Bayesian Analysis of Farmers' Decision to Sell Nothing or Some Output Through Contract Farming

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Abstract

- Contract farming (CF) is a pre-output agreement between agricultural producers and buyers.
- CF helps to integrate farmers in developing countries to global agricultural value chains (Barrett et al. 2012).
- But research also shows that value chain intermediary agents acquire superior earnings than farmers.
- This study employs a Bayesian zero-one-inflated beta regression model to analyzes determinants of farmer's decision to sell zero or some output in CF.

Introduction

- Numerous studies (e.g., Sharma 2008; Miyata et al. 2009; Wang et al. 2011; Barret et al. 2012; Kiwanuka and Machethe, 2016; Kiwanuka et al. 2021) have examined impacts of CF, which is important in view of the growing policy support.
- Most of these studies focus on the crop sector.
- Those that model the dairy sector's participation and intensity in CF mostly consider farmer involvement in CF as a binary decision; censored proportion of output farmers in CF, or the types of commodities sold in CF using multinomial models.
- All these methods, have their own appeal and nuance
- But sometimes farmers may sell output in CF as proportions, fractions, e.g. 0, 0.5, 0.85, rendering OLS, Tobit, fractional regressions inappropriate.
- Such methods assume all values in proportional data come from the same process (Buis, 2010) which is unrealistic. A zero-one-inflated beta (ZOIB) model is appropriate for such data and this paper uses a ZOIB in a Bayesian framework which is exact and accounts for uncertainty in data and parameters.

Data and Methods

- Consider a model in which the response variable *ytj* is the *j*th variable from a total of p response variables that are measured on t independent units. Then:

(1)
$$f(y_{tj}) = \begin{cases} p_{tj} & \text{if } y_{tj} = 0 \\ (1-p_{tj})q_{tj} & \text{if } y_{tj} = 1 \\ (1-p_{tj})(1-q_{tj})\text{Beta}(\alpha_{tj1}, \alpha_{tj2}) & \text{if } y_j \in (0,1) \end{cases}$$

where p_{tj} is the probability of $y_{tj} = 0$, and q_{tj} is the conditional probability $P(y_{tj} = 1 | y_{tj} \neq 0)$, while α_{tj1} and α_{tj2} are shape parameters of the beta distribution when $y_{tj} \in (0,1)$.

- This can be shown through link functions. The natural choices of the link functions for p_{tj} and q_{tj} and the mean of the beta density are logit, probit, and/or complementary log-log functions.
- It therefore follows that there exists a mixture of probability parameters from the binominal distribution and beta distribution's shape parameters with observed explanatory variables $\boldsymbol{x}_{tj}$ or unobserved latent variables $\boldsymbol{z}_{tj}$.

Consider the parameter vector $\boldsymbol{\Theta} = \{\boldsymbol{\beta_1}, \boldsymbol{\beta_2}, \boldsymbol{\beta_3}, \boldsymbol{\beta_4}, \boldsymbol{\Sigma}\}$ to represent a set of parameters from the zoib model where $\gamma_m = \gamma$ and $\Sigma_m = \Sigma \forall m$.

Using Bayes' Theorem, the joint posterior distribution of $\boldsymbol{\Theta}$ and γ given data $\boldsymbol{y}$ is $p(\Theta,\gamma|y) \propto p(y|\Theta,\gamma)p(\gamma|\Theta)p(\Theta)$.

The full likelihood function $p(y|\boldsymbol{\Theta},\gamma)$ can be derived from equation (1) is shown below

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(2)
$$p(y|\boldsymbol{\Theta},\gamma) \propto \prod_t \prod_j \left\{p_{ij}^{I(y_{tj}=0)}(1-p_{tj})^{I(y_{tj}>0)} q_{tj}^{I(y_{tj}=1)} (1-q_{tj})^{I(y_{tj}=1)}\right\} \times$$
$$\left\{\frac{\Gamma(v_{tj})}{\Gamma(v_{tj}\mu_{tj}^{(0,1)})\Gamma\left(v_{tj}(1-\mu_{tj}^{(0,1)})\right)}(y_{tj})^{v_{tj}\mu_{tj}^{(0,1)}-1}(1-y_{tj})^{v_{tj}(1-\mu_{tj}^{(0,1)})-1}\right\}^{I(y_{tj}\in(0,1))} \quad (11)$$

- Evaluating equation (2) analytically is not easy, and Bayesian methods are quite useful for this type of application.
- We use Hamiltonian Monte Carlo (HMC) and its extension, No-U-Turn sampler (NUTS) for estimation.
- HMC and NUTs are more efficient for estimation of nonlinear models than Metropolis-Hastings and Gibbs Sampling (Gelman et al., 2013; Burkner, 2017). Analysis is performed in R and Stan software.
- We use cross-sectional data collected from 203 dairy farmers involved in CF in Zambia (Figure 1).
- Data were collected in 2017. The farmers owned between 1 and 50 dairy animals.

- **Fig. 1: Map of Zambia**

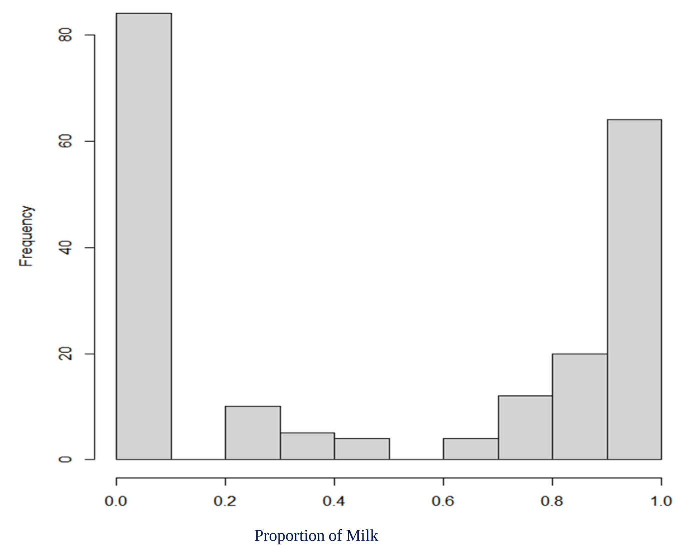

Fig. 2: Frequency Histogram of Milk Proportion Sold in Contract Farming

- A multi-stage sampling design used.
- Mean value: 48%; about 40% sold 0%, and about 30% sold it all in CF. The dependent variable is in proportions and Fig. 2 depicts its full distribution between 0 and 1.
- Proportion of milk sold to milk contractors is inflated at 0 and 1. Also has values in [0,1] which means that clearly a ZOIB model is more appropriate to be fitted by these data.

Results

Table 1. Bayesian ZOIB Parameter Estimates

(1)	(2)				(3)			
	Proportional Preferences				Zero-Inflated Preferences			
Variable Name	Posterior Mean	Std. Dev	90% Credible Interval		Posterior Mean	Std. Dev	90% Credible Interval	
Dependent variable								
Proportion of milk sold to contracts								
Explanatory variables								
Demographic characteristics								
Age (years)	-0.002	0.003	-0.006	0.003	0.001	0.005	-0.008	0.009
Sex	-0.369*	0.182	-0.676	-0.079	-0.424	0.362	-1.027	0.156
Marital status	0.297*	0.114	0.108	0.484	-0.129	0.197	-0.456	0.189
Household size	-0.035*	0.016	-0.062	-0.009	0.101*	0.039	0.039	0.166
Education	0.008	0.010	-0.008	0.025	0.016	0.020	-0.017	0.049
Contract dairy farming related factors								
Duration in farmer cooperation	0.011	0.008	-0.002	0.024	0.019	0.022	-0.016	0.056
Experience selling to MCC	-0.004	0.008	-0.016	0.009	-0.053*	0.030	-0.103	-0.006
Livestock holding (tlu)	0.004	0.004	-0.003	0.011	-0.022*	0.009	-0.037	-0.007
Crossbreeding	0.083	0.084	-0.055	0.219	0.345*	0.201	0.019	0.679
Access to dairy information	0.072	0.074	-0.052	0.193	0.908*	0.216	0.564	1.276
Contractor's milk price (ZMW)	-0.001	0.027	-0.045	0.043	-0.442*	0.080	-0.580	-0.317
Payment within a month	-0.135*	0.070	-0.251	-0.021	0.302	0.234	-0.071	0.696
Milk parlor	0.244*	0.095	0.090	0.404	0.584*	0.219	0.230	0.948
Own a fridge	-0.226	0.159	-0.489	0.031	0.472	0.334	-0.063	1.034
Borehole	0.043	0.106	-0.132	0.216	0.586*	0.225	0.224	0.966
Well	-0.048	0.077	-0.176	0.079	0.237	0.163	-0.028	0.509
Dam	0.029	0.127	-0.176	0.237	-1.205*	0.521	-2.108	-0.429
Distance to MCC					0.003	0.008	-0.009	0.017

- What positively drives zero-inflated preferences include household size, access to dairy marketing information, milking parlor, and using boreholes as a water resource for dairy animals.
- However, farmers' experience of selling to milk collection centers, livestock holding, and increased milk price are significantly associated with reduction in their probability to sell zero milk through CF.
- Female headed-farms are more likely to sell milk proportions in CF
- Household size significantly determines both farmers' preferences to sell proportions or zero amount of milk through CF.

Conclusion

- Buyers should tailor contracts to farmers' conditions through such avenues as instant payments, spot prices to avoid delayed payments.
- More attractive prices needed to motivate farmers to sell more.
- More female farmers should be considered in CF arrangements
- This study provides opportunities to overcome farmer engagement barriers in contract farming.
- We offer an initial evidence of an excellent empirical application of a Bayesian ZOIB model for proportional data in agricultural and applied economics.

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