which rely heavily on livestock as a source of nutrition, store of wealth, and for cultural status (Hesse and MacGregor, 2006; Coppolillo et al., 2009; Lybbert et al., 2004), are particularly affected by livestock disease losses.

The likelihood and severity of livestock diseases are important threats to livelihoods and the burden of losses is high, especially for households in less developed rural settings where veterinary services are limited (Allport et al., 2005). Preventive measures like vaccination, commonly referred to as averting actions or decisions, can lower the expected loss to disease (McInerney, 1996). Pastoralists' averting decisions are based on risk preferences, but are likely also shaped by previous experience with disease infection and loss. Their decision mechanism is a complex issue, and depends on various socio-economic and household behavioral factors. The literature on livestock keepers' vaccination averting decisions is limited, especially for pastoralist households. In the context of high exposure to livestock diseases (World Bank, 2011), we empirically analyze household survey data to identify the factors that likely affect their averting actions to decrease the likelihood of future disease losses.

This paper extends the literature on households' averting decisions, incorporating information on households' livestock disease experience, through two related aspects. First, we use household survey data to examine the impacts of potential socio-economic and behavioral factors of pastoralists' averting decisions for livestock diseases, i.e., vaccination. In particular, we empirically test two major hypotheses. We test the hypothesis that the vaccination decision and number of vaccinated livestock is positively influenced by prior disease experience, i.e., illness incidence and livestock death in the past twelve months. Another hypothesis relates to vaccination cost. We hypothesize that higher vaccination cost negatively influences the vaccination decision. Second, based on pre-survey qualitative observations and empirical findings, we conclude the paper with a few policy suggestions on ways to address barriers to vaccination.

Following traditional averting behavior frameworks such as Bontemps and Nauges (2016), we assume that a pastoralist will choose to vaccinate their livestock if the expected utility when vaccinating livestock is higher than the expected utility from not vaccinating. As this decision to vaccinate or not is a latent representation of the relative difference in utility, we use their binary vaccination decision to capture differences in relative expected utility. The decision depends on a variety of economic, community, and behavioral variables. Therefore, in explaining the pastoralists' averting behavior for livestock diseases, we need to consider the role of disease experience and socio-economic factors together with related social beliefs. We assume that the binary vaccination decision and resulting number of vaccinated livestock are associated with previous disease infection and loss, with the costs of vaccination and travel to access vaccination services, the household head's age and education level, and family and herd size, among others. Additionally, we include a dummy for socially and economically active households as a control variable for households with at least one cell phone, a wage earner, and a primary school-educated household head. Another categorical control variable representing diversified sources of income is also included to identify the effect of wage income on vaccination decisions. The empirical basis of the study is a household survey conducted in 2012 in Pawaga and Idodi divisions near Ruaha National Park and community wildlife management areas in Iringa region, Tanzania. We collected household-level data on livestock disease and vaccination and related household and community characteristics using a structured questionnaire to analyze factors influencing households' averting decisions through descriptive and econometric analyses.

We consider an averting decision model where pastoralists' have a binary choice variable that includes the decision to vaccinate or not vaccinate. Maximum likelihood approaches, such as logit and probit estimators, are frequently used as the estimation strategy to examine binary averting decisions. In logistic regression, maximum likelihood estimates can be biased when events are rare. As our binary

decision variable consists of few positive actions, we consider three variants of the logistic model that account for rare events in the outcome variable. First, we consider an exact logistic regression model that is appropriate for small samples with dichotomous covariates, but excluded from final analysis as our sample size is considerably high for this estimation. Second, the [King and Zeng \(2001\)](#) bias correction method of logistic estimation is employed. Finally, we use the penalized maximum likelihood estimation procedure proposed by [Firth \(1993\)](#). While another class of estimators, known as zero-truncated procedures, exists that produces more robust estimates, we cannot implement this procedure as it is only suitable for large datasets ( $n \geq 2000$ ) with zero-truncated data.

We extend the analysis to estimate a count data model where the number of vaccinated livestock is considered as the outcome variable. Given that most households did not administer any vaccinations, we find them with zero vaccinated livestock. This is due to the presence of both true and excess zeros. There is also a considerable gap between observed zeros (89.29%) and predicted zeros (30% using a Poisson analysis). Moreover, the distribution of non-zero counts (10.71%) shows dispersion with a possibility of over dispersion. In this case, both hurdle and zero-inflated models (with or without over dispersion) can explain the high occurrence of zeros in the outcome variable. The hurdle model assumes a two-step decision-making process and expects a positive number of vaccinated livestock if and only if the household decides to vaccinate. The reason behind this zero in the count outcome variable is structural and depends on the binary first-step vaccination decision. On the other hand, zero-inflated or zero-altered models assume that some pastoralists either do not know about vaccination or do not have the financial ability to vaccinate, which inflates the number of ‘excess’ zeros. Households that have vaccination knowledge and financial ability to vaccinate generate non-zero count values. Their counterparts are unable to vaccinate due to financial constraints and generate zero count values even though they may want to vaccinate their livestock. The latter leads to ‘true’ zeros. Therefore, we need to consider a few variants of the hurdle and zero-inflated models—for example negative binomial and Poisson—to explain true zeros and excess zeros with or without over dispersed count data simultaneously. We find that negative binomial-logit hurdle (NBLH) and zero-inflated negative binomial (ZINB) models are the most robust techniques to analyze the number of vaccinated livestock based on the [Vuong \(1989\)](#) test, [Greene \(2012\)](#) likelihood ratio test, and various information criteria.

Descriptive analyses provide a summary overview of the livestock vaccination status of three ethnic groups who faced disease infection and consequent death loss in the twelve months prior to the survey (see table 2 for details). Even though 49.74 percent of pastoralist households have experienced livestock deaths, only 10.71 percent vaccinated their livestock in the study areas. A higher percentage of the households experiencing livestock disease—compared to households not experiencing disease—vaccinated their livestock, which is uniform across the ethnic groups. A Pearson chi-square test confirms that the difference is not significant among the ethnic groups.

We further compare and contrast the findings revealed from the maximum likelihood, hurdle and zero-inflated estimations. Results from zero-inflated models, which explain excess zeros based on household types, indicate that pastoralist households that are socially and economically active, have at least one wage earner, and that are far from the nearest livestock extension officer are less likely than their counterparts to be in the excess zeros group. Additionally, households that experienced livestock illness are less likely to be in the excess zero group. Households facing higher vaccination costs, on the other hand, are more likely to be in the excess zero group. Both maximum likelihood and hurdle models estimate the binary choice of vaccination decision. Results indicate that households who are more socially and economically active and have wage earners are more likely decide to vaccinate their livestock. Pastoralists are more likely decide to vaccinate their livestock if the vaccination cost is low. We also find that higher per capita livestock negatively influences the vaccination decision, suggesting that the more livestock a household owns, the lower the probability that the household vaccinates their livestock. It seems a little bit surprising but not without plausible explanations. Given

that pastoralists hold most of their wealth in their livestock, this finding may result from diminishing marginal utility of wealth or changing risk preferences. Pastoralists with more livestock have more options and can either sell or eat the animals at home to cope with the disease occurrence without significantly affecting the sustainability of their herd. The number of ill livestock in the past 12 months, wage earnings and vaccination cost also influence the number of vaccinated livestock positively. A household head older than 30 years of age vaccinated more livestock than their younger counterparts. Additionally, socially and economically active households have more vaccinated livestock than those who are not. Households who experience more livestock deaths due to illness vaccinate fewer livestock. In most cases, we find similar results for separate data specifications in terms of ethnic groups, except Barabaig. Results from the hurdle and zero-inflated models using the pooled data reveal the similar pattern and magnitude.

The rest of the paper is as follows: Section 2 explains the conceptual framework of pastoralists’ averting decision, and resulting output in view of livestock diseases experienced in the past twelve months. Section 3 explains the sampling and survey design for data collection and the econometric estimation strategies. Section 4 discusses the empirical results and discussions with robustness checks. In the last section of the paper, we conclude with a few policy suggestions based on the major findings.

## 2 A Simple Framework of Pastoralists’ Livestock Vaccination

In the study area, most of the pastoralists have experienced disease-related livestock losses due to different types of diseases, including bovine and caprine pleuropneumonia, brucellosis, and foot and mouth disease in the past twelve months. Livestock are an important source of food, wealth, and social status (Lybbert et al. 2004). Ouma et al. (2006) and Mdoe and Mnenwa (2007) also indicate that larger livestock herds bestow prestige upon households in Tanzania. Given the substantial benefits that households derive from livestock, livestock health is important for household wellbeing. In this view, vaccination is one way for pastoralists to safeguard their herd so that they can maintain their food supply (e.g., meat, milk), wealth, and social prestige. One option for livestock disease control involves vaccination to reduce the probability of infection and loss. We further assume that the pastoralists’ decision rule is based on maximizing their expected utility by minimizing the expected loss through vaccination due to infection (Wolf, 2013).

Maximization of expected utility compares two decisions: vaccinate,  $v$ , and not vaccinate,  $nv$ . Consider a pastoralist who chooses to vaccinate if her expected utility of vaccinating,  $EU_v$ , is higher than the expected utility of not vaccinating, ( $EU_{nv}$ ):  $EU^* = EU_v - EU_{nv} > 0$ , where the utility difference,  $EU^*$ , is a latent variable. As all attributes that affect preferences cannot be observed, we consider an observable component of utility,  $Z_i$  where  $EU_i^* = Z_i + e_i$ . Assume  $Z_i$  is linear in the parameters,  $X_i\beta$ . Thus  $EU_v = Z_v + e_v = X_v\beta + e_v$  and  $EU_{nv} = Z_{nv} + e_{nv} = X_{nv}\beta + e_{nv}$ , where  $X_i$  is the observable component that affects the pastoralists’ averting (vaccination) decision,  $D_v$ . Rewriting the previous expected utility function as  $EU^* = EU_v - EU_{nv} = X' \beta_v - \beta_{nv} + (e_v - e_{nv})$ , where  $EU^*$  is not observed, but we can observe the averting decision. In this case, McFadden (1973) suggested the random utility function for separable decision analysis, which models a binary choice variable, where  $D_v = 1$  if the pastoralists’ vaccinate their livestock, or  $D_v = 0$  if not. This specification can be estimated through the following form:

$$(1) \quad D_v = X'\beta + e$$

As the pastoralists’ vaccination decision is a sequential, two-stage process, after deciding to vaccinate or not to vaccinate, they decide how many livestock to vaccinate,  $V_{ls}$ . Based on equation (1) we can write the following:

$$(2) \quad V_{ls} = \begin{cases} \geq 0 & \text{if } D_v = \text{Yes (decide to vaccinate by 'not always zero' group of pastoralist)} \\ = 0 & \text{if } D_v = \text{No (decide not to vaccinate by 'always zero' group of pastoralist)} \end{cases}$$

Pastoralists who are not concerned about vaccination decide not to vaccinate, with a number of vaccinated livestock always equal to zero. This type of pastoralist generates ‘excess’ zeros. Other households desire to have positive numbers of vaccinated livestock, but some may have zero due to several potential constraints, such as a lack of financial ability to pay for vaccination; these observations are known as ‘true’ zeros. In this respect, modeling true and excess zeros is essential to explain all potential situations.

### 3 Data and Methodology

#### 3.1 Sampling and Survey Design

The empirical basis of this paper is a pastoralist household survey conducted in 2012 in Pawaga and Idodi divisions near Ruaha National Park and community wildlife management areas of Iringa region (figure 2), Tanzania as part of a larger, long-term study on pastoralist households (Gustafson et al., 2015). As the Iringa Rural district has a large population of pastoralists (NBS, 2013) who face a considerable disease threat, we selected this area for a field survey to find out the possible influencing factors associated with livestock diseases and vaccination decision. A two-stage stratified random sampling was employed to select the pastoralist households from Pawaga and Idodi divisions. The sampling framework includes ‘village’ as a primary sampling unit, and ‘household’ as the ultimate sampling unit. We randomly selected 196 households from 21 villages to collect necessary information.

A structured questionnaire was employed to collect pastoralists’ household information. We collected data on herd size, livestock vaccination status, household-level morbidity and mortality data collected by disease signs, and variables that influence the vaccination decision, e.g., vaccination cost, distance to livestock extension officer, non-livestock sources of income, etc. In addition, information related to household size and residents, geographical, and community characteristics were collected to assess the vaccination status of the study area. We grouped all the households into three different strata based on ethnicity as a post-stratification procedure to capture any potential differences among the ethnicities.

#### 3.2 Estimation Strategy

We use a two-stage estimation strategy to examine the factors affecting households’ decision-making processes and outcomes. We analyze the effects of socio-economic, behavioral, demographic and group variables on pastoralists’ binary averting decision, and the number of livestock vaccinated. Finally, we employ various robustness checks to examine the consistency of the estimated results.

According to equation (2), the decision variable is a binary output where  $D = 1$  if the  $i^{th}$  household vaccinates their livestock, and  $D = 0$  if they do not. This binary decision outcome can be modeled using various econometric estimations. Variants of maximum likelihood estimators (MLEs), such as the probit, are frequently used technique to model binary dependent variables. In addition, logistic regression, another variant of MLE is consistent, but only unbiased for large sample sizes; that is, estimates can be biased when sample size is small. Pre-estimation descriptive statistics on survey data reveals that 21 out of 196 (10.71% of total) respondents reported vaccinating livestock. As our binary decision variable consists of very few positive responses, we consider three different logistic approaches that account for rare events in the dependent variable. First, we consider an exact logistic regression model that is appropriate when the dependent variable is binary and sample size is small. As our sample size is around 200, and the number of degrees of freedom of the regression model is

high, we don't report these results. Second, we employ King and Zeng's (2001) bias correction method for logistic estimation, which incorporates the probability of rare events. Finally, we use the penalized maximum likelihood procedure proposed by Firth (1993) to reduce small-sample bias in maximum likelihood estimation. Firth's method is an alternative to the exact logistic regression method when there are rare events (Heinze and Schemper, 2002). We also estimate the marginal effects of the covariate, which is the expected instantaneous rate of change in the outcome variable as a function of a marginal change in that covariate, holding all other covariates in the model constant. Then, we compare the marginal effects and related model fit statistics (see table 4) of four MLEs of pastoralists' averting decision. We do not consider any variants of zero-truncated techniques because they predict zero counts even though there are no zeros in the outcome variable. Most notably, this estimation procedure is only recommended for large datasets.

The second part of the econometric estimation examines the impacts of the same set of regressors on the number of vaccinated livestock as the second sequence of pastoralist's averting (vaccination) decision making. For this purpose, we consider the proportion of zeros in the outcome variable and the distribution of nonzero counts. Since the outcome variable has many zero observations, it may be that 'true' zeros—pastoralists' choices not to vaccinate made after weighing the costs and benefits of vaccinating—are conflated with 'excess' zeros, which reflect households that would never consider vaccinating. Preliminary descriptive statistics find a considerable over-dispersion in the outcome variable where the variance of the number of vaccinated livestock is quite high relative to its mean. Following Cameron and Trivedi (2009), we also test the null hypothesis of equidispersion through auxiliary regression, and find some evidence of overdispersion, though it is not statistically significant. There is also a considerable gap between observed zeros (89.29%) and predicted zeros that is 30% through Poisson analysis. In this case, both Hurdle and zero-inflated models considering with or without overdispersion are suitable to explain the high occurrence of zero in the observed outcome variable.

The reason behind excessive 'zero' observations in count data models is generally explained by two separate views. If we consider the averting decision-making process as a two-step, sequential process, the 'hurdle' model can better explain the decision tree and the outcome data. The hurdle model is "a modified count model in which the two processes generating the zeros and the positives (count data) are not constrained to be the same" (Cameron and Trivedi, 1998, pp. 137). The hurdle model assumes that all zero observations are from one structural source. In this case, we assume that only concerned pastoralists (due to disease information) vaccinate livestock, and their counterparts do not consider vaccinating their livestock. Hence, the zero observations arise only from the unconcerned pastoralist. Symbolically,

$$(3) \quad E ls_i = x_i = \underbrace{Pr \text{ not vaccinate} * 0}_{\text{generates zero observation}} + \underbrace{Pr \text{ vaccinate} * 1}_{\text{generates count observation}}$$

Letting  $ls$  be the number of vaccinated livestock by the  $i^{th}$  household where  $Pr \text{ not vaccinate}$  presents the probability that  $i^{th}$  household will exist in the zero-vaccination state, and  $Pr \text{ vaccinate}$  turns into the probability for nonzero (count)-vaccination state. Assume that  $Pr ls_i = x_i = 0 = \varphi$  and  $Pr ls_i = x_i \geq 1 = \frac{1-\varphi}{1-e^{-\lambda}} \left( \frac{\lambda^{x_i} e^{-\lambda}}{x_i!} \right)$ , where  $\lambda$  is a truncated Poisson distribution. On the other hand, standard zero-inflated count data models assume that the zero observations are generated from both structural and sampling sources. In this context, separate examinations for true zeros and excess zeros are essential for predicting count observations, and to predict membership in the excess zero group.

Zero-inflated models are generally a finite mixture model, first part predicts the excess zeros in 'always zero' pastoralist group, and second part of which predicts the number of vaccinated livestock



in ‘not always zero’ pastoralist group. Across the study area in Tanzania, we find most of the households have zero vaccinated livestock, which is due to the presence of both true (generated by ‘not always zero’ group of pastoralist) and excess zeros (generated by ‘always zero’ group of pastoralist).

$$(4) \quad E ls_i = x_i = \underbrace{Pr \text{ not vaccinate} * 0}_{\text{generates certain zero}} + \underbrace{Pr \text{ vaccinate} * E(ls = x | \text{vaccinate})}_{\text{generates count observation with excess zero}}$$

The plausible reasons for having true zeros due to deciding not to vaccinate, are basically two-fold: i) either they prefer alternative uses of the infected livestock, e.g., eating the meat in the household, or selling the livestock to others; or ii) any other financial and geographical constraints, e.g., distance to vaccination services, low availability. In some cases, both reasons may contribute. Therefore, we consider variants of the negative binomial model, which includes Poisson, zero-inflated Poisson and zero-inflated negative binomial to correct for the excess zeros and over-dispersion problem simultaneously (Lambert, 1992).

Though the response variable (figure 1) shows a Poisson distribution with inflated zeros, we cannot consider the basic Poisson regression model as this model assumes equality between mean and variance. As the data contain significant numbers of households choosing not to vaccinate, comprising both true and excess zeros, some variant of the zero-inflated model, such as zero-inflated negative binomial (ZINB) or zero-inflated Poisson (ZIP) estimation, are typically employed to correct the excess zeros and over-dispersion problem. All zero-inflated models consider two possible data generating processes. First process with probability  $\varphi_i$  generates only zero counts, whereas second process with probability  $1 - \varphi_i$  generates positive counts from either a Poisson or negative binomial model.

Specifically,  $ls_i \sim \begin{cases} 0 \text{ with probability } \varphi_i \\ g \text{ } ls_i | x_i \text{ with probability } 1 - \varphi_i \end{cases}$  where the probability of  $g \text{ } ls_i | x_i$  is the following:

$$(5) \quad Pr LS_i = ls_i | X_i, Z_i = \begin{cases} \varphi \gamma' Z_i + \{1 - \varphi \gamma' Z_i\} g \ 0 | x_i & \text{if } ls_i = 0 \\ \{1 - \varphi \gamma' Z_i\} g \ ls_i | x_i & \text{if } ls_i > 1 \end{cases}$$

Here  $\gamma$  is the vector of zero-inflated coefficients to be estimated, and  $Z_i'$  is the vector of zero-inflated covariates. Theoretically, the negative binomial (NB) incorporates the general Poisson model, whereas the ZINB model incorporates the ZIP model. The ZINB (ZIP) model consists of two separate models, a negative binomial (Poisson) model to predict the count data and the logit or probit model to predict the excess zeros. Then it combines both models by adjusting the probabilities of count information in the Poisson regression for observations that are true zeros. For our purpose, a logit model is employed to predict pastoralists’ vaccinated livestock data for true zeros. After that, a negative binomial (Poisson) model is generated to predict excess zeros.

Considering the descriptive features of the dataset, we estimate two different models and use post-estimation tests to determine which fits the data better. Significant z-test statistics from the Vuong (1989) test reveals that either ZINB or ZIP model would be preferred to the standard negative binomial model. However, a significant likelihood ratio test between ZINB versus ZIP models proposed by Greene (2012) reveals that data are over-dispersed, and that the ZIP model is more appropriate than the ZINB model. Finally, we compare all four estimated models, following Long and Freese (2014), based on AIC, BIC, and Vuong test statistics to find the preferred model(s).

We consider that the vaccination decision and resulting number of vaccinated livestock is associated with socioeconomic variables. According to Rault and Krebs (2014), a household’s vaccination decision depends on prior experiences with relevant outcomes, such as disease occurrence and the degree of severity. The expected cost of disease avoidance and preventive expenditure are other influencing factors in this analysis (Chilonda and Van Huylenbroeck, 2001). Moreover, the

decision is likely influenced by households' geographical locations. Under this framework, equation (2) can be modeled through the following vaccination equation that describes the number of vaccinated livestock equation (3), which is influenced by associated factors included in right-hand side:

$$(6) \quad D_v, V_{ls} = f(Z_{ed}, Z_{cc}, Z_{hc}; \beta, \varepsilon),$$

where  $Z_{ed}$  is the vector of disease information consisting of livestock illness and death in the past twelve months;  $Z_{cc}$  is the vector of livestock vaccination and travel costs to access veterinary services;  $Z_{hc}$  represents the vector of pastoral household's characteristics. The estimated parameters are captured by  $\beta$ , the vector of coefficients for exogenous variable  $x$ , whereas the error term,  $\varepsilon$  presents the combined effect of the omitted variables of the estimation model (Freedman, 2005). We also include a dummy variable as 'socially and economically active household' ( $S\&E\_d$ ) that has been constructed from three other variables—household head at least with primary education, household with at least one wage earner, and household with at least one cellphone. Equation (6) is the basis of our empirical estimation. Econometric estimation strategies, presented in section 4, are employed to reveal the vaccination equation to test and predict how socio-economic and behavioral factors affect pastoralists' vaccination decisions.

## 4 Empirical Results and Discussions

In this section, we present the variables included in the maximum likelihood and mixture models (see table 1), and descriptive statistics of vaccination status in terms of livestock's illness and death. We also present and explain the econometric estimations of the vaccination decision model and number of vaccinated livestock model with related discussions followed by robustness checks.

### 4.1 Descriptive Statistics

Descriptive statistics presented in table 2 provide a summary overview of the livestock vaccination status of three ethnic groups who faced disease infection and deaths in the past twelve months. Even though 49.74% of households have experienced livestock deaths, only 10.71% vaccinated their livestock in the study areas. A higher percentage of the households experiencing livestock disease—compared to households not experiencing disease—vaccinated their livestock, which is uniform across the ethnic groups. The percentage of vaccination is lower, around 11% of studied household, who experienced more livestock deaths than their counterparts. We also find that a higher percentage of pastoralists did not vaccinate their livestock who experienced livestock deaths. The difference is small, but a slightly higher percentage of pastoralists who experienced livestock illness vaccinated their livestock than those who experienced livestock deaths. However, a Pearson chi-square test shows that the difference is not significant among the ethnic groups. The ratio of vaccinating and not-vaccinating households shows the same for the pastoralist who experienced both livestock illness and death simultaneously.

### 4.2 Econometric Results

We report the results from both maximum likelihood estimations for pastoralists' averting decision and mixture models for the number of vaccinated livestock. All full reported models presented in this section include a wage earner dummy, and a socially and economically active household dummy to account for the extra monetary income and social heterogeneity in terms of livestock assets.

First, we report the results of maximum likelihood estimations to check the factors affecting vaccination decision in table 3. Furthermore, we compute essential model fit indicators to compare the relative quality of all estimated models and to reveal a parsimonious and robust model following Long and Freese's (2014) procedure. We find that the results from a penalized logit and bias corrected logit

are more appropriate from theoretical and econometric backgrounds, although we also report standard logit and probit estimations for comparison. As the coefficients of maximum likelihood estimations are not easily explainable, we calculate the marginal effects to measure the instantaneous rate of change of continuous variables and discrete change of dummy variables, respectively. Moreover, we also compare the results of hurdle mixture models that predict the vaccination decision. In every case, the magnitude and level of significance are found to be quite similar.

Table 3 and part 2 of table 4 show that the marginal effect of illness incidence on vaccination decision is positive and significant at the 1% level. We also find a statistically significant difference in the means of the number of illness incidents between vaccinating (21.112) and not-vaccinating (9.382) groups of pastoralist. This result supports our initial conjecture and hypothesis that states that experienced livestock illness events influence pastoralists to decide to vaccinate their livestock. Additionally, we find the impact of the number of dead livestock is not statistically significant in our specified model, and the mean difference, reported in table 1, is also insignificant for both vaccinated (15.085) and not-vaccinated (10.113) groups of pastoralist. Therefore, we do not find support for the hypothesis that livestock deaths increase the number of livestock vaccinated.

It is sometimes argued that monetary income such as wage earnings from family members positively affects the probability that households take measures to avoid risky events. In this study, we find that having at least one wage earner has a positive and significant impact on the vaccination decision. Moreover, pastoral households who are socially and economically active are more likely to vaccinate their livestock, which is significant at the 10% level. Across the study area, pastoralists who are educated, financially able and may have better access to information are more likely vaccinate their livestock.

On the other hand, we also observe that higher per capita livestock has negative and significant impacts on vaccination decision at 1% level. The result simply conveys that pastoralist households owning a higher number of livestock per family member are less likely vaccinate their livestock. Though it seems counterintuitive, there are a few potential explanations. Pastoralists with higher livestock per capita have more options to either sell sick livestock in nearby markets or eat at home to minimize disease risk and consequent deaths. Given that livestock represent a store of wealth, it may represent a decreasing marginal utility of wealth. Risk attitudes may also change with wealth level (cite). Vaccination cost also has a negative impact on averting decisions. When the price of a vaccine is higher, households are less likely to vaccinate. We also compute related model fit indicators for all four estimations. Finally, the predicted probabilities do not change much across the models.

Table 4 presents the marginal effects of the mixture models in two separate but consecutive parts. First we consider the estimations of predicting the vaccination decision for hurdle models, and excess zero group of the zero inflated models. Then we consider the results of the model of the number of vaccinated livestock. Results reported in part 2 of zero-inflated models determine whether the observed count is zero. It indicates that socially and economically active pastoralists are less likely to be in the always zero group. Additionally, pastoralists who experienced higher incidences of livestock illness and resided comparatively far from the livestock extension offices are less likely than their counterparts to be in always zero group. Conversely, the higher the vaccination cost, the more likely the household is in excess zero group.

Considering zero inflated models, we know that pastoralists who are not in the excess zero group, have decided to vaccinate have at least few vaccinated livestock. So, we compare the findings revealed from the two variants of hurdle and zero-inflated models that predicts the number of vaccinated livestock (see part 1 of table 4). The number of vaccinated livestock is influenced positively by the number of livestock illnesses experienced by the household in the past twelve months. This may be because pastoralists feel more risk of losing their livestock asset when they face frequent incidences of illness. Moreover, the predicted probability of vaccinated livestock is higher for the pastoralist who

has at least one wage earner. Monetary income, especially from wage earners, increases the financial ability to vaccinate more livestock to cope with future disease risks. We further find that higher expected vaccination costs increase the number of vaccinated livestock.

We also find that a few variables in the model have significantly negative impacts on the predicted number of vaccinated livestock. Both Poisson and negative binomial variants of hurdle and zero-inflated model reveal similar predictions. As per part 1 of table 4, household head older than 30 years have less vaccinated livestock than their counterparts. The estimated coefficient of the dummy variable for socially and economically active households is negative and significant at the 10% level. More active households would have fewer vaccinated livestock compared to those who are not active. The most justified explanation of this finding-they know alternative options to cope or minimize the diseases incidences and severity. Moreover, households that experienced more livestock death have a significantly lower number of vaccinated livestock. In addition, we only find significant marginal effects in case of Poisson estimations for per capita livestock and travel cost dummy. However, negative binomial estimations predict statistically insignificant marginal effects that indicate a lower level of robustness to generalize the impacts of the variables in determining the number of vaccinated livestock.

### 4.3 Robustness Check

In both discrete choice and count data models, estimations related to livestock deaths are not significant, and vaccination cost contradicts the predictions of conventional theories. Moreover, few marginal effects of both components of mixture models show same direction which is opposite in general. All these queries require further investigation through several robustness checks.

As a part of post-estimation robustness checks, we estimate both models under different specification that includes the set of covariates regarding households' prior disease experience, vaccination and travel cost, and household characteristics successively to check the consistency. Following Barslund (2007), we consider disease information as a set of core variables, and others as the set of non-core covariates. In every step, we find consistent results with a few exceptions. Further, we also estimated other variants of the hurdle model, reported in table 4, including Poisson-bias corrected logit, Poisson-penalized logit, negative binomial-bias corrected logit, and the negative binomial-penalized logit due to the presence of excessive zeros. We also calculate the predicted probabilities of all estimated models that do not meaningfully change. Moreover, we run regressions on data that pool data for the three ethnic groups together. In most cases, we find similar results in terms of relationship, magnitude and significance level for every alternative data specifications, except Barabaig. We, then, perform Hausman (1978) specification test by controlling *ex-post* disease information, cost lines, and household's characteristics to check the consistency and conditional heterogeneity. We additionally compute all models with robust standard errors to reduce any heteroskedasticity incidence following Cameron and Trivedi (2009). These estimations confirm the robustness of main results in table 2, 3 and 4. The detail results are not reported in the main text, but codes are available in respective Stata do-file.

## 5 Conclusions and Policy Implications

Vaccination, a key tool for livestock disease risk management (Keeling et al., 2003), though little is known about what factors drive pastoralists' vaccination choices. This study contributes to the existing literature in several ways. We used primary data generated from surveys with pastoralists in the Iringa region of Tanzania, and analyzed household-level as well as community-level information to address two of our general research questions on the factors influencing the vaccination decision. We employed multiple empirical procedures to explore the robustness of pastoralists' vaccination decisions and number of vaccinated livestock given diseases experienced in the last twelve months and other economic, social and behavioral variables.

We find that pastoralists are more likely to decide to vaccinate their livestock who are socially and economically active and has at least one wage earner. Moreover, the occurrence of livestock illness also has a significant positive impact on averting decision. We also find consistent results from a few variants of mixture models, for example hurdle and zero-inflated models where the same set of variables predicts that pastoralists are less likely to be in the excess zero class. We further find that a high prevalence of livestock illness, higher vaccination cost, and wage earners in the household are positively related to the number of vaccinated livestock. On the contrary, higher numbers of dead livestock, high travel cost in terms of distance from extension offices, and households with older heads of household have significantly lower number of vaccinated livestock.

Finally, we propose a few lessons relevant to policy based on our findings. First, lowering the cost of vaccination would surely increase the number of households vaccinating their livestock. A vaccination support program would be helpful for low-income pastoralists. Second, government and NGOs can invest in frequent and extensive livestock health education and management, training, and infrastructure, which would be beneficial for both pastoralist households and extension officers (Allport et al., 2005; Perry et al., 2013). Though pastoralists have traditional knowledge, training on emerging diseases and treatments should positively influence vaccination uptake. Third, infrastructure development for vaccination support programs and convenient delivery systems are essential to help low-income pastoralists (Mazet et al., 2009). Currently there are no commercial veterinarians or dispensaries operating in many rural parts of Tanzania, even though the Tanzanian government intended to phase out government veterinary services (except in the case of public goods) in favor of private practices over a decade ago (Gustafson et al., 2015). Fourth, convenient access to information (e.g., veterinary services, market price) through mobile phones would increase the awareness of disease, treatment options, and vaccination decisions. In this respect, Wolf (2005) suggests the same.

Our study considers static-type models based on cross-sectional data. We are therefore unable to provide dynamic explanations of the decision-making process of pastoralists on livestock assets and disease risk management, where an appropriate panel study can reveal time-dependent changes. Moreover, this study does not capture spatial elements that may be relevant. Future research can address these shortcomings.

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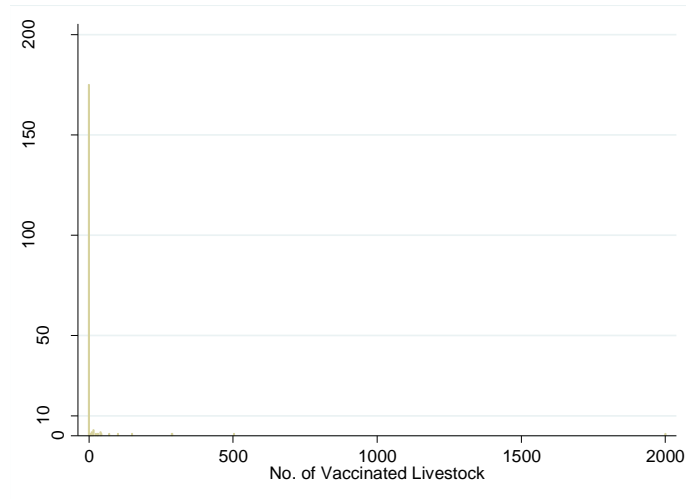
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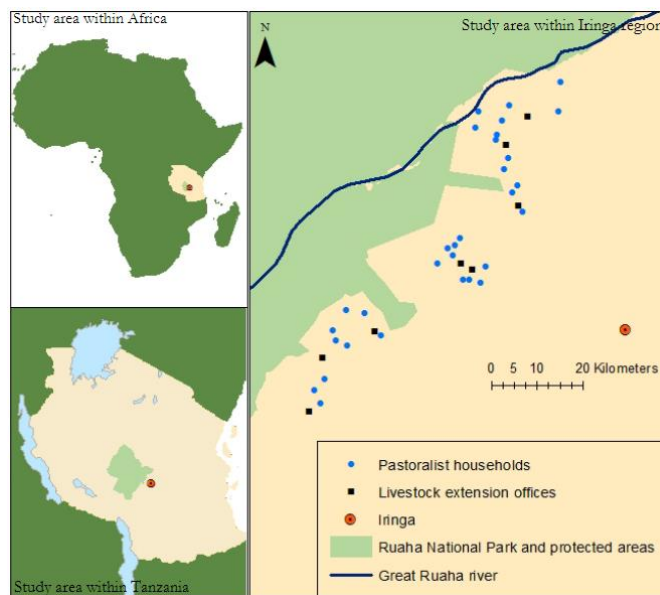
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**Figure 1.** Distribution of Vaccinated Livestock



**Figure 2.** Map of the Study Area

**Table 1.** Description of Model Variables

Variable	Description	Livestock vaccination status		
		Vaccinated $\bar{X}(sd)$	Not vaccinated $\bar{X}(sd)$	Pooled $\bar{X}(sd)$
Dependent variable				
<i>vac_ls_d</i>	Indicator variable of livestock vaccination status (1 if vaccinated, 0 if not)	-	-	0.107(0.310)
<i>vac_ls</i>	Number of vaccinated livestock (in TLU) in the past 12 months	162.933***(437.377)	0.000(0.000)	17.457(148.906)
Ex-post diseases information				
<i>ill_ls</i>	Number of livestock's ill incidence in the past 12 months	21.111***(44.488)	9.382(9.208)	10.639(17.084)
<i>dead_ls</i>	Number of died livestock (in TLU) in the past 12 months	15.085(29.669)	10.113(14.440)	10.645(16.695)
<i>pcls</i>	Per capita livestock (in TLU)	14.284***(47.906)	4.251(5.087)	5.326(16.376)
Costs of vaccination				
<i>vac_cost</i>	Expected vaccination cost (in TZS) for infected livestock	3.97e+7(2.02e+7)	1.61e+7(1.2e+6)	1.86e+7(3.46e+7)
<i>travel_cost_d</i>	Indicator variable of travel cost of vaccination (1 if distance is medium to high, 0 if none to low)	3.333*(0.967)	2.823(1.138)	2.878(1.130)
Household characteristics				
<i>age_group_d</i>	Indicator variable of household (HH) head's age (1 if HH head's age more than 30 years, 0 if unknown and less than 30)	0.810(0.402)	0.777(0.417)	0.781(0.415)
<i>wage_d</i>	Indicator variable of household's wage earners (1 if HH has at least one wage earner, 0 if not)	0.190**(0.402)	0.051(0.222)	0.066(0.249)
<i>S&amp;E_d</i>	Indicator variable of socially and economically active household (1 if primary educated HH head with at least one cellphone has extra earnings from different sources like wage labor, remittance, selling cultural goods, 0 otherwise)	0.190**(0.402)	0.057(0.233)	0.071(0.258)

Notes: \*\*\*, \*\* and \* represents the level of significant at 1%, 5% and 10% of the t-test for equality of means of the vaccinated and non-vaccinated pastoralist household.



**Table 2.** Ex-post Livestock Diseases and Vaccination Status

Ethnic group	Livestock's illness incidence				Pearson $\chi^2$ (p-value)	Livestock's death				Pearson $\chi^2$ (p-value)
	Experienced		Not experienced			Experienced		Not experienced		
	Vaccinate	Not vaccinated	Vaccinate	Not vaccinated		Vaccinate	Not vaccinated	Vaccinate	Not vaccinated	
Barabaig	6.00 (18.60)	35.00 (81.40)	0.00 (0.00)	1.00 (100.00)	0.227 (0.633)	5.00 (23.81)	16.00 (76.19)	3.00 (13.04)	20.00 (86.96)	0.855 (0.355)
Massai	12.00 (9.92)	109.00 (90.08)	0.00 (0.00)	1.00 (100.00)	0.110 (0.740)	6.00 (10.00)	54.00 (90.00)	6.00 (9.68)	56.00 (90.32)	0.004 (0.952)
Sukuma	1.00 (3.33)	29.00 (96.67)	0.00 (0.00)	0.00 (0.00)	-	0.00 (0.00)	17.00 (100.00)	1.00 (7.69)	12.00 (92.31)	1.353 (0.245)
Total	21.00 (10.82)	173.00 (89.18)	0.00 (0.00)	2.00 (100.00)	0.243 (0.622)	11.00 (10.20)	87.00 (88.78)	10.00 (10.20)	88.00 (89.90)	0.053 (0.817)

Notes: Figures in parentheses are percentage of household.

**Table 3.** Marginal Effects of Maximum Likelihood Estimations for Pastoralists' Averting Decisions

Variable	Logit	Probit	Bias Corrected Logit	Penalized Logit
	dy/dx (se)	dy/dx(se)	dy/dx(se)	dy/dx(se)
Illness incidence	0.007**(0.003)	0.007**(0.003)	0.069(0.045)	0.079**(0.035)
Dead livestock (in TLU)	0.001(0.001)	0.001(0.001)	0.007(0.010)	0.010(0.011)
Per capita livestock	-0.002(0.004)	-0.002(0.006)	-0.216*** (0.039)	-0.044*(0.027)
Expected vaccination cost (in TZS)	0.058* (0.033)	-0.066*(0.040)	-0.138(0.409)	-0.705*(0.397)
Travel cost dummy	0.080*(0.044)	0.082*(0.047)	0.887(0.635)	0.957(0.631)
Age group dummy	0.042(0.047)	0.050(0.053)	0.391(0.602)	0.465(0.622)
Wage earner dummy	0.110** (0.052)	0.129** (0.063)	1.449** (0.643)	1.495** (0.656)
S&E active HH dummy	0.105** (0.052)	0.127** (0.063)	1.407** (0.637)	1.450** (0.666)
Log likelihood	-55.349	-55.363	-	-38.972
LR $\chi^2$	22.55	22.52	-	-
Wald $\chi^2$	-	-	-	19.78 (0.011)
Pseudo $R^2$ ( $p > \chi^2$ )	0.169(0.004)	0.169(0.004)	-	-
Sample size	195	195	195	195

Notes: 'dy/dx' and 'se' indicates marginal effect after regression and standard error, respectively.

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.001$ .

**Table 4.** Marginal Effects of Mixture Models for No. of Vaccinated Livestock by Pastoralist

Variable	Poisson-Logit	Negative Binomial-	Zero-Inflated	Zero-Inflated
	Hurdle (PLH)	Logit Hurdle (NBH)	Negative Binomial (ZINB)	Poisson (ZIP)
	dy/dx (se)	dy/dx (se)	dy/dx (se)	dy/dx (se)
Part 2: Predicting number of vaccinated livestock (count data)				
Illness incidence	0.011**(0.005)	0.014(.011)	0.014(0.011)	0.011**(0.011)
Dead livestock (in TLU)	-0.010***(0.001)	-0.009***(0.003)	-0.009**(0.003)	-0.010***(0.001)
Per capita livestock	-0.002***(0.003)	-0.003(0.008)	-0.003(0.008)	-0.002(0.003)
Expected vaccination cost (in TZS)	0.711***(0.094)	0.622***(0.159)	0.621***(0.159)	0.711***(0.094)
Travel cost dummy	-0.327***(0.136)	-0.285(0.240)	-0.285(0.240)	-0.327***(0.136)
Age group dummy	-0.923***(0.075)	-0.976(0.216)	-0.976***(0.216)	-0.923***(0.075)
Wage earner dummy	0.724***(0.080)	0.640***(0.203)	0.639**(0.203)	0.724***(0.080)
S&E active HH dummy	-0.302***(0.109)	-0.225***(0.230)	-0.224(0.229)	-0.301***(0.109)
Part 1: Predicting vaccination decision (for PLH, NBH) and excess zeros (for ZIP, ZINB)				
Illness incidence	0.086**(0.039)	0.085**(0.039)	-0.086**(0.039)	-0.086**(0.039)
Dead livestock (in TLU)	0.013(0.012)	0.013(0.013)	-0.013(0.013)	-0.013(0.012)
Per capita livestock	-0.029(0.058)	-0.029(0.058)	0.029(0.058)	0.029(0.058)
Expected vaccination cost (in TZS)	-0.814*(0.445)	-0.814*(0.445)	0.814*(0.445)	0.815***(0.445)
Travel cost dummy	1.131*(0.683)	1.131*(0.683)	-1.131*(0.683)	-1.131***(0.683)
Age group dummy	0.591(0.669)	0.591(0.669)	-0.591(-0.669)	-0.591(0.669)
Wage earner dummy	1.561**(0.708)	1.561**(0.708)	-1.561**(0.708)	-1.561**(0.708)
S&E active HH dummy	1.490**(0.709)	1.490**(0.709)	-1.491**(0.709)	-1.491**(0.709)
/lnalpha	-	-2.512***(0.570)	-2.513***(0.570)	-
alpha	-	-	0.081(0.046)	-
Nonzero observations	21	-	21	21
Log likelihood	-142.997	-141.430	-141.437	-143.005
LR $\chi^2$	-	-	64.760	10038.470(0.000)
Wald $\chi^2$	16.200 (0.0400)	16.200(0.400)	-	-
LR Test ( $\bar{\chi}^2$ )	-	-	3.140(0.038)	-
$z(p - val)$ of Voung Test	-	-	3.540(0.000)	4.410(0.000)
Sample size	195	195	195	195

Notes: 'dy/dx' and 'se' indicates marginal effect after regression and standard error, respectively.

\*p<0.10, \*\*p<0.05, \*\*\*p<0.001.