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Drivers of adoption and intensity of adoption of goat Farming in Southern Malawi

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Abstract

This study identifies drivers of adoption and its intensity on smallholder goat farming in southern Malawi. A Zero-Inflated Negative Binomial model was estimated using survey data collected in Balaka and Nsanje districts in 2014/15 cropping season. The study found that farmers residing in Nsanje have higher probability of adopting goat farming as compared to farmers in Balaka. Interestingly, farmers with no extension contact have higher probability of adopting goat farming than those who have access to agricultural extension. Further, education and age of the household head, access to credit services, total household income and household size were found to positively influence the intensity of adoption. The study suggests that apart from increasing contact between farmers and extension service providers, agricultural extension should include more livestock farming messages. Furthermore, the study suggests that all relevant stakeholders should intensify efforts to educate Malawians as it positively influences intensity of adoption. Lastly, stakeholders should help smallholder farmer's accessing credit services so that they get the much needed capital to intensify goat farming

Keywords: goat farming**,** Intensity, Adoption, Malawi, Technology, Zero Inflated Negative Binomial,

1. Introduction

Goats, like other small ruminants, play a variety of important roles in smallholder farmers' livelihood. Apart from being a form of savings and an insurance against household shocks, goat farming provides farm households with nutrition, additional incomes and manure (Kosgey, et al., 2004). Goat farming has the potential to alleviate rural poverty as goats have high gross margins (Maganga et al., 2015) on top of being easily convertible into cash when the need arises (GoM, 2006). Realizing this potential, agricultural policy makers in most developing countries like Malawi have made smallholder farmer adoption of goat farming as well as increasing intensity of goat adoption a rural development policy priority (GoM, 2006).

Livestock subsector in Malawi is rather small, such that it fails to meet internal demand for meat and meat products. Currently, it contributes about 8% to total Gross Domestic Product and approximately 36% of the value of agricultural products (GoM, 2006; Maganga, et al., 2014). Within the livestock sector, goats occupy a very important role given the fact that they are second largest species of livestock kept in Malawi after chickens (Phiri, 2012). Therefore, there is also a business case for increasing the smallholder adoption and intensity of adoption of goat farming.

Surprisingly, not much research has been conducted to understand the determinants of smallholder goat farming adoption and its intensity in Malawi. Only Maganga et al., (2014), have estimated determinants of adoption of various small ruminants and non-ruminants in Malawi including goats. This study therefore contributes to their efforts in understanding smallholder farmers' goat adoption in Malawi by extending the analysis in identifying determinants of the number of goats that farmers in southern Malawi keep.

2. Methodology

2.1 Sampling and data

Data used in the study was collected in 2014/15 cropping season from smallholder farm households using a semi-structured questionnaire. The study employed multistage sampling where by Nsanje and Balaka districts in southern Malawi were purposely selected due to their vulnerability to climate-related disasters of droughts and floods. And the need to find strategies that can make households in these districts more resilient to shocks. Within a district, the study randomly selected Traditional Authorities. From these Traditional Authorities, the study also randomly selected some villages. Households that were interviewed were obtained using simple random sampling from the selected villages.

The sample size was determined following a formula recommended by Krejcie and Morgan (1970) as follows;

$$n = \frac{\chi^2 NP(1-P)}{d^2(N-1)+\chi^2 P(1-P)} \quad (1)$$

Where n is the sample size, x^2 is tabulated Chi-Square for 1 degree of freedom at the desirable confidence level (3.841); N is the population size; P is proportion of adopters (P=0.5, was assumed and obtained from maximum sample size as the true population P was not known) whereas d is the degree of accuracy presented as a proportion (0.1). 10% of the calculated sample size was used to account for possibilities of non-response. A total of 619 questionnaires were collected from the two districts. However, only 428 of these were used, as they completely contained information that could allow us carry out a proper analysis on goat adoption and its intensity.

2.2 Analytical framework

Agricultural technology adoption is perhaps one of the most studied areas in agriculture (for example see Feder et al., (1985), Saha et al., (1994), Langyintuo and Mekuria (2008) and Adjognon and Liverpool-Tassie (2015)). Since the dawn of modern agriculture, efforts have been made by agriculturists and policy makers to have farmers adopt more productive and profitable farming technologies that maximize some utility or profit function (Saha, et al., 1994). It is therefore only natural that there are numerous models that have been developed by economists to empirically study drivers of adoption and adoption intensity of agricultural technologies.

Following Feder et al., (1985), an adopter is defined as one who has made a conscious decision to adopt an element or more of a technology and continue to use it. The decision to adopt an agricultural technology is based on the farmer's perceived maximization of some latent utility function that is not directly observable (Saha, et al., 1994). According to Saha and others (1994), only the decision that the farmer makes (either to adopt or not) is observable. The decision to adopt "D" equals one if a farmer adopts a technology and zero if otherwise. In adopting a technology, a farmer makes more that one decision though. Upon deciding to adopt a given technology, the farmer also makes a conscious decision on the extent of adoption of the technology (Katengeza, et al., 2012).

It is worthy noting that intensity of adoption is fundamentally a function of resources that are available to the farmer (Katengeza, et al., 2012). In this study, the number of goats that a smallholder kept as an indicator of intensity of adoption is used. A presumption that all farmers that adopted goat farming, reared at least a goat. To avoid a scenario whereby observations with all explanatory variables (X) fully completed but with an unobserved dependent variables (Y), a latent dependent variable Y^* was assumed such that farmers interest in goat farming is not observed until a certain fixed constant threshold L is reached. This implies that Y^* is observed only when $Y^*>L$. According to Katengeza et al., (2012), although the decision to adopt a technology is interrelated with the decision on intensity of adoption, the two decisions follow different decision-making processes. However, Katengeza et al., (2012), noted that most determinants of adoption will also determine intensity of adoption, and vice versa.

Literature suggests that adoption of agricultural technologies, generally, is conditioned by socioeconomic and biophysical environment from within farmers operate and attributes of the technology in question (Feder, et al., 1985; Saha, et al., 1994; Batz, et al., 1999). Factors like gender, level of education, access to extension services and markets, proximity to main roads, household incomes as well as social capital somehow influence the adoption of agricultural technologies (Doss, 2006; Katengeza, et al., 2012).

Estimating drivers of technology adoption and its intensity of a technology is a complex issue. For example, it is possible to estimate drivers of adoption and its intensity using binary and censored models, respectively. However, the problem with such scheme of analysis is that it overlooks the fact that the error term for the adoption model may be jointly distributed with the error term for the intensity model (Katengeza, et al., 2012). In this respect, parameter estimates for the determinants of adoption and its intensity may become inefficient as the analysis fails to put into consideration any potential correlation of the error terms of the two models. This is because intensity of adoption decision is a sufficient condition for adoption decision.

The realization of the fact that intensity of adoption decision is a sufficient condition for adoption decision brings to the fore two important issues associated with analyzing such decisions. Firstly, there is no theoretical evidence to allow us assume that adoption and intensity of adoption decisions are made successively (Katengeza, et al., 2012). The two decisions are made jointly as farmers decide on the intensity of adoption (for example how many goats to keep) by the time they make the decision to adopt the technology. Secondly, the intensity of adoption measured as the number of goats that a farmer kept has observed "zero" values. The zero value represents a choice by the decision maker and is not a non-observed value of the response variable (Katengeza, et al., 2012). In our case, a preponderance of zeroes in the intensity model with 71% of the respondents owning zero goats was found.

Three issues have informed our decision on the choice of analytical technique. The realization that adoption and intensity of adoption decisions are made concurrently, the meaningfulness of zero values in the intensity model as well as the preponderance of zeroes in the intensity model helped us select Zero Inflated Negative Binomial (ZINB) model as the best analytical technique given the study's objective and data. In empirical research, adoption and adoption intensity are increasingly being estimated using Cragg-based Double-Hurdle models (Aristei & Pieroni, 2008; Yen & Jones, 1997; Fennema & Sinning, 2007).

Double-Hurdle models assume that for a positive level of intensity to be achieved, two hurdles must be passed. The first hurdle entails the decision to adopt a given technology whereas the second hurdle entails deciding on the level of adoption of the given technology. The most important feature of double hurdle models, however, is that they assume a bivariate normal probability distribution (Aristei & Pieroni, 2008). Ibid indicate that once the bivariate normal distribution assumption has been violated, one gets inconsistent parameter estimates. This is why a ZINB model was used for parameter estimation. Our data follow a negative binomial probability distribution with a preponderance of zeroes such that a Double Hurdle models can give me inconsistent results.

Zero Inflated Negative Binomial distribution is a mixture distribution that assigns a mass of *P* to excess zeroes and a mass of *(1-P)* to a negative binomial distribution (Mwalili, et al., 2007). Ibid notes that the negative binomial distribution is a continuous mixture of Poisson distributions which allows the mean λ to be gamma distributed. This property allows us to model over dispersion in the intensity model. The gamma distribution is especially instrumental when count data emanates from binary random variables; which is the case with our adoption and intensity of adoption case. Mathematically, the negative binomial distribution is presented as

$$P(Y=y)=\frac{\Gamma(y+\tau)}{y!\Gamma(\tau)!}\left(\frac{\tau}{\lambda+\tau}\right)^{\tau}\left(\frac{\lambda}{\lambda+\tau}\right)^{y}, y=0,1,...;\lambda,\tau>0 \qquad (2)$$

Where $\lambda=E(Y)$, τ is a shape parameter which measures the amount of dispersion, and *Y* is the amount of goats owned by a farm household. The variance of *Y* is specified as $\lambda+\lambda^2/\tau$. The negative binomial distribution tends to a Poisson distribution as τ tends to ∞. Mwalili et al., (2007), gave the Zero-Inflated Negative Binomial distribution as

$$P(Y=y)\begin{Bmatrix} p+(1-p)\left(1+\frac{\lambda}{\tau}\right)^{-\tau}, y=0 \\ (1-p)\frac{\Gamma(y+\tau)}{y!\Gamma(\tau)}\left(1+\frac{\lambda}{\tau}\right)^{-\lambda}\left(1+\frac{\tau}{\lambda}\right)^{-y}, y=1,2,3,... \end{Bmatrix} \qquad (3)$$

They further present the mean and variance of the ZINB distribution as $E(1-p)\lambda$ and $Var(Y)=(1-p)\lambda(1+p\lambda+\lambda/\tau)$, respectively. Accordingly, ZINB distribution approaches the Zero-Inflated Poisson distribution when $\tau\rightarrow\infty$ and the negative binomial distribution when $p\rightarrow 0$. If $1/\tau$ and $P\approx 0$ then the Zero Inflated Negative Binomial distribution reduces to the Poisson distribution.

The Zero Inflated Negative Binomial model relates P and λ to covariates such that

$$\log(\lambda_i)=x_i'\beta \text{ and } \operatorname{logit}(p_i)=z_i'\gamma,(i=1,2,3,...,n) \qquad (4)$$

Where X_i and Z_i are d- and q-dimensional vectors of covariates associated with the ith farmer, and β, γ the corresponding vectors of regression coefficients, respectively (Mwalili, et al., 2007). These are the adoption and intensity of adoption models that were estimated.

The models maximize the log of likelihood that is obtained from putting in Equation (3) the dependence of the parameters on the covariates by making use of Equation (4) such that for the total sample, the log-likelihood is

$$L_z(\beta,\gamma,\tau,X,Z) = \sum_{i=1}^{n}\log\left(1+e^{z_i'\gamma}\right) - \sum_{i:yi=0}\log\left(e^{z_i'\gamma}+\left(\frac{e^{x_i'\beta}+\tau}{\tau}\right)^{-\tau}\right) +$$
$$\sum_{i:y_i>0}\left(\tau\log\left(\frac{e^{x_i'\beta}+\tau}{\tau}\right)+y_i\log\left(1+e^{-x_i'\beta_\tau}\right)\right)+ \quad (5)$$
$$\sum_{i:y_i>0}\left(\log\Gamma(\tau)+\log\Gamma(1+y_i)-\log\Gamma(\tau+y_i)\right)$$

Where $X=(x_1,x_2,...,x_n)$ and $Z=\left(z_1,z_2,...,z_n\right)$.

A parameter estimation using the ZINB command in Stata version 13.1 MP was conducted. The first derivatives of the Zero inflated Negative Binomial in appendix 2 is presented as in the report by Mwalili et al., (2007), that the optimization requires the first derivatives.

A critical concern in estimating zero inflated negative binomial model arises due to over dispersion in data whereby variance is greater than the mean (Shankar, et al., 1997). This is true for our sample. When, as in our case, a two stage model is required to assess drivers of goat adoption and its intensity and it is estimated using a single count model. In this case, over dispersion may be erroneously indicated, suggesting that a Negative Binomial model is appropriate when actually the most appropriate model is a Zero Inflated Poisson. Shankar, et al., (1997), eloquently illustrate how overdispersion occurs. They show that the Negative Binomial has the following variance

$$\operatorname{var}[Y_i] = E[Y_i]\{1+\alpha E[Y_i]\} \quad (6)$$

where α is the over dispersion parameter while for Zero Inflated Poisson has

$$\operatorname{var}[Y_i] = E[Y_i]\left\{1+\frac{p_i}{1-p_i}E[Y_i]\right\} \quad (7)$$

Such that it is very easy for the term $P_i/(1-P_i)$ to be mistakenly interpreted as α.

When using zero inflated models then the problem becomes one of distinguishing the underlying Negative binomial and Poisson distributions (Shankar, et al., 1997). Vuong (1989) suggested a statistical test that ably does this. The Voung test is discussed in detail in appendix 4. The Vuong Test is widely used whenever count data is concerned. For example, Greene (1996) asserted that the test is reasonably robust in count data applications.

3. Results and discussion

3.1 Characteristics of households

The attributes of goat and non-goat farming households is compared first. From a sample of 428 farm households, only 29% kept goats in the year of the study. Of the households that reared goats, only 5% percent were female headed. Fishers Exact tests (Table 1) show a significant relationship between gender and district of residence to adopting goat farming at 1% level of significance (P=0.000), respectively. The table also indicates a signifacant relatonship between secondary education and adoption at 10% and 5% levels of significant using the Fishers Exact and 1-Sided Fishers Exact, respectively.

Overall, majority of the respondents had access to agricultural extension (68%). Only 21% of respondents who rear goats reported that they did not access agricultural extension services in the preceding year against 80% of those who reared goats. Access to credit, however, seems to be a problem as only 41% of the respondents reported to have accessed loans through a multiplicity of sources. For goat farmers, only 46% of the respondents reported that they had accessed credit during the previous year.

Table 1: Descriptive statistics of important variables using Fisher's Exact and 1-Sided Fisher's Exact Test

Parameter	Fisher Exact	1-sided Fisher Exact
District	0.000***	0.000***
Formal education	1.000	0.527
Primary education	0.134	0.068
Secondary education	0.080*	0.043**
Tertiary education	1.000	0.626
Adult literacy	0.564	0.374
Access to credit	0.165	0.083*
Gender	0.007***	0.004***

*** p<0.01, ** p<0.05, * p<0.1

Table 2 shows that the difference in means for household sizes for goat and non-goat farmers is statistically significant at 1% level of significance (p<0.01). In our sample, goat-farming households had an average of have 6.4 members whereas non-goat farming households had a mean of 5.9 members. However, there are no significant differences in total household incomes as well as age of household head between the adopters and non-adopters.

Table 2: T-test mean comparison test (with unequal variances)

Parameter	Mean for goat farmer	Mean for non-goat farmer	Mean Difference[1]	t-value
Total household income (MK)	144525	146411	-1886	1.986
Age of household head (years)	43.4	45.1	-1.7	1.496
Household size	6.4***	5.9	0.5	-2.584

*** p<0.01

3.2 Adoption of goat farming

The ZINB Model indicates that adoption of goat farming is affected by two factors, district of residence of the farmers and extension contact. At country level, a significant majority of goats are reared in lower shire districts of Nsanje and Chikwawa in southern Malawi (Freeman, 2008). This is perhaps the reason the probability of adoption for farmers in Nsanje is 0.615 higher than for farmers in Balaka. Empirical research in smallholder farmer goat technology adoption has shown that farmers in a society where a given technology is widely practiced have higher probability of adopting it due to exposure known as “neighborhood effect.” Due to exposure, there are technological spillover effect as adopters implicitly influence others to adopt (Langyintuo & Mekuria, 2008; Adjognon & Liverpool-Tassie, 2015).

Katengeza, et al., (2012), Feder, et al., (1985) and Doss (2006) have shown that agricultural extension is very important in smallholder farmer adoption of agricultural technologies. Interestingly however, our results as seen in table 3 below, show that, all things equal, extension contact significantly affects non-adoption of goat farming as given by the logistic inflation model (p<0.050). Generally, households that had access to agricultural extension had 0.112 higher probability of not adopting goat farming than those who had access to extension. our results strongly concur with Maganga et al., (2014). Using third round of Integrated household Survey for Malawi, Maganga et al., (2014) found that agricultural extension contact reduced the probability of adopting goat farming by 25%. This findings were attributed to how agricultural extension in Malawi, which is dominated by crop-related services than livestock-realated services. This study concurs with tthese findings, that the nature of agricultural extension that smallholder farmers are receiving generally favours crop production, hence signaling to the farmers that livestock production is not that important.

3.3 Intensity of adoption of goat farming

Maximum likelihood estimation of ZIMB model indicates that, *ceteris paribus*, households whose heads have

[1] Assumption of equal variance was rejected and hence statistic is based on unequal variance

primary and secondary school education tend keep more goats as compared to households whose heads have no formal education (5% and 10% significant levels, respectively). The study anticipated this result given that scaled adoption of a technology requires a certain level of technical understanding of the husbandry practices associated with the given technology. For this reason, the study theorized that some level of education is required. These results are consistent with Huffman (1999) as well as Feder et al., (1985) who indicated that education is a valuable driver of intensity of agricultural technology adoption.

Table 3: Determinants of adoption and intensity of adoption of goat farming

	Intensity model		**Adoption Model (Logistic Inflation)**		**Marginal effects after logistic inflation**	
Parameter	**Coefficients**	**Standard Errors**	**Coefficients**	**Standard Error**	**Average Marginal Effects**	**Delta-method Standard Errors**
District (Balaka=1)	0.350	1.020	5.569***	1.044	0.599**	0.055
Primary Education(1=yes)	0.997***	0.328				
Secondary Education(1=yes)	0.939***	0.356				
Adult literacy(1=yes)	-16.00	1,906				
Extension contact(1=no)	0.141	0.257	0.902**	0.407	0.122**	0.054
Household size	0.105**	0.045	-0.0200	0.086	-0.003	0.011
Access to credit (1=yes)	0.390*	0.222	0.456	0.437	0.057	0.053
Total household inc.	2.45e-06**	1.07e-06	1.40e-06	1.85e-06	1.77e-07	2.30e-07
Gender of household head (1=male)	-0.098	0.390	-0.590	0.657	-0.075	0.082
Age of household head	0.0173**	0.009	0.0123	0.015	0.002	0.002
Constant	-1.362*	0.714	-1.119	1.216		
/lnalpha	-0.250	0.268				
Alpha	0.779					
Log likelihood	-477.687					
LR chi2(10)	25.90					
Prob > chi2	0.004					
Zero observations	304					
Nonzero observations	124					
Observations	428		428		428	

Likelihood-ratio test of alpha=0: chibar2 (01) = 216.95 Pr>=chibar2 = 0.0000
Vuong test of zinb vs. standard negative binomial: z = 2.77 Pr>z = 0.0063

The intensity of adoption of goat farming is found to be positively affected by household size. The results indicate that, holding all factors constant, the number of goats that a household keeps increases by 1.13 as the size of the household increases by 1 member. The study also anticipated a positive significant relationship between household size and number of goats a household keeps since household size proxies the amount of available family labour that can be allocated to tending their flock of goats at some point. Generally, households with more family labour available can afford to have higher flock sizes as compared to smaller households who have less family labour available. In fact, our results vindicate Melesse (2015) who found similar relationship between intensity of adoption of smallholder output-market participation and household size.

As expected, the study found a positive relationship between age of the household head and intensity of goat farming at 1% level of significance. A one year increase in age of household head increases the number of goats a household keeps by 1.02, ceteris paribus. The study anticipated age of household head to drive intensity of adoption of goat farming. It was hypothesized that goats being assets that are relatively easy to keep and convert into cash, their farming becomes increasingly important as a farmer grows in age since productive asset accumulation becomes more important. Further, older farmers tend to have more experience in goat farming such that they may reduce goat mortality rates as well as ensure relatively larger kidding rates as compared to younger farmers. As Katengeza et al., (2012), Maganga et al., (2014), and Feder, et al., (1985) have shown that age of the farmer affects farmer's technology adoption.

Furthermore, the study found a positive ralationship between access to credit and the intensity of goat farming at 10% level of significance. Holding other factors constant, having access to credit increases the number of goats that a household keeps by one. This result was anticipated as already indicated in the analytical framework that intensity of adoption is a function of availability of resources.

The ZINB model results further indicate that total household income positively affects intensity of adoption ($p<0.05$). This result was expected since, intensity of adoption of an agricultural technology essentially depends on availability of necessary resources at the household (Katengeza, et al., 2012). Generally, higher income households can manage to care for bigger flock sizes as they have the ability to hire labour as well as purchase necessary equipment and medication that allow maintanance of a bigger stock as opposed to households with lower incomes. Furthermore, when a shock hits the households, higher income households are generally not as pressed to sale livestock compared to their low income counterparts, such that their flock can easily grow as compared to flocks of low income households.

4. Conclusion

This study has estimated factors affecting adoption and its intensity on goat farming in southern Malawi. The study has established that farmers in Nsanje district as well as those who have no access to agricultural extension services have higher probabilities of adopting goat farming as compared to farming households in Balaka and those having access to agricultural extension, respectively. Intensity of adoption to goat farming is positively correlated with primary and secondary education of the household head, household size, age of the household head, total household income as well as access to credit.

From our results, it is clearly that there is a need to increase access to livestock agricultural extension services if more smallholder farmers are to adopt goat farming. Furthermore, government should incentivize its citizens to pursue at least primary school education as the study has shown that educated farmers own larger flocks of goat. The study also suggests that all interested stakeholders should help smallholder farmer's to access credit services so that they get the needed capital to intensify goat farming.

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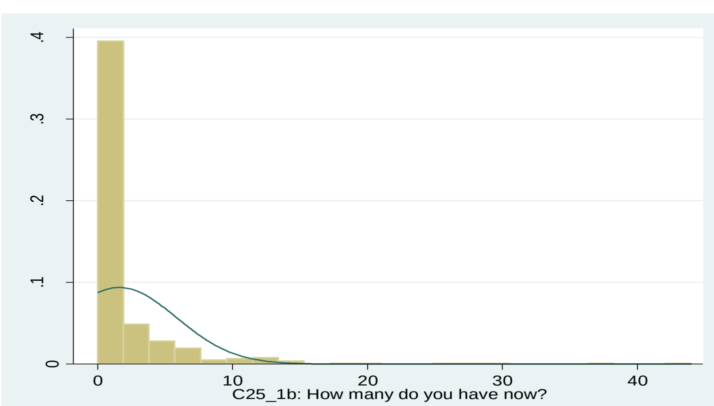
APPENDIX 1: DISTRIBUTION OF GOATS IN THE SAMPLE

Variable	Mean	Std. Dev.	Variance	Min	Max
Number of goats kept	1.60	4.25	18.08	0	44

APPENDIX 2: PREPONDERANCE OF ZEROES IN NUMBER OF GOATS



APPENDIX 3: DERIVATIVES OF THE ZINB MODEL

The first order conditions of L_z with respect to $\theta = (\beta, \gamma, \tau)'$ parameters

$$\frac{\delta L_z}{\delta \beta_j} = \begin{cases} \sum_{i=1}^{n} \left(\frac{\lambda_i \tau}{(\lambda_i + \tau)(1 + q_i r_i)} x_{ij} \right), y = 0 \\ \sum_{i=1}^{n} \left(1 - \frac{\tau + y}{\lambda_i + \tau} \right) \tau x_{ij}, y > 0 \end{cases}$$

$$\frac{\delta L_z}{\delta \gamma_j} = \begin{cases} \sum_{i=1}^{n} \left(\frac{1}{1 + q_i r_i} z_{ij} - \frac{1}{1 + q_i} \right), y = 0 \\ \sum_{i=1}^{n} \left(\frac{q_i}{1 + q_i} z_{ij} \right), y > 0 \end{cases}$$

$$\frac{\delta L_z}{\delta \log \tau} = \begin{cases} \sum_{i=1}^{n} \frac{\left(-\lambda + (\lambda + \tau)/\tau \log r_i\right)}{(\lambda + \tau)(1 + \mathrm{q}_i \mathrm{r}_i)} \tau, y = 0 \\ \sum_{i=1}^{n} -1 + \frac{\tau + y}{\lambda_i + \tau} + \log\left(\frac{\lambda_i + \tau}{\tau}\right) + \log \Gamma'(\tau) - \log \Gamma'(\tau + \mathrm{y})\tau, \mathrm{y} > 0 \end{cases}$$

Where $\lambda_i = e^{x_i' \beta}$, $r_i = \left(\lambda_i + \tau / \tau\right)^{\tau}$, $q_i = e^{z_i' \gamma}$ **and** $\Gamma(\mathrm{x}) = \delta \log \Gamma(\mathrm{x}) / \delta\, \mathrm{x}$

APPENDIX 4: MODEL SPECIFICATION TEST

According to Shankar, et al., (1997), the Vuong test is obtained as

$$V = \frac{\bar{m}\sqrt{N}}{S_m}$$

Where $\bar{m}$ is mean with $m = \log\left[f_1(.) / f_2(.) \right]$, with $f_1(.)$ being the density function of ZINB distribution.

And $f_2(.)$ being the density function for the native Negative Binomial distribution. Where N and S_m are sample size and standard deviation, respectively. when V is greater than 1.96, ZINB is appropriate whereas when it is less than 1.96 then native Negative Binomial is most appropriate. Values of V between -1.96 and 1.96 mean the test is indecisive (Vuong, 1989).