

Available online at www.jeeir.com

Journal of Emerging Economies and Islamic Research

Journal of Emerging Economies & Islamic Research 6(2) 2018, 47-61.

Determination of poverty among the poor and needy in a developing country

Ahmad Fahme Mohd Ali*, Mohd Faisol Ibrahim

Faculty of Economic and Muamalat, Universiti Sains Islam Malaysia

ARTICLE INFO

Article history: Received 17 April 2018 Received in revised form 8 May 2018 Accepted 12 May 2018 Published 31 May 2018

Keywords: Zakat Poverty Logistic regression Malaysia

ABSTRACT

This article attempts to analyse the determination of poverty among the poor and needy of the zakat recipients in Kelantan, Malaysia. The study is motivated from the Kelantan zakat collection (2003-2015) that suggests that the growth alone (high collection) is not enough to eliminate poverty, there are indeed, other elements of poverty eradication like the socio economic, demographic factors, remittances and the investments in social and economic factors like the food subsidy for the poorest, good quality education, opportunities for the most needy, regulation of job markets, and purposively designed social security nets also have significant impact on permanent reduction in poverty. In Kelantan, despite zakat centres having disbursed an increasing amount of expenditure annually on the two categories of zakat recipients, hitherto the number of fuqara (poor) and masakin (needy) households is still increasing (MAIK, 2014; JAWHAR, 2012). Thus, it is important to understand the nature and scale of poverty, the various driving forces that affect it and the determinants of poverty among the poor and needy as linked to this process. A sample of 505 households from 2016 Household Expenditure Survey (HES) among the poor and needy zakat recipients in Kelantan has been used in this study. The findings have important policy implications for Kelantan Zakat Department (MAIK) in making the zakat distribution becomes more efficient and uplift the important role of zakat as one of the poverty alleviation tools among the Muslims. This study recommends the method of zakat distribution should be improved and channelled accordingly in order to strengthen the Muslims economy condition and then, it would facilitate the poverty alleviation programmes by the zakat department.

1. Introduction

A well-constructed poverty line enables policy makers to map the poverty profile in order to identify the pattern of poverty but it would not explain the causes of poverty. For policy implementation it is important for policy makers to understand the causes of poverty at household and individual levels,

^{*} Corresponding author. E-mail address: ahmadfahmee@gmail.com

especially among the poor and needy (Mok et. al, 2007). The most common type of measuring relation between the dependent variable (DV) and the independent variable (IV) that the researchers choose to evaluate the linear regression. Linear regression produces a mathematical equation (or "model") for a "best fit" line to describe the relation.

However, the reliability of the regression in estimating the determinants of poverty has been questioned. The crucial limitation of linear regression is that it cannot deal with DV that are dichotomous and categorical. Many interesting variables in the business world are dichotomous: for example, consumers make a decision to buy or not to buy, a product may pass or fail quality control, there are good or poor credit risks, an employee may be promoted or not. Gaiha (1988) proved that the income or expenditure distribution data often contain non-negligible errors. Diamond et al. (1990) demonstrated that the restrictions imposed by the regression may result in a poor fit of the distribution. Grootaert (1997) argued against the assumption made by the regression. As it imposes constant parameters over the entire distribution, it assumes that the impact of the independent variables on welfare is constant over the distribution. Thus, the poor are assumed to be not fundamentally different from their richer counterparts, which were viewed as not tenable by Grootaert. Another complication which could arise is from the selection of independent variables which are endogenous. For example, if per capita income is used together with education and the like as independent variables, income could be determined by education level and vice versa. Thus, the selection of the variables is crucial to avoid such complications.

Alternatively, binary response models have been initiated by Bardhan (1984) as a better measurement of the determinants of poverty and have been widely used (Egondi et al, 2015; Ranathunga, 2015; Alderman & Garcia, 1993; Gaiha, 1988; Grootaert, 1997; Lanjouw & Stern, 1991; Rodriguez & Smith, 1994; Serumaga Zake & Naude, 2002; Thompson & McDowell, 1994; Ntuli, 2007). This model collapses the distribution into two values; poor or non-poor. It is estimated by probit or logit, assuming a normal or logistic distribution of the error term, respectively. Diamond et al. (1990) extended the analysis by using a multinomial logit model to predict the probability of belonging to an income quintile. Grootaert (1997) supported the use of this method if the income groups of interest are not equal in size.

In multiple regression models, real household expenditure per capita is commonly chosen as the dependent variable with exogenous household characteristics mentioned above as independent variables in a reduced form regression equation (Glewwe, 1991; Mukherjee & Benson, 2003). This follows the standard household utility maximisation model where household expenditure serves as a basis to rank households and to define a poverty line (Deaton & Muellbauer, 1980). Logistical regression is regularly used rather than discriminant analysis (DA) when there are only two categories of the dependent variable (1 poor, 0 not poor). Logistic regression is also easier to use with SPSS than DA when there is a mixture of numerical and categorical Independent Variables (IV), because it includes procedures for generating the necessary dummy variables automatically, requires fewer assumptions, and is more statistically robust. DA strictly requires the continuous independent variables (though dummy variables can be used as in multiple regressions). Thus, in instances where the independent variables are categorical, or a mix of continuous and categorical, and the DV is categorical, logistic regression is necessary.

The binomial distribution is used when there are exactly two mutually exclusive outcomes of a trial. These outcomes are appropriately labelled "success" and "failure". The binomial distribution is used to obtain the probability of observing x successes in N trials, with the probability of success on a single trial denoted by p. The binomial distribution assumes that p is fixed for all trials. Since the dependent variable is dichotomous which there are only two values to predict: that probability (p) is 1 rather than 0, that is, the event/person belongs to one group rather than the other. The logistic regression forms a best fitting equation or function using the maximum likelihood method, which maximises the probability of classifying the observed data into the appropriate category given the regression coefficients. Like ordinary regression, logistic regression provides a coefficient 'b', which measures each IV's partial contribution to variations in the DV. The goal is to correctly predict the category of outcome for individual cases using the most parsimonious model. There are two main uses of logistic regression:

1. The first is the prediction of group membership. Since logistic regression calculates the probability of success over the probability of failure, the results of the analysis are in the form of an odds ratio (Pallant, 2013; Field, 2012)

2. Logistic regression also provides knowledge of the relationships and strengths among the variables (e.g. marrying the boss's daughter puts you at a higher probability for job promotion than undertaking five hours' unpaid overtime each week) (Pallant, 2013; Field, 2012)

Furthermore, the use of poverty maps is important tools that provide information on the spatial distribution of poverty within a country. They are used to affect various kinds of decisions, ranging from poverty alleviation programmes to emergency response and food aid. However, the use of poverty maps alone does not furnish an estimate of the causal linkage between poverty and the variables influencing it; such maps furnish only "visual" advice. For this reason, researchers usually look for the possible existence of empirical relationships between poverty and socio-economic indicators. They make use of statistical methods such as the econometric model that combines census and survey data as applied in South Africa and Ecuador (Hentschel et al., 2000).

Most of previous studies have used income to identify poor households. We have two problems with this procedure. First, the official poverty line in Malaysia is consumption expenditure. Secondly, data on household incomes are known to be less reliable than consumption data obtained from household expenditure surveys. We therefore compare a person's consumption expenditure with the poverty line to determine its poverty status. This agrees with the idea that poverty is the inability to attain a critical minimum amount of consumption. We study the effect of human capital, region of residence and other household characteristics on urban poverty using this benchmark.

Findings from the Kelantan zakat collection (2003-2013) suggest that growth alone (high collection) is not enough to eliminate poverty (Ali et al., 2014). There are indeed, other elements of poverty eradication like the socio economic, demographic factors, remittances and the investments in social and economic factors like the food subsidy for the poorest, good quality education, opportunities for the neediest, regulation of job markets, and purposively designed social security nets also have significant impact on permanent reduction in poverty (Krishna, 2005). Further, the use of poverty maps is important tools that provide information on the spatial distribution of poverty within a country. They are used to affect various kinds of decisions, ranging from poverty alleviation programmes to emergency response and food aid. However, the use of poverty maps alone does not furnish an estimate of the causal linkage between poverty and the variables influencing it; such maps furnish only "visual" advice. For this reason, researchers usually look for the possible existence of empirical relationships between poverty and socio-economic indicators. They make use of statistical methods such as the econometric model that combines census and survey data as applied in South Africa and Ecuador (Hentschel et al., 2000).

2. Methodology

2.1 Data

This study utilises the Household Expenditure Survey (HES) which was collected between June 2016 and December 2016. The reference groups for this study are the zakat recipients in Kelantan. There are ten districts in Kelantan, namely Kota Bharu, Pasir Mas, Tumpat, Bachok, Pasir Putih, Tanah Merah, Kuala Krai, Gua Musang, Machang and Jeli. For this study we used the monthly expenditure to analyse the monthly effect of zakat distribution. In order to solve the recall problem, respondent were requested to participate every two weeks, that is, two times for one month full cycle. The optimal length of the diary keeping period has received a lot of attention (Kemsley, 1961; Kemsley and Nicholson, 1960; Lewis, 1948; Sudman and Ferber, 1971; Turner, 1961). It has been found that reporting is generally higher at the outset, and declines after 2-3 weeks. At that point, cooperation has become difficult to maintain, so most authors recommend two to three weeks as the optimal record keeping period. As a rule, households were asked to participate in the HES by filling out daily expenditure records for a period of two weeks, that is, for one entire cycle.

The stratified multi-stage probability (proportional to the households and collector's districts) sampling procedure was followed for selecting the households, who were interviewed evenly throughout the survey. A set of questionnaire was set as a survey module. The target population was the zakat

recipients of the MAIK from the Fuqara (Poor) and Masakin (Needy) categories. There are five major parts of the questionnaire.

The *first part* (Part A) is on the background, size and basic information of the head of households and their household's members. This includes the gender, relation to the head of household, marital status, and occupation of all the household members. Household size and number of dependents of the household's head are also asked in this part. The second part (Part B) is on the sources of monthly household's income. Sources of income are divided into four, i.e. income from wages or salary, transfer payment and contribution from others (such as their relatives), income from property, and income from any economic activities. To get the amount of total household income, all types of income of all the household members are transformed into money value. The third part (Part C) is on monthly food and non-food expenditure of household. Expenditure data for food are acquired from two sources: (First) food purchases, including food purchased and (Second) consumed away from home. To calculate daily energy availability for a household, the quantities of each food item are first converted to kilocalorie values using conversion tables. The kilocalorie values are then summed and divided by the number of days in the reference period. This figure is then divided by the number of people or adult-equivalent persons living in the household in order to assess the sufficiency of available energy to meet the dietary needs of household members. The non-food expenditure are collected on non-food acquired from nine sources (EPU, 2006): (1) Housing, including household utilities and housing contents and services; (2) Clothing and Foot wear; (3) Medical; (4) Transportation; (5) Education; (6) Religious; (7) Miscellaneous goods and services, including recreation and insurance; and (8) Other Expenditure, including other payment, saving, fines and money given to others. The fourth part (Part D) is details on job involvement, the level of nutrition and health of the household head which will only focussed on the household head. It includes the number of different type work per week, number days of working, number working off days, type of nutrition and health condition of the household and medical insurance of the family.

2.2 Sample Selection

Samples selection ranged 68 percent (344) for urban and 32 percent (161) for rural area. Based on gender of the respondent, the female headed household represent 45 per cent (227 families) while male headed household represent 55 per cent (278 families) so, giving a total of 505 respondents. Generally, from the household unit, 201 (54 per cent) respondents were drawn from urban female headed household and 174 (46 per cent) are rural female headed household. The remaining 130 household unit come from male urban (70 families) and male rural (60 families).

2.3 Model Specification

This article adopts the current zakat poverty line for household head as reference group, the per capita zakat poverty line estimated for Kelantan is MYR 297. The dependent variable is dichotomous; 0 when a household is above (not poor) and 1 when below the poverty line (poor). Predictor variables are a set of socioeconomic and demographic status indicators and the dwelling endowment of the household. They contain both dichotomous and continuous variables. The predicted dependent variable is a function of the probability that a particular subject will be in one of the categories. It contains both dichotomous and continuous variable in the form of binary (1 and 0) and most of the independent variables are used in form of dummy variables, therefore it is appropriate to estimate all variables using logistic regression models. The model is generally estimated as follows:

$$y_i = \beta x_i + \mathcal{E}_i \tag{1}$$

where y_i denotes per capita expenditure for household *i*; β is the vector of parameters to be estimated; x_i is the vector of household characteristics; and ε_i is the error term. The binary variable is defined as:

$$P_i = 1$$
 if $y_i \le z$; $P_i = 0$ otherwise (2)

where z denotes the poverty line. The binary model is:

$$Prob (P_i = 1) = F (z - \beta x_i)$$
(3)

where F represents the cumulative probability function. Where;

$$Log P(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n$$
(4)

Which;

$$Y = \left[\frac{probability(choose)}{probability(not - to - choose)}\right] = P_i / (1-P_i)$$
(5)

 β_0 =constant

 $\beta_1, \beta_2, \beta_3, \ldots, \beta_n$ = parameter of the variables

This means that the logistic coefficient could be described as a change in the form of the log 'odds' as a result of unit change in independent variables. Equation (5.0) above may be simplified to be restated as:

$$Y = \left[\frac{probability(choose)}{probability(not - to - choose)}\right] = P_i / (1 - P_i) = e^{\beta 0 + \beta 1 X1 + \beta 2 X2 + ... + \beta n Xn}$$
(6)

If the value of β_1 is positive then the odds ratio would increase if X_i increases. But if β_1 is negative, the odds ratio would reduce if X_i declines. The logistic regression defines the log odds of the event (poverty) occurring. The general equation for the logistic regression may be written in the form of:

$$\ln (\text{Odds}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \epsilon$$
(7)

Where ln (Odds) is the natural log of the odds, and its quantity is called a *logit*. On the right-hand side of the equation (7.0) are the standard linear regression terms of the independent variables and the intercept. The logistic regression equation can be expressed as the following equation:

$$P(Y) = \frac{1}{(1 + e^{-z})}$$
(8)

where:

P(Y) is the probability of the event (poverty) occurring

 $\begin{aligned} z &= \beta o + \beta_1 X_1 + \beta_2 X_2 + \dots \beta n Xn + \epsilon \\ e &= 2.71828 \text{ (the base of natural logarithms)} \\ \epsilon &= \text{error term} \end{aligned}$

Let P_j denote the probability that the j-th household is below the poverty line. We assume that P_j is a Bernouli variable and its distribution depends on the vector of predictors X, so that:

$$P_j(X) = \frac{e^{\alpha + \beta X}}{1 + e^{\alpha + \beta X}}$$
(9)

where β is a row vector and α a scalar. The logit function to be estimated is then written as

$$\ln \underline{Pj}_{1-P_j} = \alpha + \sum_{i} \beta_i X_{sj} \tag{10}$$

The logit variable $\ln \{P_j/(1-P_j)\}$ is the natural log of the odds in favour of the household falling below the poverty line. Equation (10.0) is estimated by maximum likelihood method and the procedure does not require assumptions of normality or homoskedasticity of errors in predictor variables. The regression technique in this study will allow us to isolate and compare the influence of zakat and any demographic variable on household's poverty status, while holding other determining variables constant. Using this technique, we estimate the impact of demographic, human capital and resources variables of the poor and needy among the zakat recipients in Kelantan. By showing which characteristics have the largest impact on determine the causes of poverty and how much does the impact give among the poor and needy, we can identify household types that could merit special attention in designing strategies to increase the effectiveness of welfare enhancing programmes.

The Wald test or also known as the F test is used to test the significance of the estimated parameters at 10 per cent level. If the Wald test shows that the estimated parameters are not significant, then the determinant variables would be practically worthless to be used to describe the model. Efficient model gives a value of F* which is greater than the critical value of F at α significance level, degrees of freedom (k-1) and (nk) which n is the number of observations and k is the number of parameters in the model. It is shown in equation (11.0), namely:

Wald test =
$$\frac{R^2 / k - l}{1 - R^2 / n - k} \sim F_{k-1, n-k, \alpha, \alpha} = 5\%$$
 (11)

Logistic regression methods of analysis allow the use of a mix of continuous and categorical predictor variables to explain a categorical outcome or dependent variable. When the variables are categorical, the use of logistic regression is useful for locating explanations between variables (Stearns et al., 1995). The main objective of logistic regression is to attain the highest predictive accuracy possible with the given set of predictors (Hair, 1995). The principle of logistic regression is to express the multiple linear regression equation in logarithmic terms and thus overcome the problem of violating the assumption of linearity. The values of the parameters are estimated using the maximum-likelihood method, a technique where coefficients that make the observed values most likely to have occurred are selected.

Household unit has become the unit of observation for this study. A household may be either a oneperson household or a multi-person household. The households can be defined as an arrangement where all the activities and cooperation centre round the members living in the same household. The head of household/family regardless of sex is considered as the respondents. Each household/family is registered zakat recipient under the poor and needy category. In certain exceptional cases, some other responsible member of the family (usually the wife) will be used as a respondent to replace the absentee head (usually the husband) of the household or the family.

2.4 Dependent Variable Measures

Income of the poor and needy is selected as the dependent variable for this study. Based on current zakat poverty line for household head as reference group, the per capita zakat poverty line estimated for Kelantan is MYR 297. The dependent variable is dichotomous; 0 when their income is above and 1 when below the zakat poverty line. To enable these qualitative measures to be regressed in multivariate regression technique, logistic regression methods were used.

2.5 Independent Variable Measures

Generally, the determinants are grouped into three categories: household demographic, socioeconomic, human capital and regional variables. Below are the detailed definitions and descriptions of the independent variables used in the poverty regression. Where:

=	age of household head (in years)
=	1 if household is male, 0 otherwise,
=	size of household
=	1 if household head did not has partner, 0 otherwise,
=	1 if household live in urban area, 0 otherwise,
=	highest formal education obtained by household head (in
	years),
=	1 if working 8 hours per days, 0 otherwise,
=	1 if working 5 days per week, 0 otherwise,
=	1 if headed of the household is health, 0 otherwise,
=	1 if female adults is higher, 0 otherwise,
=	total of zakat received,
=	total income received

The model is estimated using the expenditure cut off point corresponding to Kelantan's official zakat poverty line: per household consumption expenditure of MYR 297. This forms a benchmark. Demographic variables of the respondent are measured size, region, household head gender, age, household head marital status and number of male/female adults in family. Human capital is measured by education level, working hours, number of job and household head health status. Dummy variables have been used for gender, regions, marital status, number of male/female adults in family, working hours, working days, and household head health status. Therefore, according to equation (4.10), the specific model estimated in this study is:

$$L = In (Pi / (1-Pi) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_{6+} \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9$$
(12)
+ $\beta_{10} X_{10} + \beta_{11} X_{11} + \beta_{12} X_{12}$

Where;

L is the log ratio of 'odds' of becoming poor; 0 when their income is above poverty line (not poor) and 1 when below the zakat poverty line (poor).

X₁ is age of household head (in years)

 X_2 is the gender of the household head; dummy = 0 if household head is female, 1 otherwise

X₃ is size of family

 X_4 is marital status of household head; dummy = 0 if household head did not has partner, 1 otherwise

 X_5 is region of the family; dummy = 0 if household live in rural area, 1 otherwise

X₆ is highest formal education obtained by household head (in years)

 X_7 is household head working hours; dummy = 0 if working 8 hours per days, 1 otherwise

 X_8 is number of household work days; dummy = 0 if more than 5 days, 1 if less or equal 5 days

 X_9 is health status of household head; dummy = 0 if headed of the household is healthy, 1 otherwise

 X_{10} is number of male gender adults in households; dummy = 0 if male adults is higher, 1 for otherwise

 X_{11} is total of zakat received

X₁₂ is total income received.

2.6 Testing for multicollinearity

Multicollinearity among the variables may lead to a biasing effect on the parameters of a regression model. The results for Multicollinearity of this study are presented in Table 7.13 where two values are given: Tolerance and Variance Inflation Factor (VIF). Tolerance is an indicator of how of the variability of the specified independent is not explained by other independent variables in the model and is calculated using formula 1- R squared for each variable. If the value is small (less than 0.10) it indicates that the multiple colleration with other variables is high suggesting the possibility of multicollinearity. The other value given is the VIF which is just the inverse of the tolerance value (1 divided by Tolerance), values above 10 would indicating multicollinearity (Pallant, 2013).

From the collinearity diagnostics table depicted in Table 1, the Variance Inflation Factor (VIF) of all the independent variables was within the range of 1.074 to 2.347. The value is far less than 10 which there was no issue of collinearity between the predictor variables. The tolerance values of all the predictive variables of these data were within the range of 0.426 to 0.931, which were far above the critical tolerance value of 0.1 as suggested by Pallant (2013). Therefore, it could be concluded that there was no serious multicollinearity among the variables used in this predictive model.

T 1 1 1			0		4	
	Louous of ou	aatumaataa	+	the o	Lo oratro	#0.0#0.00t.0#
Tame I	Parameter	estimates	101	ine.	nousine	reoression
1 4010 1	 i urumeter	countates	101	une	ICLIDUC	regression
					<i>u</i>	<u> </u>

M- 1-1	Collinearity Statistics				
Model	Tolerance	VIF			
(Constant)	-	-			
HH_SIZE	.928	1.077			
REGION	.931	1.074			
HH_GENDER	.552	1.810			
EDU_FORMAL	.568	1.761			
HH_STATUS	.514	1.945			
HH AGE	.621	1.610			
MALE_ADULTS	.538	1.834			
NOM_WORK	.873	1.145			
WORK_HOURS	.854	1.172			
HEALTH_STATUS	.681	1.468			
INCOME	.470	2.129			
ZAKAT	.426	2.347			

3. Results and discussion

In general, the logit model fitted the data quite well. A test of the full model against a constant only model was statistically significant, indicating that the predictors as a set reliably distinguished between acceptors and decliners of the offer (chi square = 157.734, p < .000 with df = 10). The appropriate test for the overall significance of the model is the goodness-of-fit statistic. It is a test of the statistical significance of the combined effects of the independent variables within the model. The probability of the observed results, given the parameter estimates, is known as likelihood. In logistic regression goodness-of-fit is measured by the log-likelihood (LL) statistic. The log-likelihood statistic is analogous to the error sum of squares in multiple regression and as such is an indicator of how much unexplained information there is after the model has been fitted. Therefore, large values of the log-likelihood, the more unexplained observations there are.

In SPSS the measure of log-likelihood value is multiplied by -2 and is referred as -2LL. This multiplication is done because -2LL has an approximately chi-square distribution and so makes it possible to compare values against those that might be expect by chance alone. The chi-square for this statistic is used to test the significant level of the model. In this analysis the value of -2LL when only a constant was included in the model was 564.575. However, when all the 12 predictive variables were included in the model, the values of -2LL reduced to 123.047, the smaller value of -2LL suggesting the unexplained information in the model was minimised. For a perfect fit model, the value of -2LL would be equal to

zero. It was shown that the model was much better with independent variables included (in this case 12 predictive variables) rather than having only the constant.

In order to understand on how much the model predicts the outcome variable, the model chi-square statistic has to be calculated. This model chi-square was used as a measure of the difference between the model with predictive variables included and the model when only the constant was included. Therefore the value of the model chi-square statistic was equal to the value of -2LL when only the constant was included minus the value of -2LL with 12 predictive variables were included (699.633 - 129.275 = 570.358). This value has a chi-square distribution and in this analysis it was significant at p=<0.001 levels as depicted in Table 2. Therefore, the model was predicting survival significantly better than it was with only the constant included.

Table 2. Logistic regression model test results

55

Test for the Goodness of Fit of the Model						
-2 Log Likelihood	129.275	Significant				
Model Chi-square	570.358	0.000				
Improvement	570.358	0.000				

Cox and Snell's R-Square attempts to imitate multiple R-Square based on 'likelihood', but its maximum can be (and usually is) less than 1.0, making it difficult to interpret. Here, it is indicating that 84.1% of the variation in the DV is explained by the logistic model (Table 3). Results from Nagelkerke's R-Square (0.888) indicated a moderately strong relationship between prediction and grouping. The Nagelkerke modification that does range from 0 to 1 is a more reliable measure of the relationship. Nagelkerke's R-Square will normally be higher than the *Cox and Snell* measures. Nagelkerke's R-Square is part of SPSS output in the 'Model Summary' table and is the most-reported of the R-squared estimates. In our case it is 0.888, indicating a moderately strong relationship of 88.8% between the predictors and the prediction. Prediction success overall was 75.8% (76.7% for YES and 75.0% for NO).

Table 3. Logistic regression model summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square		
1	570.358ª	.841	.888		
F .: .: .	1 1 1 1 1 1 1		001		

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

The appropriate test for significance of individual variables in logistic regression is based on the parameter estimates. The parameter estimates of Table 4 contain the estimated beta coefficients for all 12 predictive variables of this model. The crucial statistic is the Wald statistic, which is the square of the ratio of the coefficient to its standard error. It is in the form of a chi-square distribution and tells whether or not the beta coefficient for that predictor is significantly different from zero. If the coefficient is significantly different from zero then it is assumed that the predictor is making a significant contribution to the prediction of the outcome (Y).

The 'B' values are the logistic coefficients that can be used to create a predictive equation (similar to the b values in linear regression). It can be interpreted as the change in the average value of Y, from one unit of change in X. The values can be positive or negative which will tell us about the direction of the relationships (which factors increase the likelihood of a yes answer and which factors decrease it). If the dependent and independent categorical variables are coded correctly (0 = poor and 1 = non poor), the negative B values indicate that an increase in the independent variable score will result in a decreased probability of the case recording a score of 1 in independent. Table 4 explain the results.

	В	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
					-	- · ·	Lower	Upper
HH SIZE*	.329	.149	4.889	1	.027	1.389	1.038	1.860
REGION*	.556	.208	7.169	1	.007	1.744	1.161	2.621
HH_GENDER*	630	.290	4.707	1	.030	.533	.302	.941
INCOME*	-1.507	.272	30.657	1	.000	.222	.130	.378
HH_EDUCATION*	072	.030	5.754	1	.016	.931	.878	.987
HH_STATUS*	422	.116	13.235	1	.000	.656	.523	.823
HH_AGE	.151	.143	1.113	1	.291	1.163	.879	1.539
NOM_WORK	286	.287	.997	1	.318	.751	.428	1.318
WORK_HOURS	.528	.409	1.663	1	.197	1.695	.760	3.782
HEALTH_STATUS	.289	.446	.421	1	.516	1.335	.558	3.198
MALE_ADULTS*	.055	.217	.063	1	.801	.047	.619	1.448
ZAKAT*	.002	.000	12.397	1	.000	.832	.761	1.002
Constant	.791	1.183	.447	1	.504	2.206		

Table 4. Parameter estimates for the logistic regression

a. Variable(s) entered on step 1: HH_SIZE, REGION, HH_GENDER, INCOME, HH_EDUCATION, HH_STATUS, HH AGE, NOM WORK, WORK HOURS, HEALTH STATUS, MALE ADULTS, ZAKAT.

b. Dependent Variable: 0 = Not Poor; 1= Poor

c. *p<0.05

The Wald statistic and associated probabilities provide an index of the significance of each predictor in the equation. The Wald statistic has a chi-square distribution. The simplest way to assess Wald is to take the significance values (Sig.) and if less than .05 (p< .05) reject the null hypothesis as the variable does make a significant contribution. The significant level for the Wald statistics for all predictor variables in the model equation was significant at 0.05 and 0.01 levels. The Wald criterion demonstrated that Household size (HH_SIZE), Region (REGION), Household Head Gender (HH_GENDER), Household Head Education (HH_EDUCATION), Household Head Marital Status (HH_STATUS), number of male adults in family (MALE_ADULTS), Income (INCOME) and Zakat (ZAKAT) were significant while age of Household head (HH_AGE), number of job (NOM_WORK), working hours (WORK HOURS) and Health status of Household Head (HEALTH STATUS) were not significant.

The Exp(B) column in Table 4 presents the extent to which raising the corresponding measure by one unit influences the odds ratio. We can interpret Exp(B) in terms of the change in odds. If the value exceeds 1 (>1) then the odds of an outcome occurring increase; if the figure is less than 1 (<1), any increase in the predictor leads to a drop in the odds of the outcome occurring. For example, the Exp(B) value associated with family size is 1.389 (more than 1). Hence, the odds of poverty when family size is raised by one unit (one person) the odds ratio is 13.89 per cent higher and therefore, the chances of householders to become poor is increased 13.89 per cent more.

The results show household size is an important determinant, which supports the findings of most previous researches (Lanjouw et al., 1995; Ray, 2000; Meenakshi et al., 2002; Peichl et al., 2012). The results show that higher household size increases the probability of a household falling into poverty. Based on Table 4, an increase in household size increases the probability of a household falling into poverty by 1.389. Basically, for those who have a bigger family, they will have mouth to feed compare to a smaller family which require higher expenditure. Basically, for those who have a bigger family, although they have higher expenditure, they also will higher have a higher income through paid employment which come from other member of the family. However in Kelantan, a high number of children (compare to adults) in the household which results a higher number of mouths to feed compare to a smaller family that will increase their expenditure and at the same time they have less income breadwinner for their family. Further, a high number of children in the household will make the family have less income breadwinner for their family. Thus, bigger size family will have a higher probability of falling into poverty.

Results of the study also found out that rural households are found to be at a higher risk compared to other regions. The rural household has 1.744 higher probability of falling poverty compared to urban household. Lower job opportunity and higher income job in rural area had make the rural resident has a higher chance of being in poverty. Further, the average number of earners and household adults' years of

education from the survey in rural area is 1.5 person and 9.5 years, respectively. This indicates that the average adults in the household (above 15 years old) are mainly seeking higher education in urban area and not generating income. Thus, this increases the family dependency ratio in rural areas. With the inclusion of number of children and elderly in households, this trend suggests that the rural households' incomes are insufficient to support the extended families. Hence, this would create a 'temporary' poverty until the adults seek employment. Therefore, with the low average earnings, the rural poor would certainly face hardship, especially with the rising cost of living. On the contrary, the results suggest that the household with male headed household reduces the chances of the household being poor by 2.47 per cent. This phenomenon could best be explained by the relatively high number of earners in the household among the female headed household.

The gender of the household head family show that the female household head family will have a greater chance of becoming poor with 0.55 higher chances of becoming poor. Lower income due to lack of capability to work in a job that is dominantly by male had make the female headed household, finding a job that is suitable with their capability, skills and qualification will be hard mostly with the competition from male gender (Moghadam, 1997; Makinwa-Adebusoye, 1988; Ruzika & Chowdhury, 1978; Ellickson, 1975; Cain et al., 1979; Tey, 1991; Youssef & Hetler, 1983; Kabeer, 2003; Klasen et.al, 2015). This result had supported our previous results that poverty is prevalent among the households with female household's head.

The results show education is an important determinant, which supports the findings of most previous researches (Wong et. Al., 2017; Thompson & McDowell, 1994; Rodriguez & Smith, 1994; Grootaert, 1995; Zake & Naude, 2002). Based on Table 4, an increase of a year of formal education after the mean number of years of the sample reduces the probability of a household falling into poverty by 0.931. The results also show that a higher household size increase the probability of a household falling into poverty. Status of the household head is also significant in determine the poverty of the family. From the results we can see that those who had partners (married or live separated) have 0.656 lower chances of being poor compared to household who has partners (not married or widow). This can be caused by higher number of income earners in the family that contribute more on fulfilling the expenses of the family.

A high number of adults in the household are expected to increase the income of the household through paid employment, thus reducing the incidence of poverty. Results show that an increase in male adults in household had reduced the chances of the household being poor. Results show that an increase of one male adult the chances of the household falling into poverty is reduced by 2.4 per cent. This phenomenon supports the relatively male household had become income earners of the family while for female household members a large number of years of education had made them less contribute to family income.

The results show income of the household is an important determinant, which supports the findings of most previous researches (Narayan et al., 1999; Rao et al., 2011; MacInnes et al., 2013; House et al., 2013). An increase in income of the poor and needy had reduced 0.222 the probability of them falling into poverty. It is obvious that the higher the income, the well-off the household will be. Zakat distribution has the highest significant effect towards eliminating poverty for the poor and needy. Zakat distribution has a positive effect towards improving the income distribution of the poor and needy because through zakat distribution the probability of a household becoming non poor is 0.832. It shows how significant the role of zakat fund towards reducing the burden of poverty which increases their income and purchasing power of the poor and needy.

4. Conclusion

This article indicates that size, gender, status, highest education, income, region and zakat received variables have a significant effect towards determinant factor for poverty while age, number of job, working hours and household head health status variables did not have any significant effect towards determinant factor for poverty among the poor and needy. It is a signal that those who have a bigger family, they have higher expenses and acquire more needs compare to a smaller family who mostly

acquire smaller amount of expenses. Family size is closely related to child poverty, with larger families at greater risk of poverty, including persistent poverty. The percentage of children living in poverty rises considerably for families with three or more children. Single parent households, where the ratio between adults and dependent children is lowest, are at particular risk. Further, larger families have greater caring responsibilities and are more likely to contain younger children which impacts on parental labour market engagement. In addition, large families are at considerable extra risk of being poor both in the year before they become large and in the two years after the older children become adults and the family is no longer large. Bigger family will require higher need such as larger amount of food, better house, and higher expenses for education and medication compared to smaller family size. Furthermore, education reflects the human's ability to succeed both academically and socially. It requires physical well-being and appropriate motor development, emotional health and a positive approach to new experiences, age-appropriate language skills, and age-appropriate general knowledge and cognitive skills. Higher education will result a better job opportunity and a better income which can reduce their probability of becoming poor.

Further, urban and rural region has a different phenomenon of poverty. There is a further need to consider a set of prices including a broader bundle of goods and services representative of the purchases of consumers in different region. The rural poor, who are unable to compete for scarce resources or protect themselves from harmful environmental conditions, are most affected by the negative impacts of urbanization. Less job opportunity and higher income job in rural area has been accompanied by an increase in rural poverty which tends to be concentrated in certain social groups and in particular locations. Causes include an increasing gap between incomes and land prices, and the failure of housing markets to provide for low-income groups.

The gender of household head shows that female household head mostly a single mother is often deliberated as more severe than male parent households because they are not only dispossessed of an adult male's earnings, but have more dependents to support. In terms of time and energy constraint, female household heads have less time and energy to perform the full range of non-market work that is so vital to income saving among poor household, such as finding the cheapest foodstuffs, or self-made rather than purchase. Instead, their source of finding income often limited to part-time, flexible, or home-based occupations. This is exacerbated by women's disadvantage in respect of education and skills, low average earnings, gender discrimination in the workplace, and minimal support for parenting. Female headed households also have more disadvantages in labour supply and most of the opportunities are given to the male members. Studies in Vietnam, Bangladesh and South Africa suggest that female has a lower average earnings and this had caused a nearly unconditional risk of poverty in households that mostly have only female members.

Further, the current method in which zakat was distributed did not differentiate between the true cost of living between urban and rural. Income of the poor and needy certainly contributes to the probability of them falling into poverty. Most of them require economic supports which most of them lost their financial resources results from less opportunity of job, lower skills and lower education. Lastly, zakat distribution has a significant effect on bringing the poor and needy out of poverty. It improves the income as well as the expenditure of the poor and needy. Further, they will have a higher purchasing power which can bring them out of poverty. The right allocation of zakat distribution can bring more effective result on reducing poverty and income gap of a family rather than distributing the zakat based on the amount and omitting these variables.

The age, number of job, working hours and household head health status variables did not show any significance effect towards determinant factor for poverty among the poor and needy. The age distribution reveals that majority of the poor and needy were energetic, young and agile to actively participate in the programme activities. Hence, they will be expected to benefit immensely from the programme and improve their productivity to reduce their poverty level. Evidence indicates that poverty among older people is generally low in countries where there exists a generous pension or safety net coverage for the elderly. It is now widely recognized that in developing countries older people and reducing poverty. Moreover, evidence suggests that in developing countries the positive effects of pensions go

beyond the direct beneficiaries (the older people) and spill over on the other members of their households. This study reveals that the number of job, working hours and household head health of the poor and needy towards the poverty was not significant. This result is in line with the observation that had been made by previous study that most of the poor and needy participation in the economic activities are involved in non-formal or business activities at average level where they feel that their income is sufficient enough for their family.

References

- Alderman, H., & Garcia, M. (1993). Poverty, household food security, and nutrition in rural Pakistan (Vol. 96). Intl Food Policy Res Inst.
- Ali, A. F. M., Rashid, Z. A., Johari, F., & Aziz, M. R. A. (2015). The Effectiveness of Zakat in Reducing Poverty Incident: An Analysis in Kelantan, Malaysia. Asian Social Science, 11(21), p355.
- Ali, A. F. M., & Ab Aziz, M. R. (2014). Zakat Poverty Line Index and Gender Poverty in Malaysia: Some Issues and Practices. *International Journal of Business and Social Science*, 5(10).
- Bardhan, P. K. (1984). Land, labor, and rural poverty: Essays in development economics. Columbia University Press.
- Cain, M., Khanam, S. R., & Mahmud, S. N. (1979). Class, patriarchy, and the structure of women's work in rural Bangladesh (No. 43). Population Council.
- Deaton, A., & Muellbauer, J. (1980). An almost ideal demand system. The American economic review, 312-326.
- Diamond, C. A., Simon, C. J., & Warner, J. T. (1990). A multinomial probability model of size income distribution. Journal of Econometrics, 43(1), 43-61.
- Unit, E. P. (2006). Ninth Malaysia Plan 2006-2010. Percetakan Nasional Malaysia Berhad, Kuala Lumpur, 490-498.
- Egondi, T., Oyolola, M., Mutua, M. K., & Elung'ata, P. (2015). Determinants of immunization inequality among urban poor children: evidence from Nairobi's informal settlements. International journal for equity in health, 14(1), 24.
- Eliot, T. S. (1995). Tradition and the individual talent. NEW STUDIES IN AESTHETICS, 26, 61-72.
- Ellickson, J. (1975). "Rural Women", Women for Women: Bangladesh, University Press. Dacca.
- Field, A. (2013). Discovering statistics using IBM SPSS statistics. Sage.
- Foster, J. E., & Santos, M. E. (2013). Measuring chronic poverty. G. Betti and A. Lemmi (eds.).
- Gaddis, I., & Klasen, S. (2014). Economic development, structural change, and women's labor force participation. Journal of Population Economics, 27(3), 639-681.
- Gaiha, R. (1988). Income mobility in rural India. Economic Development and Cultural Change, 279-302.
- Glewwe, P. (1991). Investigating the determinants of household welfare in Côte d'Ivoire. journal of Development Economics, 35(2), 307-337.
- Grootaert, C. (1997). The Determinants of Poverty in Cote d'Ivoire in the 1980s. Journal of African Economies, 6(2), 169-196.

- Grootaert, C., Kanbur, R., & Oh, G. T. (1995). The dynamics of poverty: why some people escape from poverty and others don't-an African case study (No. 1499). The World Bank.
- Hair, J. F., Wolfinbarger, M. F., Ortinau, D. J., & Bush, R. P. (2008). Essentials of marketing research. McGraw-Hill/Higher Education.
- Hentschel, J., Lanjouw, J. O., Lanjouw, P., & Poggi, J. (2000). Combining census and survey data to trace the spatial dimensions of poverty: A case study of Ecuador. The World Bank Economic Review, 14(1), 147-165.
- House, J. S., Kessler, R. C., Herzog, A. R., Mero, R. P., Kinney, A. M., & Breslow, M. J. (2013). Social stratification, age, and health. In *Aging, health behaviors, and health outcomes* (pp. 13-44). Psychology Press.
- Kabeer, N. (2003). Gender Mainstreaming in Poverty Eradication and the Millennium Development Goals: A handbook for policy-makers and other stakeholders. Commonwealth Secretariat.
- Kemsley, W. F. F. (1961). The Household Expenditure Enquiry of the Ministry of Labour: Variability in the 1953-54 Enquiry. Applied Statistics, 117-135.
- Kemsley, W. F., & Nicholson, J. L. (1960). Some experiments in methods of conducting Family Expenditure Surveys. Journal of the Royal Statistical Society. Series A (General), 307-328.
- Klasen, Stephan; Lechtenfeld, Tobias and Povel, Felix (2015) 'A feminization of vulnerability? Female headship, poverty, and vulnerability in Thailand and Vietnam', *World Development*, 71(C), 36–51.
- Krishna, A., Kapila, M., Porwal, M., & Singh, V. (2005). Why growth is not enough: Household poverty dynamics in Northeast Gujarat, India. Journal of Development Studies, 41(7), 1163-1192.
- Lanjouw, P., & Ravallion, M. (1995). Poverty and household size. The economic journal, 1415-1434.
- Lanjouw, P., & Stern, N. (1991). Poverty in Palanpur. The World Bank Economic Review, 23-55.
- Lewis, O. (1948). On the edge of the Black Waxy: a cultural survey of Bell County, Texas (No. 7). University Studies.
- MacInnes, T., Parekh, A. & Kenway, P., (2011). London's Poverty Profile 2011, London: New Policy Institute.
- Makinwa-Adebusoye, P. K. (1988). Upgrading and Urban Squatter Settlement in Nigeria: the experiment in Olaleye-Iponri. Urban Services in Developing Countries, 175-194.
- McDowell, D. R., & Allen-Smith, J. E. (1995). Poverty Among Southern Workers: Metro and Nonmetro Differentials. American Journal of Agricultural Economics, 77(3), 796-802.
- Meenakshi, J. V., & Ray, R. (2002). Impact of household size and family composition on poverty in rural India. Journal of Policy Modeling, 24(6), 539-559.
- Menken, J., & Phillips, J. F. (1990). Population change in a rural area of Bangladesh, 1967-87. The Annals of the American Academy of Political and Social Science, 510(1), 87-101.
- Moghadam, V. M. (1997). The Feminization of Poverty?: Notes on a Concept and Trends. Illinois State University, Women's Studies Program.
- Mok, T. Y., Gan, C., & Sanyal, A. (2007). The determinants of urban household poverty in Malaysia. Journal of Social Sciences, 3(4), 190-196.

- Mukherjee, S., & Benson, T. (2003). The determinants of poverty in Malawi, 1998. World Development, 31(2), 339-358.
- Narayan, D., & Pritchett, L. (1999). Cents and sociability: Household income and social capital in rural Tanzania. Economic development and cultural change, 47(4), 871-897.
- Ntuli, M. (2007). Determinants of South African women's labour force participation, 1995-2004.
- Pallant, J. (2013). SPSS survival manual. McGraw-Hill Education (UK).

61

- Peichl, A., Pestel, N., & Schneider, H. (2012). Does size matter? The impact of changes in household structure on income distribution in Germany. Review of Income and Wealth, 58(1), 118-141.
- Perera, P. J., Fernanado, M. P., Ranathunga, N., Sampath, W., Samaranayake, R., & Meththananda, S. (2014). Growth parameters of Sri Lankan children during infancy: A comparison with world health organization multicentre growth reference study. Journal of Human Growth and Development, 24(1), 11-15.
- Ranathunga, S. (2015). Do poverty determinants differ over expenditure deciles? A Sri Lankan case from 1990 to 2010.
- Rao, E. J. and M. Qaim. (2011). Supermarkets, farm household income, and poverty: insights from Kenya. World Development 39(5):784-796.
- Ray, R. (2000). Poverty, household size and child welfare in India. Economic and Political Weekly, 3511-3520.
- Rodriguez, A. G., & Smith, S. M. (1994). A comparison of determinants of urban, rural and farm poverty in Costa Rica. World Development, 22(3), 381-397.
- Serumaga Zake, P., & Naudé, W. (2002). The determinants of rural and urban household poverty in the North West province of South Africa. Development Southern Africa, 19(4), 561-572.
- Sudman, S., & Ferber, R. (1971). Experiments in obtaining consumer expenditures by diary methods. Journal of the American statistical Association,66(336), 725-735.
- Stern, S. (1995). Estimating family long-term care decisions in the presence of endogenous child characteristics. *Journal of human Resources*, 551-580.
- Thompson, A., & McDowell, D. R. (1994). Determinants of poverty among workers in metro and nonmetro areas of the South. The Review of Black Political Economy, 22(4), 159-177.
- Turner, R. (1961). Inter-week variations in expenditure recorded during a two-week survey of family expenditure. Applied Statistics, 136-146.
- Wong, M., & Morton, M. (2017). Parents' Lived Experiences of Teachers' Construction of Giftedness. In *Inclusive Education* (pp. 213-229). SensePublishers, Rotterdam.
- Youssef, N. H., & Hetler, C. B. (1983). Establishing the economic condition of woman-headed households in the Third World: a new approach.