Effect of Remittance on Intensity of Agricultural Technology Adoption in Nepal

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Abstract

We analyzed data collected from face to face interviews of farmers in East Chitwan, Nepal to understand the factors affecting the intensity of improved agriculture technologies adoption. We used parametric and nonparametric instrument variable count data models. Results from the Poisson Quasi Likelihood model indicated the positive role of remittance payment on agricultural technology adoption, consistent with the results from the nonparametric model. Additionally, the following variables have a positive impact on technology adoption in the nonparametric model: landholding size and number of animals.

Key words: agricultural technologies, Nepal, nonparametric instrument variable model, Poisson quasi likelihood model, technology adoption

JEL Classifications: Q16, O13

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Nepal is a small landlocked country in south Asia with a substantially underdeveloped agricultural economy. Every year, a significant percentage of the young workforce migrates to foreign countries for education and employment opportunities. The Government of Nepal (GON) started encouraging migration with the objective of reducing poverty. Remittance already accounts for 23 percent of GDP in the country, and it is expected to grow (Agrawal et al. 2005, Thieme et al. 2005, Yang 2011). The potential impact of remittance on technology adoption in a country where mass migration is common and more than 80 percent of households still depend on home production makes Nepal a perfect case study to explore the role of migration in agricultural technology adoption.

The problem is that migration may lead to a growing dependence on remittance income, and could result in unfavorable outcomes in the long run, including the lack of labor force in the home country. One solution to the labor shortage is to switch labor intensive agriculture to a more mechanized form of agricultural operations. Remittance has the potential to fund agricultural development in rural economies by financing technologies (Firdaus et al. 2010). If a farmer/household uses remittance income to adopt improved agricultural technology, that should help increase his/her profitability and reduce food imports in this country.

Our objective is to identify the impact of pertinent explanatory variables on the intensity of agriculture technology adoption using parametric and nonparametric Poisson models. Variables affecting the intensity of technology adoption and possible policy solutions are outlined.

Method

Traditionally, econometric models in the intensity analysis literature have used Poisson (or Zero Inflated Poisson) and negative binomial (NB) models. The explanatory variables in these models have always been entered in a parametric fashion. There are many variables that impact technology adoption intensity yet we do not know whether those should be entered in a parametric or a nonparametric fashion. An ad hoc model specification is thus troubling and points a need to look at alternative specification. Additionally, some variables in the regression model are potentially endogenous. If this occurs, it is necessary to estimate the regression using a nonparametric endogenous variable model.

Within the intensity literature focusing on parametric models, Zhou et al. (2012) proposed using a log-normal based NB distribution. However, Staub and Winkelmann (2013) claimed that estimates obtained from the zero-inflated maximum likelihood estimates have both consistency and efficiency concerns if the model is misspecified. They proposed a Poisson quasi-likelihood estimator (PQL) because of its robustness to misspecification, when compared to the ML estimation of fully parametric zero-inflated count models. The Poisson quasi-likelihood can be presented as

(1) $$ql(\beta,\delta) = \sum_i^n y_i \ln\, \tilde{\lambda}(X_i, T_i, \beta, \delta) - \tilde{\lambda}(X_i, T_i, \beta, \delta)$$

Here, $\widetilde{\lambda}(X_i, T_i, \beta, \delta) = \exp(X_i\beta)/(1+\exp(T_i\delta))$, X is a vector of variables, β represents parameters corresponding to the variables, and T represents variables entered in the zero-inflated part with corresponding parameters δ.

Using a nonparametric approach to study technology adoption intensity is relatively new. Sharma et al. (2011) used nonparametric (NP) count data models to study the number of technologies and pest control strategies adopted by UK cereal farmers. They found that a nonparametric model specification was preferred over a parametric model. We found that the conservation practices adopted in a technology adoption model is an endogenous variable, so we use a nonparametric instrumental variable approach of estimation. Given an already well developed literature on the count data models, we provide a brief introduction to the nonparametric instrumental variable model relevant to this study.

The nonparametric regression model is given by:

$$P = g_y(y) + \sum_{j=1}^{p} g_j(x_j) + \epsilon \ , \tag{2}$$

where P is the number of agricultural technology adopted, $g_y(.)$ is an unknown smooth function for endogenous variable y, and $g_j(.)$ is the unknown function for other factors x_j.

When there are ordinal explanatory variables, we need an estimation procedure that can address the ordinal nature of the variables. For simplicity, let us consider $g(y, X) = g_y(y) + \sum_{j=1}^{p} g_j(x_j)$. Then, equation (2) can be written as:

$$P = g(y, X) + U; \qquad E(U|W = w, X = x) = 0 \tag{3}$$

for all instruments w and exogenous covariates x, which is equivalent to:

$$E[P - g(y, X)|W = w, X = x] = 0 \ . \tag{4}$$

In this model, y denotes endogenous variable, X denotes exogenous explanatory variables, and W denotes our instrument. To address ordinal and categorical variables in a nonparametric model, we use a method suggested by Ma and Racine (2013), Nie and

Racine (2012), and Ma et al. (2011) to estimate the nonparametric instrumental variable model[1] given in equation (4).

Data

In order to test the hypothesis that migration and remittance have an overall positive effect on the number of agricultural technology adoption, we collected data from face to face interviews using a stratified random sample of households from Chitwan, Nepal, between February and April of 2013. Before conducting the survey, we used the feedback from the focus group survey that was conducted in two locations within the survey area to modify the questionnaire and make it relevant to our study. The study location was chosen based on the sample of the population participating in migration, and dominance of the agricultural sector in the economy. There were a total of 21 technologies considered in the study; however, four technologies were not adopted by any farmers surveyed in the study area. The technologies considered are Iron Plough, Power Tiller, Shallow Tube Well, Deep Tube Well, Rower/Dhiki Pump, Tractor, Thresher, Pumping Set, Animal Drawn Cart, Combined Harvester, Sprayer, Biomass Gasifiers, Manual Seed-cum-Fertilizer Jab Planter, Pedal Millet Thresher, Coffee Pulpers, Minimum Till Drill, Zero Till Drill, Mini SRR (Simple, small, low-cost dryers), Low-Cost Solar Dryer, Rice Husks Stove for Cooking, and Poly-house. The number of farmers adopting each technology is given in Table 1. Intensity of technologies and the number of technologies adopted by farmers are given in Figure 1.

[1] The 'crs' R package is available to estimate the nonparametric model which contains both categorical and continuous variables. See Racine et al. (2012) for the 'crs' package manual.

Results

We estimated the impact of remittance on the intensity of agriculture technology adoption by Nepali farmers. The dependent variable used was the number of agricultural technologies adopted by farmers as shown in Figure 1. It is evident from the figure that most farmers have adopted about five different agricultural technologies. The analysis was performed by using a Poisson quasi-likelihood (PQL) model. The results indicated that an increase in the household's income from remittances increased the number of agricultural technologies adopted. Farmers getting remittance money are able to afford better technologies. The farmers who know their soil quality is either good or bad adopt less agriculture technologies than those who do not know their soil quality at all. On the other hand, the farmers who use more conservation technologies are also using more improved agriculture technologies. The farmers who lack information on soil quality may be adopting haphazardly (therefore quantity does not reflect appropriateness); or they may be adopting more of the cheaper technologies, subsided technologies, or the ones that do not require knowledge of soil quality. The farmers who practice conservation (mitigating poor soil/water quality or improving good soil/water quality) are more likely to be using the technologies that are most appropriate for improving productivity. The negative impact of age on the number of agricultural technologies adopted may reflect the predominance of cultural subsistence practices among older farmers.

We also estimated the model using a nonparametric instrument variable model. As identified in the PQL model, the number of conservation practices adopted by farmers is an endogenous variable. Therefore, in the nonparametric instrument variable model, the number of conservation practices used is an endogenous variable, and we used total number of infrastructure used in the farm the previous year as the instrument variable.

Results from a nonparametric instrument variable model are shown in Figure 2. The number of conservation technology used does not impact technology adoption beyond the level at which farmers use five conservation technologies. Age has a positive impact on up to a total of four technologies adopted. In general, existing literature in technology adoption states that the age has negative effect on technology adoption. Our finding is different. This may be because farmers are older and they are forced to farm in the absence of their young able children due to short or long term migration. Therefore, to take advantage of what is going on and to take advantage of modern labor saving farming technologies, they adopt higher number of improved technologies. They may have more experience with some of the farming technologies we tested (they were disseminated in their youth), so they may have more confidence in using them, for example the iron plow, shallow tube wells, and pumping set. We found education to have a cubic relationship with technology adoption although the relationship is not as distinct as one would have expected. As the level of schooling increases the number of technologies adopted decreases, and then at around [certain education level] years of schooling, the households begin to adopt a greater number of agricultural technologies. The highest number of technology adoption (4.5) occurs when a respondent has 13 years of schooling. Increasing educations levels could be leading to off-farm employment initially, but at some point, in corroboration with previous literature, the education levels increase adoption rates. We find that remittance receiving households have adopted slightly higher numbers of technologies than the households who did not receive remittances. The non-remittances receiving households could have used income or agricultural loans to purchase the technology. Chitwan is also one of the more agriculturally developed districts in Nepal; there are cooperatives (farmers are able to use technology if they belong to the cooperative) and a renting market for technologies like tractors. Households with more animals are likely to adopt more technologies. In Chitwan, farmers are commercially producing dairy, poultry, vegetables and fisheries. The commercial production of animals/vegetables requires that they adopt more improved technologies. We also found that farmers with larger landholdings adopting more technology, but the trend declines after the landholding size reaches 1.8 bighas (1.5 bigha =1 hectare). Large landholders may be renting out their land in the sharecropping market, and sharecropping has been associated with lower adoption rates in other countries.

Conclusions

We estimated parametric Poisson Quasi-Likelihood and nonparametric endogenous Poisson models to understand the agriculture technology adoption behavior of farmers in Chitwan, Nepal. Our results indicated that remittance has positive impact on the number of technologies adopted. Other variables impacting technology adoption are animal number and age of the household.

Widespread availabilities of technologies may help to improve adoption pattern. Farmers do not have easy access and availability of technologies in the study region. Additionally, government and policy makers can focus on providing loan to farmers to increase the adoption. Targeting older farmers and those who operate commercial agriculture may be helpful in this aspect.

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Table 1. Number of Farmers Adopting Different Agriculture Technologies

Technology ID	Technology	Frequency	Percentage
1	Iron Plough	152	8.52
2	Power Tiller	16	0.90
3	Shallow Tube Well	196	10.99
4	Deep Tube Well	81	4.54
5	Rower/Dhiki Pump	4	0.22
6	Tractor	350	19.63
7	Thresher	326	18.28
8	Pumping Set/Mortor	142	7.96
9	Animal Drawn Cart	58	3.25
10	Combined Harvester	8	0.45
11	Sprayer	347	19.46
13	Manual Seed Cum Fertilizer Jab Planter	10	0.56
14	Pedal Millet Thresher/Pearler	3	0.17
15	Coffee Pulpers	21	1.18
19	Low Cost Solar Dryer	2	0.11
20	Rice Husks Stove for Cooking	59	3.31
21	Poly House	8	0.45

Table 2. Summary Statistics

Variable	Variable Definition	Obs	Mean	Std. Dev.	Min	Max
Age	Age of household operator (year)	385	52.756	13.738	22	92
Gender	=1 if female	394	0.046	0.209	0	1
Education	Number of schooling years of household operator	396	5.369	5.039	0	22
squality1	=1 if good soil quality-yes	388	0.936	0.246	0	1
squality2	=1 if good soil quality-no	388	0.041	0.199	0	1
tot_inc	Total income (Rs. 1000)	396	23.715	48.419	0	887
Remittance	=1 if remittance received	384	0.102	0.302	0	1
total_animal	Total animals in farm	396	0.676	3.636	0	32
tot_area	Total area cultivated	365	0.349	0.298	0	2.1
tot_machinary	Number of machinery and equipment used	388	4.595	1.848	0	14
tot_tech	Number of conservation technology used	396	5.316	3.055	0	19
tot_inf_available	Number of agricultural infrastructure used last year	389	7.442	2.738	0	22

Table 3. Estimated Parameter and Marginal Effects from the PQL Model

Variables	Coef.	P-value	Marg. Eff.	P-value
Age	-0.007	0.574	0.021	**0.025**
Gender	0.135	0.122	0.636	0.122
Education	0.005	0.321	0.023	0.320
squality1	-0.196	**0.034**	-0.922	**0.033**
squality2	-0.339	**0.027**	-1.590	**0.026**
tot_inc	0.009	0.371	0.013	**0.060**
Remittance	0.157	**0.007**	0.737	**0.007**
total_animal	-0.006	0.450	-0.026	0.450
tot_area	0.010	0.870	0.046	0.870
tot_tech	0.122	**0.000**	0.573	**0.000**

Note: Vung test for zero inflated = 1.6 with P-value=0.039.
Number of conservation technology is found to be endogenous and total infrastructure used last year is used as instrument variable.

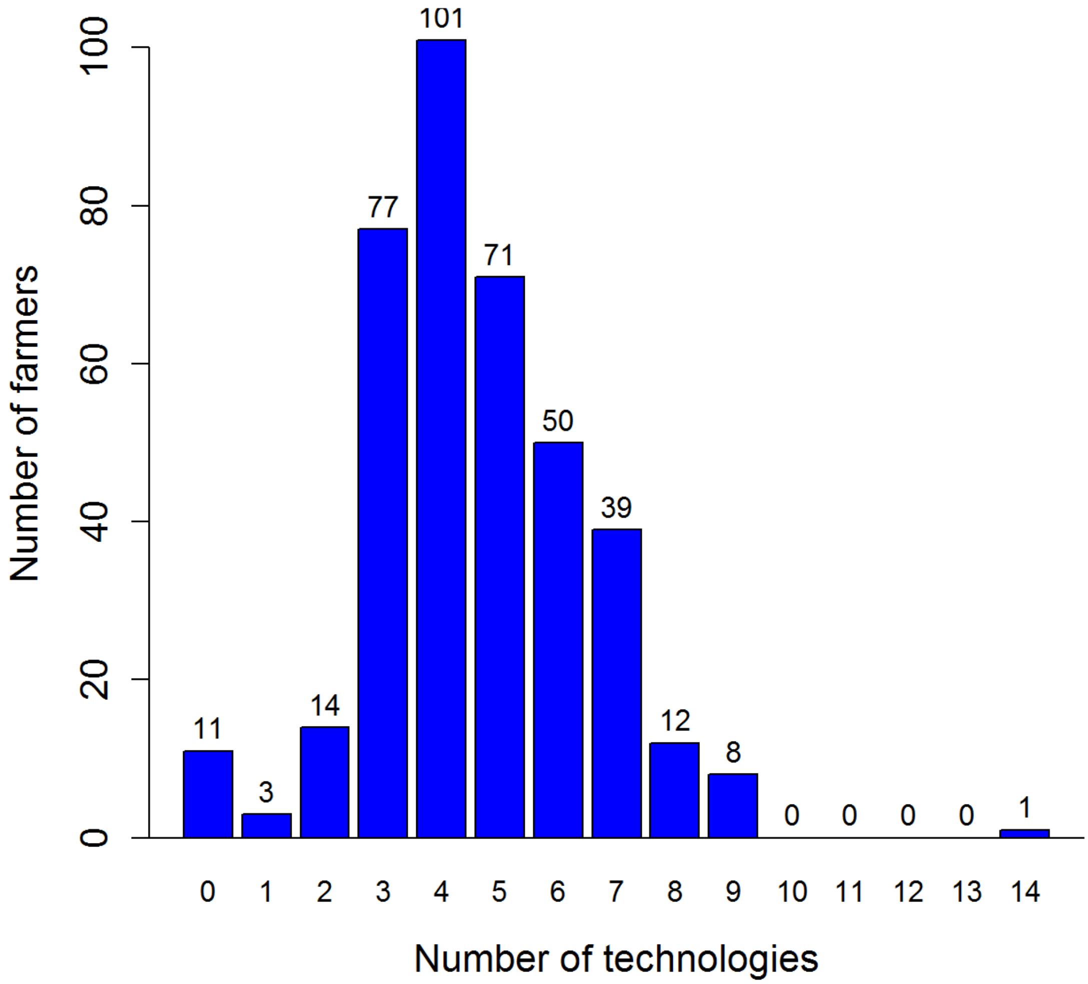

Figure 1. Number of technologies used by farmers.

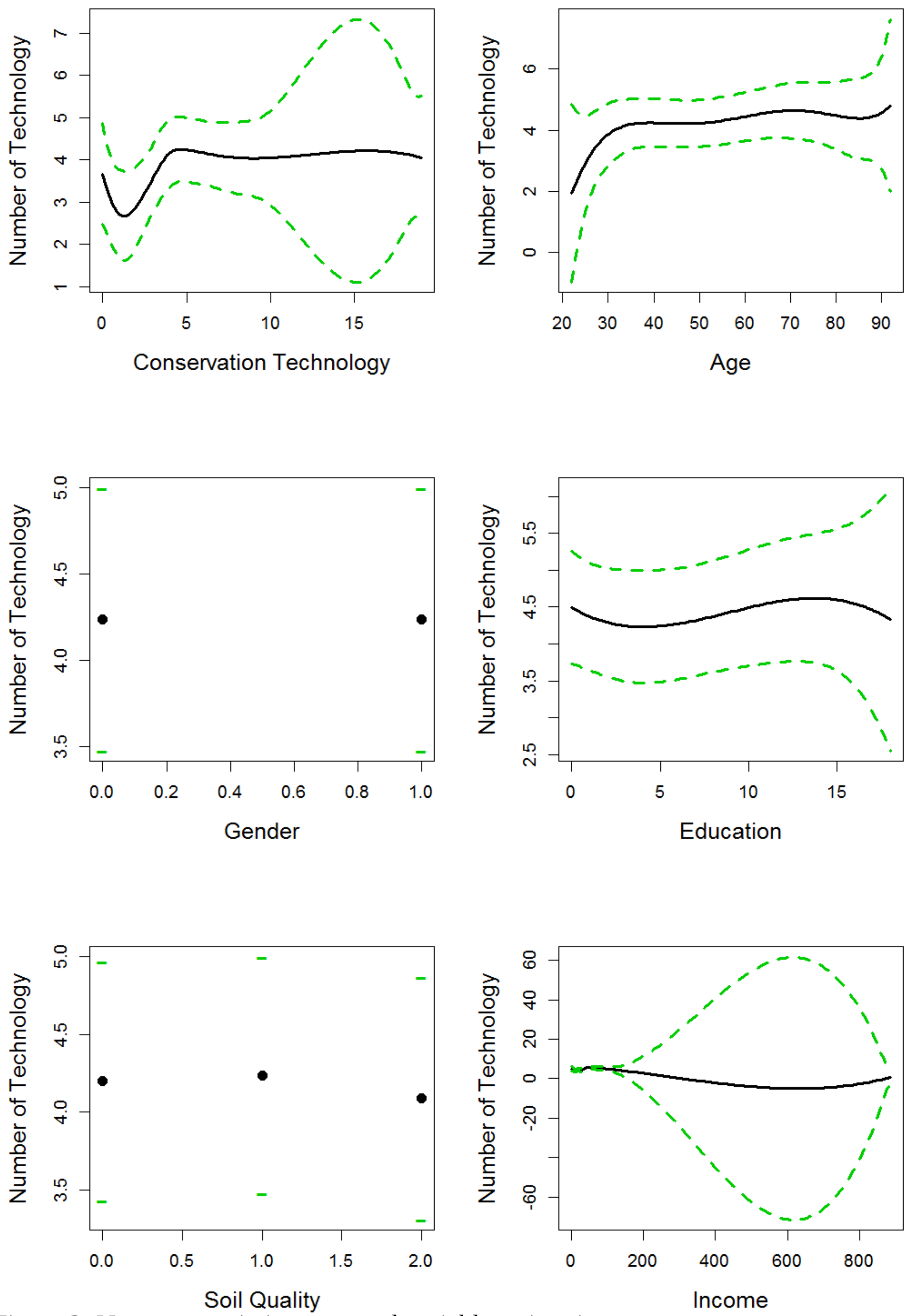

Figure 2: Nonparametric instrumental variable estimation.

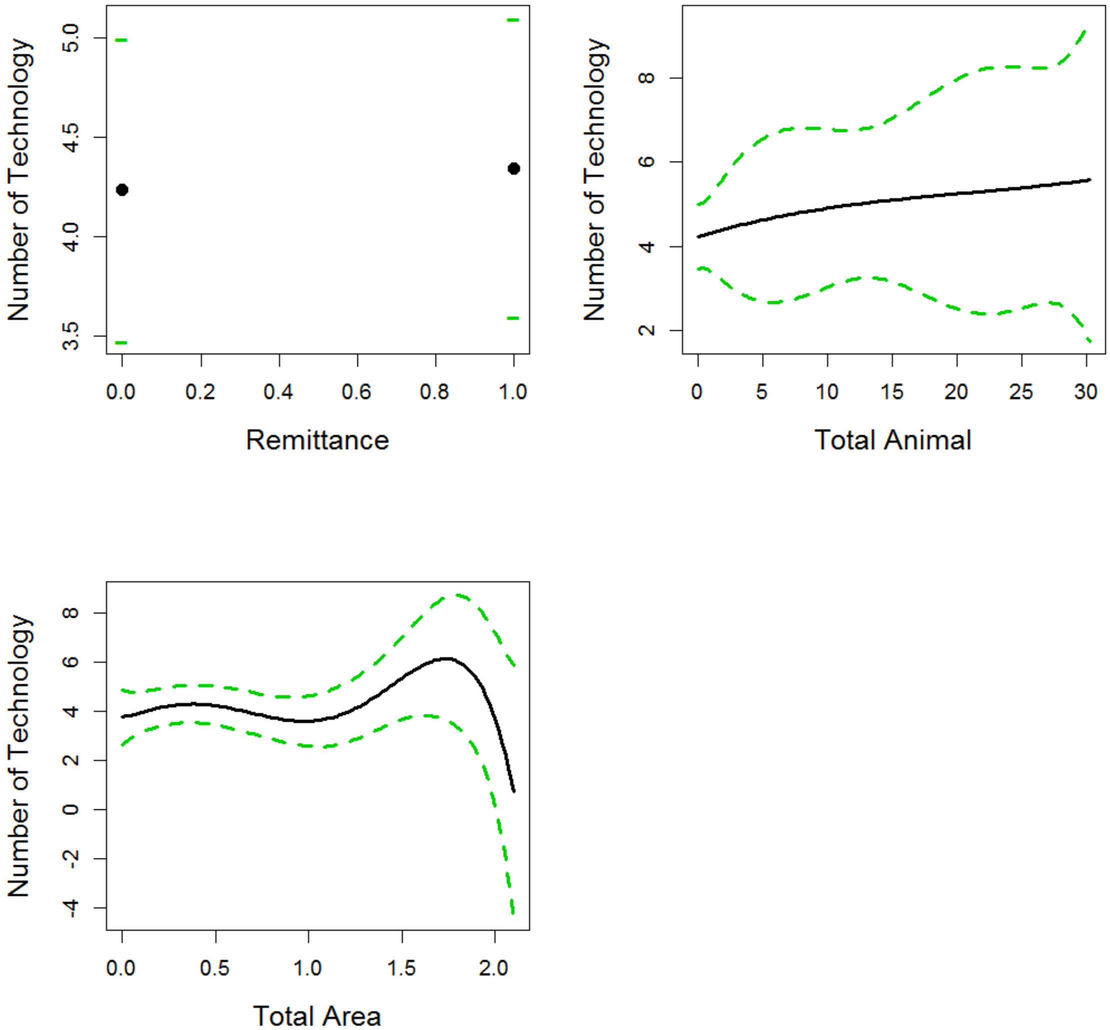

Figure 2: Contd.