Does Extreme Weather Events Impact the Frequency of Loan Take-up by Bangladeshi Households in Vulnerable Communities? An Analysis with Count Data Models.

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Abstract

This paper analyzes whether facing extreme weather events increases the probability of households taking up multiple loans. We test four separate models: (a) Poisson model, (b) Negative Binomial model, (c) Hurdle model and (d) Zero inflated Poisson model. The Zero inflated Poisson model was the most appropriate model to use for the data because of the presence of overdispersion and as well as a very high percentage (about 68%) of zero observations and the fact that the zero observations were both "structural" and due to "sampling". We see that households that face extreme weather events, households that own agricultural or non agricultural enterprises, households with members suffering from chronic illness and those who have faced sudden illness or death of an earning member are all significantly likely to make up multiple loans as predicted by each of the models separately.

Keywords: Paycheck Protection Program

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1 Introduction

Extreme weather events such as heavy flooding, drought, tornadoes or cyclones are phenomenons that adversely impact households in Bangladesh, both in rural and urban areas. The degree to which such an effect is felt increases for households in urban slum areas and households located near the river basins in the rural areas. Meanwhile, some of the adverse impacts of global warming are exacerbating extreme weather events in Bangladesh Shahid et al. (2016) Choi et al. (2021). Coping strategies as a result of such extreme events have been studied before Chowdhury et al. (2020). Extreme weather events usually causes two kinds of hardships for households, the first is the loss of material wealth (in terms of structural damages to households, loss of crops, livestock, other necessities in the household) while the second is the loss of income, as those affected by severe weather tend to be absent from work. This paper tries to understand whether households in Bangladesh that face extreme weather events try to cope with the following financial difficulties by taking up multiple loans. In the next section we briefly discuss the proliferation of micro credit loan providers in Bangladesh alongside those who provide informal loans, a.k.a loan sharks

1.1 Micro credit Institutions and Loan Sharks

Microcredit loans are usually taken up by low income households in Bangladesh that do not have access to private and public commercial banks. These families also tend to take up informal loans from relatives or local money lenders. These same households also face different kinds of insecurities to income due to environmental factors such as flooding, drought, tornadoes and fire.

In many instances, these households tend to take up multiple loans from multiple sources. One caveat of such behaviour is that since these loans are provided at higher interest rates, multiple loans end up as a further financial burden for these households as they have to meet interest payment obligations for each of these loans given limited income and everyday expenses Khandker et al. (2013); Afroze et al. (2014). Supply side issues of multiple loans (density of micro credit institutions and competition among micro credit institutions) have also been studiedMia (2017). There are also demand side factors that affect the number of loans taken up as well such as owning an enterprise, requiring college education, health emergency etc.

2 Models for Count Data

This section provides a detailed overview of each model used in the analysis of the data and lays out the advantages and disadvantages of using each model. Since our response variable is the number of loans taken up by households, we employ count data models for our analysis. The models are: (1) Poisson Model, (2) Negative Binomial Model, (3) Hurdle Model and (4) Zero Inflated Model.

2.1 Poisson Model

Poisson models have been extensively used in the analysis of count data Haberman (1974); Frome et al. (1973); Frome (1983). However, it has also been observed that count data often display substantial extra Poisson variation, also known as overdispersion or underdispersion Lawless (1987a); Cox (1983); Paul and Plackett (1978). The probability density function (pdf) of the Poisson distribution is written:

$$Prob(Y_i = y) = \frac{e^{-\lambda_i}\lambda_i^y}{y!} \tag{2.1}$$

where $y = 0, 1, 2, 3...$ and $\lambda_i > 0$. We introduce the covariates X_i by making them an exponential function of the Poisson parameter:

$$\lambda_i = exp(X_i' \beta) \tag{2.2}$$

This specification ensures that the endogenous variable is nonnegative Zorn (1998). However, in the Poisson model we have:

$$E(Y) = Var(Y) = \lambda \tag{2.3}$$

This restriction does not allow for either overdispersion or underdispersion. More generally, when the variance of the dependent variable Y exceeds its mean, the data are said to be overdispersed and when the converse is true, the data are said to be underdispersed Zorn (1998); Lawless (1987a); Dean and Lawless (1989); Cameron and Trivedi (1986). For more advanced approaches to working with count data using the Poisson model, please refer to Terza and Wilson (1990); Wilson and Einbeck (2018).

2.2 Negative Binomial Model

One way to get around the restriction in the Poisson model is to introduce the Negative Binomial model Engel (1984); Lawless (1987b); Manton et al. (1981). A simple way to think about the negative binomial distribution is to consider the probability that the rth success happens on the $(k + r)th$ coin flip. Therefore we consider:

1. The probability that there are $r - 1$ successes on the first $k + r - 1$ flips, times
2. The probability of success on the $(k + r)th$ flip.

Finally, there are $(k + r - 1)$ choose k orderings for $(r - 1)$ successes and k failure on the first $k + r - 1$ flips. Each has the same probability of occurring. This gives the probability mass function (pmf)Charan (????):

$$P(X=k) = \binom{k+r-1}{k} \cdot p^r \cdot (1-p)^k \tag{2.4}$$

The expectation of the Negative Binomial Distribution is given by:

$$E(X) = \frac{r(1-p)}{p} \tag{2.5}$$

The variance of the Negative Binomial Distribution is given by:

$$Var(X) = \frac{r(1-p)}{p^2} \tag{2.6}$$

Now, letting $\lambda(x) = E(X)$, we get:

$$p = \frac{r}{\lambda(x)+r} \tag{2.7}$$

Putting eq(2.7) in eq(2.4), we get:

$$P(X=k) = \binom{k+r-1}{k} \cdot \left(\frac{1}{1+\frac{\lambda(x)}{r}}\right)^r \cdot \left(\frac{\lambda(x)}{\lambda(x)+r}\right)^k \tag{2.8}$$

Now, letting $\frac{1}{r} = a$ and letting $k = y$, we rewrite eq(2.8):

$$P(X=y) = \frac{\Gamma(y+a^{-1})}{y! \cdot \Gamma(a^{-1})} \cdot \left(\frac{1}{1+a\lambda(x)}\right)^{a^{-1}} \cdot \left(\frac{a\lambda(x)}{a\lambda(x)+1}\right)^y \tag{2.9}$$

where $y = 0, 1, 2..$ and $a \geq 0$ which is referred to as the dispersion parameter Lawless (1987a). The mean and variance of X are:

$$E(X|y) = \lambda(x) \tag{2.10}$$

$$Var(X|y) = \lambda(x) + a \cdot (\lambda(x))^2 \tag{2.11}$$

Finally, the Negative Binomial model can be written as $X \sim NB(\lambda(x), a)$. In the limit that a goes to zero, eq(2.9) denotes the Poisson case Lawless (1987a). The variance-mean relationship in the Negative Binomial model usually represents count data better than the Poisson model as the restriction $E(X) = Var(X) = \lambda$ is relaxed.

2.3 Hurdle Models of Event Counts

When the response variable contains a significant number of zero observations than would be allowed by the Poisson model, another approach used is the Hurdle Model, first proposed by Mullahy in his 1986 paper. The model is also extensively discussed in the Econometrics literature Cameron and Trivedi (2005). The model assumes that a "binary probability model governs the binary outcome of whether a count variate has zero or positive realization." If the count data has a positive realization, "the hurdle is crossed" and then the conditional distribution of the positive counts will be estimated by a "truncated at zero count data model" Mullahy (1986).

Formally, the model combines a count data model $f_{count}(y|x, \beta)$, that is left-truncated at $y = 1$ and a zero hurdle model $f_{zero}(y|z, \gamma)$, that is right-censored at $y = 1$ Zeileis et al. (2008). Therefore $f_{hurdle}(y|x, z, \beta, \gamma)$:

$$f(x) = \begin{cases} f_{zero}(0|z, \gamma) & \text{if y} = 0 \quad (2.12a) \\ \dfrac{(1 - f_{zero}(0|z, \gamma)) \cdot f_{count}(y|x, \beta)}{(1 - f_{count}(0|x, \beta))} & \text{if y} > 0 \quad (2.12b) \end{cases}$$

The corresponding mean regression relationship is given by:

$$log(\mu_i) = x_i^T \beta + log(1 - f_{zero}(0|z,\gamma)) - log(1 - f_{count}(0|x,\beta)) \tag{2.13}$$

It should be noted that one can use the same regressors, $x_i = z_i$ in the count model for both components such that $f_{count} = f_{zero}$. After which a test of the hypothesis $\beta = \gamma$ tests whether the hurdle is needed or not Zeileis et al. (2008).

2.4 Zero-inflated Poisson model

Another model which is able to deal with a excess of zeros in the dependent variable is the Zero-inflated model Mullahy (1986); Lambert (1992). These consist of two component mixture models that combine a point mass at zero with a count distribution such as Poisson or Negative binomial. The primary difference between the Hurdle models and the Zero-inflated models are that the Hurdle model assumes that the zero arises from a different data generating process whereas in the Zero-inflated models zeros may come from both the point mass and the count component Zeileis et al. (2008). The zero-inflated density is a mixture of a point mass at zero $I_0(y)$ and a count distribution $f_{count}(y|x,\beta)$ Zeileis et al. (2008). The probability of observing a zero count is demonstrated with probability π where $\pi = f_{zero}(0|z,\gamma)$:

$$f_{zeroinf}(y|x,z,\beta,\gamma) : f_{zero}(0|z,\gamma) \cdot I_0(y) + (1 - f_{zero}(0|z,\gamma)) \cdot f_{count}(y|x,\beta) \tag{2.14}$$

The corresponding mean regression equation is Zeileis et al. (2008):

$$\mu_i = \pi_i \cdot 0 + (1 - \pi_i) \cdot exp(x_i^T \beta) \tag{2.15}$$

3 The Data

As mentioned in the introduction, this paper examines whether extreme weather (or environmental) shocks (such as seasonal excess flooding, drought, tornadoes and fire) lead to households taking up multiple loans from lending institutions or individuals (in case of loan sharks). We examine data from 45,785 households surveyed in the year 2014-2015. The response variable is the number of loans that each household has taken up the year preceding the survey. From the data set, we observe data regarding each loan that the household has taken up even if they are from the same institution.

The explanatory variables are whether the household faced any extreme weather event(floods, drought, tornadoes, fire), whether the household owns any agricultural enterprise (or asset), whether the household owns any non-agricultural enterprise (or asset), if there are any other chronic illness within the household, any other shock (such as sudden sickness or death of primary earner) experienced in the preceding year, total expenses on education, total expenses on health care and household monthly income. All these variables are based on the 12 months preceding the survey. A description of the variables are given in Table 1.

3.1 Distribution of response variable

Figure 1 provides the distribution of the number of loans in terms of the relative frequency of households. From the data, we see that there are 31,221 households who have not taken up any loan in the preceding year of the survey, 11,672 households have taken up one loan and 2252 households have taken up two loans and the rest 638 households have taken up at least 3 loans.

3.2 Summary of the variables

A brief summary of the explanatory and response variables are provided in Table 2. We see from the data that facing extreme weather events, owning agricultural assets, owning non agricultural assets, chronic illness and facing sudden illness or death are discrete variables whereas health expenditure, education expenditure and monthly income are continuous variables. The expenditure and income values are calculated using the Bangladeshi currency, Taka where 1 USD = 87 TakaExc (????).

4 Empirical Results

In this section, we provide a full explanation of our results. We test two Poisson and two Negative Binomial models, two restricted models with the variables health expenditure, education expenditure and monthly income jointly excluded and two unrestricted models which include the mentioned variables. An LR test confirms that the restricted model fits as well as the unrestricted model in both cases.

4.1 Restricted Poisson and Negative Binomial Models

The coefficients and the average marginal effects of the restricted Poisson and Binomial models are shown in the Table 3. An additional extreme weather event increased the probability of multiple loans by 3.33 percent in the Poisson model. An additional agricultural asset and an additional non-agricultural asset increased the probability of multiple loans by 2.63 percent and 14.81 percent respectively. Similarly, chronic illness and sudden illness or death of primary earner increased the probability of multiple loans by 5.27 percent and 14.16 percent respectively, also in the Poisson model. Almost identical average marginal effects are shown in Table 3 for the restricted Negative Binomial model.

4.2 Unrestricted Poisson and Negative Binomial Models

We also test the unrestricted Poisson and Negative Binomial models. Health expenditure does appear to be a significant coefficient at the 5% level. Although the joint effect of health expenditure, educational expenditure and monthly income appear not to be significant. The coefficients of the unrestricted models and the average marginal effects are provided in Table 4.

An additional extreme weather event increased the probability of multiple loans by 3.4 percent in each model. An additional agricultural asset and an additional non-agricultural asset increased the probability of multiple loans by 2.60 percent and by 14.82 percent respectively in the Poisson model. Similarly, chronic illness and sudden illness or death of primary earner increased the probability of multiple loans by 5.11 percent and 13.71 percent respectively in the Poisson model. Even though health expenditure was statistically significant, it increased the probability of multiple loans by only 0.00028 percent, which is a negligible amount. Interestingly, educational expenditure of the households or average monthly income showed no significance in the unrestricted Poisson model. Almost identical average marginal effects are also shown in Table 4 for the unrestricted Negative Binomial model.

An LR test between the restricted and the unrestricted Poisson models gives a χ^2 statistic of 4.33. Similarly, an LR test between the restricted and the unrestricted Negative Binomial models gives a χ^2 statistic of 4.53. Given the three degrees of freedom, we fail to reject the restricted models in each case. This has implications when we will test a Zero Inflated Poisson using the restricted model. We also do a simple overdispersion test, implemented in R, as specified by Cameron and Trivedi (1990) and we see that we cannot rule out overdispersion. The dispersion value was 1.095242 with a p-value less than 2.16×10^{-16}.

4.3 Hurdle Model

We manually fit a Hurdle model. The Zero Hurdle model is estimated using a Probit model where as the Count model is estimated using a left truncated Poisson model. The coefficients and the average marginal effects of the Hurdle model are provided in Table 5.

An additional extreme weather event increased the probability of taking up a loan by 3.14 percent in the Zero hurdle model, very similar to the Poisson and the Negative Binomial models. However, an additional extreme weather event did not affect the probability of multiple loans in the Count model, which was very different from the models we tested before. An additional agricultural asset and an additional non-agricultural asset increased the probability of taking up a loan by 1.61 percent and 11.12 percent respectively in the Zero Hurdle model and 3.93 percent and 14.07 percent respectively in the Count Hurdle model. Similarly, chronic illness or sudden illness or death of primary earner increased the probability of taking up a loan by 3.53 percent and 9.98 percent respectively in the Zero Hurdle model and by 6.10 percent and 13.71 percent respectively in the Count Hurdle Model.

Even though educational expenditure was statistically significant, it decreased the probability of taking up a loan by only 0.0003 percent in the Zero Hurdle model. Whereas, in the Count Hurdle model, health and educational expenditure increased the probability of multiple loans by only 0.0007 and 0.002 percent respectively, which are negligible amounts.

4.4 Zero Inflated Poisson Model

We finally test a Zero Inflated Poisson model. We could not test the unrestricted model for the Count portion due to convergence issues, therefore the count model is estimated without the variables health expenditure, education expenditure and monthly income. As a result, we test both the restricted and the unrestricted Poisson and Negative Binomial models using Likelihood Ratio and show that we fail to reject the restricted model in either case.

Unfortunately, we also could not carry out the average marginal effects for this model as a suitable R package was not available at the time of writing the paper. However, from the results we see that an additional extreme weather event had a significant impact for both the Count model and the Zero inflated model, meaning that an additional extreme weather event impacted both the probability of taking up a loan as well as the probability of taking up multiple loans. However, to what degree the probability is affected is uncertain due to the unavailability of a suitable "margins" package for the Zero Inflated Poisson model in R. The coefficients of the Count model and the Zero Inflated model are shown in Table 6.

4.4.1 Zero-Inflated Poisson vs Hurdle Models

A significant difference between the Zero-Inflated Poisson and Hurdle models are discussed by Hu et al. (2011); Rose et al. (2006). A zero-inflated model assumes that the zero observations have two different origins: “structural” and “sampling”, in other words, we may have some zero observations because some households never took any loans whereas some other zero observations may be due to households who have taken up a loan (or loans)in the past however, they took none in the preceding 12 months of the survey.

In contrast, a hurdle model assumes that all zero data are from one “structural” source, in other words, it assumes that if a household shows that they have taken zero loan, they have never taken up a loan. It is obvious that our model fits the assumptions of the zero-inflated model rather than the hurdle model because it is more likely that the households in our sample that seem to have taken zero loans either may never have taken up a loan or simply did not take up a loan in the past twelve months.

4.5 Some characteristics of the Poisson, Negative Binomial, Zero-Inflated and Hurdle Count Models

From Table 7 in Appendix A we see that the fit of the Poisson, Negative Binomial and Zero-inflated models are comparable although the Zero-inflated model provides the best fit after the Hurdle Count model. We also compare how each of the models accurately predict the true number of zero observations in the data except for the Hurdle Count model. The Poisson model underestimates the zero observations whereas the Negative Binomial model overestimates the zero observations. The Zero-inflated Poisson model is the closest to the actual number of zero observations.

5 Conclusion

In this paper we analyze whether households facing extreme weather events increase their probability of taking up multiple loans. The other explanatory variables we considered are whether the household owns any agricultural enterprise, whether the household owns any non-agricultural enterprise, whether any other chronic illness exists within the household, whether any other shock (such as sudden sickness in the household or death of primary earners) is experienced, total expenses on health care, total expenses on education and household average monthly income, all measured in the preceding 12 months of the survey. We test four separate models: (1) Poisson model, (2) Negative Binomial model, (3) Hurdle model and (4) Zero inflated Poisson model. The Zero Inflated Poisson model turned out to be the most appropriate model to use for the data because of the presence of overdispersion and as well as the presence of a high percentage (about 68%) of zero observations. We also show that our data contains both ”structural” and ”sampling” zero observations. We see that households that face extreme weather events, households that own agricultural or non-agricultural enterprises, households with members inflicted with chronic illness and those who have faced sudden illness or death of an earning member are all significantly likely to make up multiple loans as predicted by each of the models separately.

Only the Hurdle count model fails to give any significance to the fact that households that are facing extreme weather events are likely to take up more than one loan. However, we have also discussed how the Zero Inflated Poisson model is more appropriate for the data compared to the Hurdle model. In the Zero Inflated model we see that the likelihood of taking up multiple loans and taking up a loan increases when households face extreme weather events.

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Table 1: Description of Data

Variables	Definition
No. of loans	The total number of loans taken up by the household
No. of extreme weather events	The total number of extreme weather events faced by household
Agricultural Asset	Number of agricultural enterprise owned by household
Non-agricultural Asset	Number of non-agricultural enterprise owned by household
Chronic illness	Whether the household has someone who suffers from chronic illness
Faced illness or death	Sudden major illness or death of primary earner
Health expenditure	Total expenses on health
Education expenditure	Total expenses on education
Monthly Income	Average monthly income of household

Table 2: Brief summary of response and explanatory variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Faced extreme weather	45,785	0.121	0.367	0	0	0	4
Owns Agricultural asset	45,785	0.249	0.540	0	0	0	6
Owns Non-agricultural asset	45,785	0.214	0.469	0	0	0	5
Chronic illness	45,785	0.733	0.916	0	0	1	12
Faced illness or death	45,785	0.018	0.139	0	0	0	3
Health expenditure	45,785	674.264	1,729.480	−135.800	83.300		116,591.700
Education expenditure	45,785	787.972	1,797.458	0.000	0.000	906.700	105,541.700
Monthly income	45,785	15,721.660	50,340.460	−1,107,087	7,300	18,250	4175,607
Number of loans	45,785	0.400	0.672	0	0	1	8

Table 3: Coefficients and Average Marginal Effects of the restricted Poisson Model and Negative Binomial Model

	Dependent variable:			
	Number of loans			
	(P.Coeff)	(P.dF/dx)	(NB.Coeff)	(NB.dF/dx)
Faced extreme weather	0.084***	0.033***	0.084***	0.033***
	(0.019)	(0.008)	(0.020)	(0.008)
Owns agricultural asset	0.066***	0.026***	0.067***	0.027***
	(0.013)	(0.005)	(0.014)	(0.006)
Owns non-agricultural asset	0.371***	0.148***	0.379***	0.152***
	(0.013)	(0.005)	(0.014)	(0.006)
Chronic illness	0.132***	0.053***	0.135***	0.054***
	(0.007)	(0.003)	(0.008)	(0.003)
Faced illness or death	0.354***	0.142***	0.358***	0.143***
	(0.040)	(0.016)	(0.043)	(0.017)
Constant	−1.157***		−1.163***	
	(0.011)		(0.012)	
Observations	45,785	45,785	45,785	45,785
Log Likelihood	−37,430.730	−37,430.730	−37,345.220	−37,345.220
θ	–	—	4.740*** (0.409)	4.740*** (0.409)
Akaike Inf. Crit.	74,873.460	74,873.460	74,702.450	74,702.450
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4: Coefficients and Average Marginal Effects of the unrestricted Poisson model and Negative Binomial model

	Dependent variable:			
	Number of Loans			
	(P. Coeff)	(P. dF/dx)	(NB. Coeff)	(NB. dF/dx)
Faced extreme weather	0.084***	0.034***	0.084***	0.034***
	(0.019)	(0.008)	(0.020)	(0.008)
Owns agricultural asset	0.066***	0.026***	0.066***	0.026***
	(0.013)	(0.005)	(0.014)	(0.006)
Owns non-agricultural asset	0.370***	0.148***	0.378***	0.151***
	(0.013)	(0.005)	(0.014)	(0.006)
Chronic illness	0.129***	0.051***	0.132***	0.053***
	(0.007)	(0.003)	(0.008)	(0.003)
Faced illness or death	0.344***	0.137***	0.347***	0.139***
	(0.041)	(0.016)	(0.044)	(0.018)
Health expenditure	0.00001**	0.000003**	0.00001**	0.000003**
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Education expenditure	0.00000	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Monthly income	−0.00000	−0.000	−0.00000	−0.000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Constant	−1.160***	–	−1.165***	–
	(0.012)		(0.012)	
Observations	45,785	45,785	45,785	45,785
Log Likelihood	−37,428.560	−37,428.560	−37,343.070	−37,343.070
θ	–	—	4.739*** (0.409)	4.739*** (0.409)
Akaike Inf. Crit.	74,875.120	74,875.120	74,704.140	74,704.140
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 5: Coefficients and Average Marginal Effects of the Zero and Count Hurdle models

	Dependent variable:			
	Number of loans			
	(Z. Coeff)	(Z. dF/dx)	(C. Coeff)	(C. dF/dx)
Faced extreme weather	0.088***	0.031***	-0.0498	-0.0235
	(0.017)	(0.006)	(0.026)	(0.011)
Owns agricultural asset	0.045***	0.016***	0.0832**	0.039**
	(0.011)	(0.004)	(0.029)	(0.007)
Owns non-agricultural asset	0.317***	0.111***	0.297***	0.1407***
	(0.013)	(0.004)	(0.025)	(0.010)
Chronic illness	0.099***	0.035***	0.129***	0.061***
	(0.007)	(0.002)	(0.015)	(0.002)
Faced illness or death	0.281***	0.098***	0.290***	0.137***
	(0.043)	(0.015)	(0.069)	(0.021)
Health expenditure	0.00000	0.00000	0.00002***	0.000007***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Education expenditure	−0.00001**	−0.000003**	0.00004***	0.000016***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Monthly income	−0.00000	−0.00000	0.00004***	0.000016***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Constant	−0.642***		−1.046***	
	(0.009)		(0.009)	
Observations	45,785	45,785	45,785	45,785
Log Likelihood	−28,131.960	−28,131.960	−9216.7975	−9216.7975
Akaike Inf. Crit.	56,281.920	56,281.920	17,281.920	17,281.920
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6: Coefficients of the Zero and Count Inflated Poisson Model

	Dependent variable:	
	Number of loans	
	(Z. Coeff)	(C. Coeff)
Faced extreme weather	-0.4440^{*}	0.066^{***}
	(0.256)	(0.020)
Owns agricultural asset	-0.4061^{*}	0.057^{***}
	(0.192)	(0.014)
Owns non-agricultural asset	-118.6^{***}	0.319^{***}
	(14.49)	(0.013)
Chronic illness	0.1404	0.131^{***}
	(0.091)	(0.007)
Faced illness or death	0.1893	0.350^{***}
	(0.556)	(0.041)
Health expenditure	-0.0003^{***}	–
	(0.000)	
Education expenditure	-0.2187^{***}	–
	(0.0152)	
Monthly income	-0.0003^{***}	–
	(0.000)	
Constant	1.402^{***}	-1.080^{***}
	(0.012)	(0.012)
Observations	45,785	45,785
Log Likelihood	−37,099.680	−37,099.680
Note:	*p<0.1; **p<0.05; ***p<0.01	

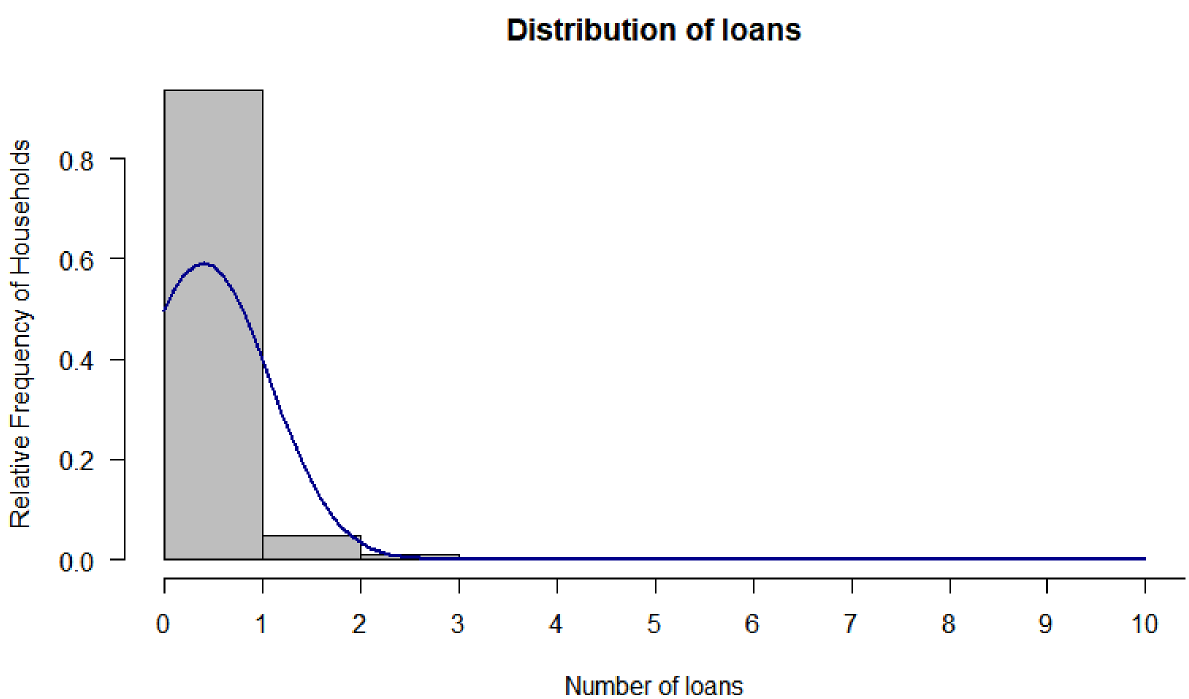

Figure 1: Number of loans in terms of frequency of households

Appendix A: Supplementary Files

Some characteristics of the Poisson, Negative Binomial and the Zero-Inflated Model

Table 7: Log Likelihood values and number of zero observations predicted by the Poisson, Negative Binomial, Zero Inflated and Hurdle Count Models

	Data	Poisson	Negative Binomial	ZIP	Hurdle Count
Log likelihood	—	−37429	−37342	−37100	−9216.798
DF	—	9	10	15	14555
No.	31221	30892	31391	31036	—